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Time-varying spillover effects within and between industrial metal markets

Amelie Schischke¹ · Andreas Rathgeber¹

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Abstract

In this study, we examine the evolution of commodity markets, focusing on the role of fundamentals and cross-market co-movement in shaping commodity price dynamics over time. To capture these time-varying spillover effects, we apply a Markov-switching global vector autoregressive (MS-GVAR) model to industrial metal markets in the period from January 1995 to December 2020. By distinguishing between calm and volatile regimes, our results reveal significant cross-commodity responses, emphasizing the importance of modeling commodity markets jointly. Spillover effects from supply and demand fundamentals within and across markets further highlight the critical role of fundamental drivers in commodity price formation. While the significance of spillover effects remains consistent across regimes, their magnitude intensifies during volatile periods, indicating heightened spillover risks. Additionally, we demonstrate that our time-varying model provides a superior representation of interdependencies between commodity prices compared to a time-invariant benchmark model, as validated through an out-of-sample forecasting analysis.

Keywords Time-varying spillover effects · Industrial metal markets · Co-movement · Microeconomic factors · Markov-switching global vector autoregressive model

Introduction

Industrial metals, as their name suggests, are fundamental to industrial processes and are often co-mined and increasingly traded on a global scale. Over the past two decades, an emerging trend has seen a growing integration of diverse raw materials into individual products, driving an increase in demand, see Reller (2011) and Zhou (2023) among others. Whereas in the 1980s, consumer goods typically contained only a few elements, modern production can require up to 40 different elements. These shared production and processing dependencies contribute to a synchronization of supply and demand volumes, which in turn fosters greater co-movement in commodity prices. At the same time, metals are also used

as financial assets, attracting investor demand that can further drive price synchronization. However, this investment-driven demand is inherently more volatile, leading to excess co-movement, where commodity prices move more closely together than can be explained by fundamental supply and demand factors alone, suggesting the influence of financial market dynamics beyond real economic linkages.

The seminal study by Pindyck and Rotemberg (1990) first identified the phenomenon of excess co-movement among commodity prices, prompting extensive research into its determinants and magnitude, see Byrne et al. (2013) and West and Wong (2014) among others. More recent studies, such as Le Pen and Sévi (2017); Ohashi and Okimoto (2016); Poncela et al. (2014) and Yin and Han (2015), reveal that commodity price co-movement varies over time, with several attributing its increase to the financialization, of commodity markets. However, Zarembo et al. (2021) challenge this view, arguing that financialization did not cause an unprecedented surge in co-movement, as similar peaks occurred in earlier periods, suggesting alternating phases of strong synchronization and more divergent price behavior. While Zhang and Broadstock (2020) suggest the co-dependence among commodity classes tripled after the global financial crisis,

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Peersman et al (2021) name, besides the financialization, the demand increase from emerging countries, as well as spillovers due to substitutions as possible reasons for the stronger co-movement in commodity prices and underline the importance of time-varying analyses of commodity markets. In this context, the question arises how the interdependencies between commodity markets changes over time.

Our initial graphical analysis of the aluminum and copper price and their returns, presented in Fig. 1, displays similar patterns in both prices, whereby the copper price fluctuates more. The time-varying standard deviation, calculated using a rolling 18-month window¹ underline copper prices exhibit greater volatility, particularly during the financial crisis. Moreover, the bi-variate and time-varying correlation analysis based on the rolling 18 months² Pearson correlations, reveals the correlations between the prices fluctuate around the time-invariant correlation based on the entire sample period from 1995 to 2020, underlining previous findings of time-varying co-movement between commodity prices. Thereby, periods of higher correlation coincide with phases of financialization and the commodity price boom, consistent with Peersman et al (2021). However, the sharp oil price decline in 2014, combined with slowing Chinese demand, led to a drop in copper prices, while supply concerns drove up aluminum prices. Ultimately, as industrial metals are fundamentally driven by individual supply and demand conditions, the commodity-specific shocks of 2014 resulted in a divergence in metal price correlations.

This graphical analysis underscores that time-independent analyses of commodity price relationships, or simple trend analyses, fail to fully capture the complex interactions within commodity markets. Moreover, our findings suggest that major market disruptions, particularly crises, amplify price co-movement, reinforcing the need for a dynamic approach to studying commodity market interdependencies.

In this context, the question arises how the structure and interconnections of commodity markets evolve over time. To address this, we aim to disentangle the interdependencies within and between commodity markets, while accounting for both commodity-specific and global determinants of price dynamics. Hereby, we model the industrial metal markets within a Global Vector Autoregressive (GVAR) framework, originally introduced by Pesaran et al. (2004) for economies and later extended to commodity markets by Schischke et al. (2024). To account for time-varying

relationships, we integrate a Markov-Switching component, following Binder and Gross (2013), which allows for regime-dependent dynamics in commodity markets. Unlike previous studies, we are the first to apply the Markov-Switching Global Vector Autoregressive (MS-GVAR) model to commodity markets, capturing time-varying spillover effects not only between commodity prices but also across supply, demand, and price interactions within and between industrial metals. Given the structural shifts in commodity markets, such as financialization, a dynamic analysis is essential. Hereby, our study contributes to the literature by employing the MS-GVAR model to disentangle the evolution of market linkages over time, offering deeper insights into spillover effects, particularly their shifts between calm and volatile periods, a crucial aspect that traditional time-invariant models fail to capture. To further underscore the importance of a time-varying approach, we evaluate out-of-sample forecasting performance, demonstrating that our methodology offers superior insights compared to time-invariant models. By applying the econometric framework to commodity markets, our study offers new insights into the dynamic nature of industrial metal markets, filling a critical gap in the literature on time-dependent commodity price interdependencies.

Analyzing the regime inference of each commodity market, we detect the aluminum, copper, lead, tin and zinc markets are stable, as they show long periods in the calm regime with only few (brief) periods in the volatile regime, which correspond to the commodity price boom, the financial crisis, the European debt crisis as well as the oil price drop in 2015. In contrast, the nickel market displays fluctuations between the regimes. Under two distinct regimes (calm/volatile), we examine spillover effects in commodity markets using generalized impulse response functions. Our analysis reveals numerous significant cross-commodity responses in both regime configurations, emphasizing the necessity of jointly modeling commodity markets. Hereby, various spillover effects from supply and demand variables within and across the commodity markets highlight the importance of fundamentals in commodity models. Moreover, our analysis identifies strong interdependencies between the commodities, in particular, between the prices.

While we do not observe significant differences in the presence of spillover effects between the calm and volatile regimes, their magnitude is consistently larger in the volatile regime. This suggests that market reactions to shocks intensify during periods of high volatility, leading to elevated spillover risks. Albeit the significance in responses do not change across the regimes, the out-of-sample forecast analysis underlines the importance of a time-varying consideration of commodity markets, as the MS-GVAR model significantly outperforms the time-invariant GVAR model. Moreover, the time-varying model reflects the dependency structure over time.

¹ To reduce the impact of potential influential points, we only include data of the previous 18 months, however, the rolling window measures based on 24 or 36 months reveal similar patterns.

² Similar to the time-varying standard deviations, the rolling window correlations based on 24 or 36 months reveal analogous patterns. In particular, the time-varying correlations fluctuate and do not follow a trend. Moreover, the correlations between all industrial metals show a comparable behavior.

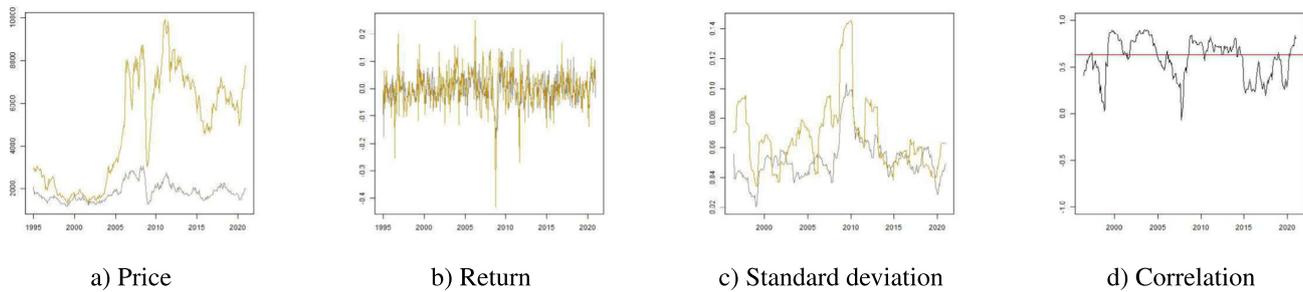


Fig. 1 These figures show the monthly prices and their returns of aluminum (Al) and copper (Cu) over the entire sample period from January 1995 to December 2020, the time-varying standard deviation of the prices, based on a rolling window, capturing 18 months, as well as

the correlation between the two prices. Hereby, the Pearson correlation is calculated based on a rolling window capturing 18 months and the red line indicates the corresponding correlation derived over the entire sample period from January 1995 to December 2020

The remainder of this paper is structured as follows: Section “[Overview of commodity markets](#)” provides an overview over previous empirical work on commodity markets. In Section “[Methodological framework](#)”, the methodological approach is presented in detail. The empirical analysis, as well as the results, are described in Sections “[Empirical application to industrial metal markets](#)” and “[Empirical results](#)”, while Section “[Conclusion](#)” concludes.

Overview of commodity markets

In the following, we provide a brief literature overview on important determinants of commodity prices. First of all, industrial metals are industrial goods in real economies and, particularly, key elements of industrial and technological development. Therefore, economic factors, representing the global demand, as well as commodity-specific supply and demand changes affect their prices due to the classical fundamental theory. Moreover, empirical studies detect commodity prices co-move together, indicating the commodity markets are interrelated.

Determinants of commodity markets

According to the classical fundamental theory, a good’s price is the result of its supply and demand equilibrium, see Hotelling (1931); Deaton and Laroque (2003); Frankel and Rose (2010). Therefore, the prices of commodities, especially of industrial metals, are theoretically determined by the commodity-specific supply and demand.

Empirical studies provide strong evidence supporting this fundamental relationship. Lutzenberger et al. (2017) highlight the significance of global mine production, secondary production, reserves, and stock levels in shaping metal prices, while Shojaeinia (2023) emphasizes the crucial role of supply and demand in shaping copper prices. Similarly, Chen

et al. (2019) confirm that fundamental factors remain key drivers of copper prices, even after the financialization of commodity markets. Papenfuß et al. (2025) further demonstrate that metal-specific demand is an influential predictor of metal prices, especially in more recent periods.

Given the challenges in obtaining granular supply and demand data, many studies use economic activity as a proxy for global demand. Empirical findings consistently indicate that rising economic activity leads to significant increases in commodity prices, see for example (Akram 2009; Issler et al. 2014; Kagraoka 2016) and Lombardi et al. (2012). Hereby, Ahumada and Cornejo (2014) provide further insight by identifying long-run price effects of supply fluctuations and a negative elasticity of real commodity prices with respect to production. While Stuermer (2018) finds mixed evidence regarding supply effects, his findings suggest that long-term demand growth, particularly driven by technological advancements, plays a dominant role in shaping metal prices. In contrast, Guzmán and Silva (2018) find that commodity prices are predominantly influenced by demand in the short run, whereas supply factors play a larger role in the long-term. Additionally, Frankel and Rose (2010) attribute the commodity price boom of the mid-2000s to increased demand resulting from the rapid economic growth of emerging markets and the rise of biofuels.

Collectively, these studies highlight the strong link between global demand, suggesting that broader macroeconomic conditions significantly shape commodity price fluctuations. Consequently, additional macroeconomic factors, such as exchange rates and interest rates, have been explored in the literature, see Vansteenkiste (2009) for example.

Since commodities are globally traded in U.S. dollars, but are rarely mined in the United States, a stronger dollar typically leads to lower commodity prices, due to the law of one price, according to Akram (2009). Besides Akram (2009), several studies empirically validate this negative relation between the real dollar exchange rate and commodity

prices, see Ahumada and Cornejo (2014); Baffes and Savescu (2014); Lombardi et al. (2012), and Zhu et al. (2015) among others.

While previous empirical analyses underline the impact of exchange rates on commodity prices, the empirical evidence for the effect of interest rates on commodity prices is mixed. Theoretically, lower interest rates should increase the demand and ultimately the price for commodities, due to reduced carrying costs, while simultaneously decreasing the supply, due to a less profitable extraction, according to Frankel (2008). Hereby, Akram (2009); Byrne et al. (2013) as well as Anzuini et al. (2013) empirically confirm the significant, negative impact of interest rate shocks on commodity prices, whereas Lombardi et al. (2012) and Zhu et al. (2015) do not find any significant effects and Hammoudeh et al. (2015) and Schischke and Rathgeber (2023) even detect a positive relation.

Co-movement of commodity prices

As macroeconomic variables, like the economic activity, exchange rates and interest rates, influence all commodities simultaneously, commodity prices tend to move in a synchronized way, a phenomenon called co-movement. Hereby, several studies attribute the co-movement, at least partly, to a common factor, described by macroeconomic determinants, see Byrne et al. (2013); Chen et al. (2014); Kozian et al. (2025); Liao et al. (2024); Lombardi et al. (2012), and Nicola et al. (2016). In addition, studies attempt to characterize the extent of the co-movement between prices, see *inter alia* (Le Pen and Sévi 2017; Tang and Xiong 2012; West and Wong 2014; Yin and Han 2015) and Zhang et al. (2019). However, the analyses draw different conclusions, dependent on the commodities and period under consideration. Byrne et al. (2013) identify one common factor which is related to interest rates and risk in their long-term analysis of 24 commodities, whereas Chen et al. (2014) detect two underlying common factors in 51 commodity prices, one stationary and one non-stationary, captured by the exchange rate. Further, Lombardi et al. (2012) explain the common trends in 15 individual commodity prices by a food or metals factor, while Yin and Han (2015) decompose 24 commodity prices into global, sectoral and commodity-specific components and detect a significant increase in the impact of the global as well as the sectoral component around 2004, when commodity index investment started. In contrast, Shahani and Singhal (2023) detect no cointegration relationship in the Indian metal prices of aluminium, copper, zinc, nickel and lead in the period from 2016 to 2020. Overall, the results in previous studies indicate common factors underlying in commodity prices, however, the main determinants differ between the studies.

Besides the simultaneous influence of the economy on commodity markets, the commodities are interrelated themselves

via co-production and co-consumption links. On the one hand, several metals are mined together, according to Bigerna and Campbell (2025) and Nassar et al. (2015). Hereby, Su et al. (2024) detect the spillover effects between copper and its by-products cobalt and nickel exhibit time-dependent fluctuations. On the other hand, metals are consumed together. For instance, aluminum and copper are both important metals for automotive applications, see Keyvani et al. (2025); Sivanur et al. (2021), and Zapp et al. (2002).

However, the empirically observed co-movement of prices on exchanges is larger than what would be explainable either by the common consumption and production of commodities or by the common factor, reflecting the common effects of macroeconomic determinants, see Pindyck and Rotemberg (1990). Hereby, Pindyck and Rotemberg (1990) were the first introducing the concept of excess co-movement, as they detect even unrelated commodities co-move. Nevertheless, the evidence in the literature is ambiguous, depending on the methodology applied, the included control variables as well as the considered time period.

In this context, Deb et al. (1996) only find weak to no evidence for the excess co-movement hypothesis. While Lescaroux (2009) confirms common patterns in 51 commodities, he also rejects the excess co-movement hypothesis, as the observed co-movement is mostly caused by common macroeconomic shocks on the supply and demand of the commodities. Moreover, Nicola et al. (2016) conclude energy and agricultural commodities are highly correlated with an increasing co-movement. However, besides an increasing long-run trend, starting at the beginning of the 21st century, Ohashi and Okimoto (2016) only find little short-run fluctuations. Further, the reinvestigation study of Le Pen and Sévi (2017) detects a measure of speculative intensity mainly determines the excess co-movement and attributes their results to the financialization in commodity prices. In addition, Fernandez (2015) tests for the excess co-movement in twelve commodities and confirms the extent of the excess co-movement varies over time.

In this context, the time-variation in the co-movement can be partly explained by the financialization and the financial crisis, which affected the commodity markets and their interrelations. Hereby, Basak and Pavlova (2016) state the increasing investments of index funds in commodity markets should theoretically elevate the co-movement. This hypothesis is empirically underlined in the study of Tang and Xiong (2012), as the authors detect an increase in the co-movement of commodities, starting in the year 2004, due to the financialization, which is stronger for indexed commodities, a trend that has been further confirmed in more recent periods by Kang et al. (2023). Moreover, Poncela et al. (2014) find an increased synchronization among raw materials since December 2003, further confirming the financialization changed the relationship between commodity

markets has changed fundamentally after underwent a fundamental transformation following the global financial crisis, with co-dependence among seven major commodity classes tripling. In addition, Aepli et al. (2017) emphasize the correlation structure in commodity markets changed during the financial crisis, whereas Lübbers and Posch (2016) detect an increased co-movement during this period. Moreover, Peersman et al (2021) name, inter alia, the demand increase from emerging countries, as well as spillovers due to substitutions as possible reasons for the stronger co-movement in commodity prices. In particular, they underline the importance of time-varying analyses of commodity markets. This is further emphasized by Zaremba et al. (2021). They doubt the financialization caused an unprecedented surge in the co-movement, as in their long-term analysis of the past 150 years they detect similar peaks in earlier periods, suggesting the commodity prices observe periods of strong similar patterns, followed by periods of more divergent price behavior. In this line, Ciner et al. (2020) also observe periods of increasing and decreasing co-movement between the LME non-ferrous industrial metal prices during the period from 1994 to 2016, whereby the spillover effects were stronger after the financial crisis.

Overall, several studies underline the impact of supply and demand on commodity prices, however, they predominantly focus on individual commodity markets, neglecting crucial cross-market linkages that shape price interdependencies. Furthermore, due to data limitations, most studies approximate commodity-specific factors using broader global indicators, potentially overlooking important market-specific dynamics. Additionally, prior research consistently finds that commodity prices exhibit synchronized movements, further highlighting the interconnected nature of these markets. While several studies aim to explain the co-movement, at least partly, by a common factor, Pindyck and Rotemberg (1990) reveal an excess co-movement, underlining the importance to jointly model commodity markets. Moreover, due to the rapidly growing index investments in commodity markets, starting in the early 2000s, the co-movement in commodity prices as well as the connectedness with the stock markets increased, see Büyüksahin and Robe (2014) and Tang and Xiong (2012). In particular, the financialization and the financial crisis significantly changed the commodity market structure, highlighting the importance of time-varying analyses of commodity markets.

Methodological framework

The objective of this study is the analysis of the time-varying impact of fundamentals on, as well as the time-varying co-movement between, commodity prices. Therefore, we extend

the idea proposed in Schischke et al. (2024), who jointly model commodity markets, to a Markov-switching global vector autoregressive (MS-GVAR) model, similar to Binder and Gross (2013), which allows for time-varying relations in the markets.

Hereby, the MS-GVAR framework is particularly well-suited for modeling time-varying spillovers in industrial metal markets, as it directly reflects the dual nature of metals as both industrial goods and financial assets.³ Classical fundamental theory, as proposed by Hotelling (1931), posits that commodity prices are determined by the equilibrium between supply and demand. This relationship has been empirically validated by Deaton and Laroque (2003), who confirm the fundamental role of market forces in price formation, with supply being represented by the actual production of commodities. However, industrial metals are also subject to speculative trading and macroeconomic shocks, which influence their price formation beyond pure physical market dynamics, with speculation potentially amplifying market volatility. The MS-GVAR model is particularly effective in this context, as it allows for regime-dependent spillover effects, capturing how supply, demand, and price interdependencies evolve across calm and volatile periods. Alternative frameworks, such as considering only the relationship between production and consumption, may overlook the role of co-movement in price formation, particularly as economic cycles can amplify co-movement by driving higher common demand for commodities. Similarly, a macroeconomic-commodity-specific model may capture broad market trends but lacks the granularity to assess cross-market spillovers within the industrial metals sector. By integrating supply, demand, and price in a time-varying setting, our approach provides a comprehensive framework for understanding how industrial metals respond to market conditions and policy changes over time.

In particular, we first apply individual M -state Markov-switching vector autoregressive models of order P (MS(M)-VAR(P))⁴ on all commodities $i = 1, 2, \dots, N$ of the analysis to account for the commodity-specific interdependencies between supply, demand and price, approximated

³ Traditional time-varying models such as the Constant Conditional Correlation (CCC) model by Bollerslev (1990) and the Dynamic Conditional Correlation (DCC) model by Engle (2002) have been widely applied in financial econometrics to capture time-varying correlations among asset returns. While these models are effective in identifying volatility co-movements, our study focuses on modeling structural interdependencies and spillover effects across supply, demand, and price within and between industrial metal markets. The Markov-switching GVAR framework is more suitable for this objective as it allows for regime-dependent dynamics and accommodates both contemporaneous and lagged interrelations among variables across markets.

⁴ In the terminology of Krolzig (1997), we focus on MS-VAR models with switching intercept and not on mean adjusted VAR models. Please refer to Krolzig (1997) for more details on MSM-VAR models.

by production, consumption and price data, see Section 4.1. Subsequently, we aggregate the individual models to a global commodity market model, allowing for time-varying spillover effects between the commodities.

Individual commodity market models

First of all, we reflect the relation between the individual, commodity-specific supply (**supply**_{*i*}), demand (**demand**_{*i*}) and price (**price**_{*i*}) of each commodity market, which form the ($K_i \times 1$) vector $\mathbf{x}_{i,t} = (\text{supply}_{i,t}, \text{demand}_{i,t}, \text{price}_{i,t})'$, for all time periods, $t = 1, 2, \dots, T$, via commodity-specific Markov-switching vector autoregressive (MS(M)-VAR(P)) models with M states and P lags, allowing for time-varying dependencies. In addition, we consider the impact of the economy on commodity markets, reflecting the common factor, by the exogenous vector \mathbf{e}_t of K_{exog} macroeconomic variables.

Further, we aim to account for the interdependencies between the commodity markets. Therefore, we extend the MS-VAR models by the $K_i^* \times 1$ vector $\mathbf{x}_{i,t}^* = (\text{supply}_{i,t}^*, \text{demand}_{i,t}^*, \text{price}_{i,t}^*)'$ of weighted external variables specific to commodity i , representing the aggregated impact of the other commodities on commodity i :

$$\begin{aligned} \text{supply}_{i,t}^* &= \sum_{\tilde{i}=1}^N w_{i,\tilde{i}} \cdot \text{supply}_{\tilde{i},t}, \text{demand}_{i,t}^* = \sum_{\tilde{i}=1}^N w_{i,\tilde{i}} \cdot \text{demand}_{\tilde{i},t}, \\ \text{price}_{i,t}^* &= \sum_{\tilde{i}=1}^N w_{i,\tilde{i}} \cdot \text{price}_{\tilde{i},t}, \end{aligned}$$

with weights $w_{i,i} = 0$ and $\sum_{\tilde{i}=1}^N w_{i,\tilde{i}} = 1$, for $i = 1, 2, \dots, N$. Hereby, the corresponding individual weights $w_{i,\tilde{i}}$ may be aggregated to a weight matrix $(w_{i,\tilde{i}})_{i,\tilde{i}=1,2,\dots,N}$.

This leads to the following MS(M)-VAR(P) model for commodity i :

$$\begin{aligned} \mathbf{x}_{i,t} &= \mathbf{a}_{i,0,s_{i,t}} + \sum_{p=1}^P \Phi_{i,p,s_{i,t}} \mathbf{x}_{i,t-p} + \sum_{p=0}^P \Lambda_{i,p,s_{i,t}} \mathbf{x}_{i,t-p}^* \\ &\quad + \sum_{p=0}^{P_{exog}} \Psi_{i,p,s_{i,t}} \mathbf{e}_{t-p} + \mathbf{e}_{i,t}, \end{aligned} \tag{1}$$

where $\mathbf{a}_{i,0,s_{i,t}}$ denotes the intercept, $\Phi_{i,p,s_{i,t}}$ are the $K_i \times K_i$ matrices of lagged coefficients for lag $p = 1, 2, \dots, P$, and $K_i = 3$ denotes the length of vector $\mathbf{x}_{i,t}$ for $i = 1, 2, \dots, N$. Moreover, the $K_i \times K_{exog}$ matrices $\Psi_{i,p,s_{i,t}}$ are the corresponding coefficients of the exogenous variables \mathbf{e}_t , for lags $p = 0, 1, \dots, P_{exog}$. In addition, $\Lambda_{i,p,s_{i,t}}$ are $K_i \times K_i^*$ matrices of coefficients associated with the (lagged) weakly

exogenous, external variables for $p = 0, 1, \dots, P$,⁵ and in our case $K_i = K_i^* = 3$ for all $i = 1, 2, \dots, N$. Further, we assume that the $K_i \times 1$ vectors of idiosyncratic commodity-specific shocks $\mathbf{e}_{i,t}$ are, in general, serially uncorrelated, independent and identically distributed, with mean zero and covariance matrix $\Sigma_{ii,s_{i,t}}$. Therefore, it holds $\mathbf{e}_{i,t} \sim iid(0, \Sigma_{ii,s_{i,t}})$.

To account for the time-varying dependencies in commodity markets, we attach the index $s_{i,t}$ to the parameters, which denotes these parameters depend on the regime $s_{i,t} \in \{1, 2, \dots, M\}$ prevailing in commodity i at time t , following the idea of Binder and Gross (2013). We assume that this unobserved state is generated by a discrete time, irreducible, ergodic, discrete M -state Markov chain with transition matrix \mathbf{P}_i . The corresponding transition probabilities $p_{i,lm}$, denoting the probability of a commodity to switch from regime l to regime m between the periods t and $t + 1$, are defined as:

$$p_{i,lm} = Pr(s_{i,t+1} = m | s_{i,t} = l), \sum_{m=1}^M p_{i,lm} = 1, \text{ for } l, m = 1, 2, \dots, M. \tag{2}$$

Further, using the filter of Hamilton (1989), we calculate the optimal inference of $\xi_{i,t}$, which denotes the unobserved state of the system, based on the information set $\mathbf{X}_{i,t}$:

$$\xi_{i,t} = \begin{pmatrix} \mathbb{I}(s_{i,t} = 1) \\ \mathbb{I}(s_{i,t} = 2) \\ \vdots \\ \mathbb{I}(s_{i,t} = M) \end{pmatrix}, \text{ with } \mathbb{I}(s_{i,t} = m) = \begin{cases} 1, & \text{if } s_{i,t} = m \\ 0, & \text{else} \end{cases}. \tag{3}$$

Therefore, we define the probability distribution of the state vector $\xi_{i,t}$, conditional on the information set available at time τ , $\mathbf{X}_{i,\tau}$, as:

$$\xi_{i,t|\tau} = \mathbb{E}[\xi_{i,t} | \mathbf{X}_{i,\tau}] = \begin{pmatrix} Pr(\xi_{i,t} = \iota_1 | \mathbf{X}_{i,\tau}) \\ Pr(\xi_{i,t} = \iota_2 | \mathbf{X}_{i,\tau}) \\ \vdots \\ Pr(\xi_{i,t} = \iota_M | \mathbf{X}_{i,\tau}) \end{pmatrix}. \tag{4}$$

For this study, we differentiate between the filtered, the predicted as well as the smoothed probabilities. While the filtered (predicted) probabilities depend on information available at time t ($t - 1$), the smoothed probabilities are

⁵ For a simpler notation, we assume that the lag length of the external variables equals the lag length of the commodity-specific variable and is equal for all commodities.

computed conditional on the full-sample information up to time T .

As shown in Hamilton (1990), the Expectation-Maximization (EM) algorithm, introduced by Dempster et al. (1977), can be used in conjunction with the filter of Hamilton (1989) for the calculation of the filtered, predicted and smoothed probabilities, described in Krolzig (1997), to obtain the maximum likelihood estimates of the model's parameters. First, the filtered as well as the smoothed probabilities are calculated within the expectation step of each iteration, to determine the expectations (of the states). Second the parameters are estimated given the predetermined regimes, in the maximization step, by maximizing the likelihood function.

Global commodity market model (MS-GVAR)

In order to aggregate the commodity-specific, individual MS-VAR models to a global commodity market model, the MS-GVAR model, we follow the original papers of time-invariant GVAR models by Pesaran et al. (2004) as well as of MS-GVAR models by Binder and Gross (2013). Hereby, we define the $(K_i + K_i^*) \times 1$ vector $\mathbf{z}_{i,t} = (\mathbf{x}'_{i,t}, \mathbf{x}'_{i,t})'$ and rewrite Eq. 1 for $i = 1, \dots, N$:

$$\mathbf{A}_{i,0,s_{i,t}} \mathbf{z}_{i,t} = \mathbf{a}_{i,0,s_{i,t}} + \sum_{p=1}^P \mathbf{A}_{i,p,s_{i,t}} \mathbf{z}_{i,t-p} + \sum_{p=0}^{P_{exog}} \Psi_{i,p,s_{i,t}} \mathbf{e}_{t-p} + \boldsymbol{\varepsilon}_{i,t}, \quad (5)$$

where $\mathbf{A}_{i,0,s_{i,t}} = (\mathbf{I}_{K_i}, -\Lambda_{i,0,s_{i,t}})$ and $\mathbf{A}_{i,p,s_{i,t}} = (\Phi_{i,p,s_{i,t}}, \Lambda_{i,p,s_{i,t}})$, for $p = 1, 2, \dots, P$, are $K_i \times (K_i + K_i^*)$ dimensional matrices, with \mathbf{I}_{K_i} denoting the $K_i \times K_i$ dimensional identity matrix. Moreover, we require $\mathbf{A}_{i,0,s_{i,t}}$ to have full row rank for $i = 1, \dots, N$.

Further, we denote by $\mathbf{x}_t = (\mathbf{x}'_{1,t}, \mathbf{x}'_{2,t}, \dots, \mathbf{x}'_{N,t})'$ the $K \times 1$ global vector of all commodity-specific variables, where $K = \sum_{i=1}^N K_i$. With the link matrices \mathbf{Z}_i of fixed constants defined in terms of the commodity-specific weights $w_{i,\tilde{t}}$, we can write $\mathbf{z}_{i,t} = \mathbf{Z}_i \mathbf{x}_t$. Hence, we use this in Eq. 5:

$$\mathbf{A}_{i,0,s_{i,t}} \mathbf{Z}_i \mathbf{x}_t = \mathbf{a}_{i,0,s_{i,t}} + \sum_{p=1}^P \mathbf{A}_{i,p,s_{i,t}} \mathbf{Z}_i \mathbf{x}_{t-p} + \sum_{p=0}^{P_{exog}} \Psi_{i,p,s_{i,t}} \mathbf{e}_{t-p} + \boldsymbol{\varepsilon}_{i,t}. \quad (6)$$

Stacking Eq. 6 together for $i = 1, 2, \dots, N$, we obtain:

$$\mathbf{G}_{0,S_t} \mathbf{x}_t = \mathbf{a}_{0,S_t} + \sum_{p=1}^P \mathbf{G}_{p,S_t} \mathbf{x}_{t-p} + \sum_{p=0}^{P_{exog}} \Psi_{p,S_t} \mathbf{e}_{t-p} + \boldsymbol{\varepsilon}_t, \quad (7)$$

where $S_t = \{s_{1,t}, s_{2,t}, \dots, s_{N,t}\}$ denotes the assumed regime-constellation across the commodities, while forming the matrices \mathbf{G}_{0,S_t} . Hereby, we have the $K \times 1$ intercept vector $\mathbf{a}_{0,S_t} = (\mathbf{a}'_{1,0,s_{1,t}}, \mathbf{a}'_{2,0,s_{2,t}}, \dots, \mathbf{a}'_{N,0,s_{N,t}})'$, the $K \times K$ dimensional matrices

$\mathbf{G}_{p,S_t} = ((\mathbf{A}_{1,p,s_{1,t}} \mathbf{Z}_1)')', (\mathbf{A}_{2,p,s_{2,t}} \mathbf{Z}_2)')', \dots, (\mathbf{A}_{N,p,s_{N,t}} \mathbf{Z}_N)')'$, for $p = 0, 1, \dots, P$ the $K \times K_{exog}$ dimensional matrices $\Psi_{p,S_t} = (\Psi'_{1,p,s_{1,t}}, \Psi'_{2,p,s_{2,t}}, \dots, \Psi'_{N,p,s_{N,t}})'$ and the $K \times 1$ vector $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}'_{1,t}, \boldsymbol{\varepsilon}'_{2,t}, \dots, \boldsymbol{\varepsilon}'_{N,t})'$.

In case of a non-singular matrix \mathbf{G}_{0,S_t} for a given regime-constellation S_t , we get the reduced form:

$$\begin{aligned} \mathbf{x}_t &= \mathbf{G}_{0,S_t}^{-1} \mathbf{a}_{0,S_t} + \sum_{p=1}^P \mathbf{G}_{0,S_t}^{-1} \mathbf{G}_{p,S_t} \mathbf{x}_{t-p} + \sum_{p=0}^{P_{exog}} \mathbf{G}_{0,S_t}^{-1} \Psi_{p,S_t} \mathbf{e}_{t-p} + \mathbf{G}_{0,S_t}^{-1} \boldsymbol{\varepsilon}_t \\ &= \mathbf{b}_{S_t} + \sum_{p=1}^P \mathbf{H}_{p,S_t} \mathbf{x}_{t-p} + \sum_{p=0}^{P_{exog}} \Upsilon_{p,S_t} \mathbf{e}_{t-p} + \mathbf{v}_{t,S_t}, \end{aligned} \quad (8)$$

with $\mathbf{b}_{S_t} = \mathbf{G}_{0,S_t}^{-1} \mathbf{a}_{0,S_t}$, $\mathbf{H}_{p,S_t} = \mathbf{G}_{0,S_t}^{-1} \mathbf{G}_{p,S_t}$, for $p = 1, 2, \dots, P$, $\Upsilon_{p,S_t} = \mathbf{G}_{0,S_t}^{-1} \Psi_{p,S_t}$, for $p = 0, 1, \dots, P$ and $\mathbf{v}_{t,S_t} = \mathbf{G}_{0,S_t}^{-1} \boldsymbol{\varepsilon}_t$. This enables to model markets of all commodities simultaneously, while accounting for their (time-varying) dependencies in the cross-commodity dimension.

The global model can only be solved by assuming a regime-constellation S throughout the sample period, see Binder and Gross (2013). Therefore, we define a $M \times N$ matrix Ξ indicating the desired regimes for the N commodities, where the columns, denoted by Ξ_i each sum to one. There are two possible ways to solve the global model:

1. Choose an arbitrary regime constellation, such that each commodity i is set to the desired regime m_i with weight 1.
2. Set the regimes according to the estimated constellation at a selected point in time τ . Then, $\Xi_i = \hat{\xi}_{i,\tau|T}$.

With the definition of Ξ , the weighted average of the local models' parameter space can be calculated for $p = 0, 1, \dots, P$:

$$\tilde{\mathbf{A}}_{i,p} = \sum_{m=1}^M \mathbf{A}_{i,p,s_i=m} \cdot \Xi_{m,i}, \quad (9)$$

where $\Xi_{m,i}$ denotes the m -th row of Ξ_i . Analogously, we calculate the intercept $\tilde{\mathbf{a}}_{i,0}$, as well as the parameter matrices $\tilde{\Psi}_{i,p}$ for the exogenous variables. Subsequently, we solve the global model according to Eq. 7, using the parameters $\tilde{\mathbf{A}}_{i,p}$, $\tilde{\mathbf{a}}_{i,0}$, $\tilde{\Psi}_{i,p}$ corresponding to the predefined regime-constellation Ξ_i . For the block-wise calculation of the global covariance matrix under a given regime constellation, we refer to Binder and Gross (2013) and Andersson (2014).

Analysis of MS-GVAR models via generalized impulse response functions

We analyse the spillover effects in 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 general, the GIRF analysis benefits from the invariance of the ordering of the commodities, see Déés et al (2007). However, the GIRFs of Markov-switching models are regime-dependent, see Ehrmann et al. (2001).

For a given regime-constellation S , the generalized impulse response function is defined as:

$$\mathbf{GI}(n, \delta, \Omega_{t-1}) = \mathbb{E}[\mathbf{x}_{t+n} | \boldsymbol{\varepsilon}_{t,S} = \delta, \Omega_{t-1}] - \mathbb{E}[\mathbf{x}_{t+n} | \Omega_{t-1}] \quad (10)$$

where δ denotes the shock and Ω_{t-1} is the known information until time $t - 1$, including all necessary information about the exogenous variables. In our study, we consider the generalized impulse response functions of the effect of a shock of the j -th variable of \mathbf{x}_t , corresponding to the ℓ -th variable in the i -th commodity, by one standard deviation and calculate the responses via Monte Carlo integration, following Koop et al. (1996).

Empirical application to industrial metal markets

Data

To investigate whether the impact of fundamentals and the co-movement of commodity prices varies between calm and volatile periods, we apply the MS-GVAR model to the six LME-traded industrial metals aluminum, copper, nickel, lead, tin, and zinc. On the one hand, the financial markets for industrial metals are very liquid and therefore, attractive for investors. On the other hand, industrial metals are essential for commercial and industrial development, especially for the energy transition. Consequently, their prices are significantly influenced by fundamental supply and demand dynamics. Hereby, we model each individual metal market via individual MS-VAR models, using the commodity-specific attributes supply, demand and price as endogenous variables, for the period January 1995 to December 2020. While the actual supply and demand of the metals are not observable, we approximate the individual supply of a commodity by the monthly world total production (**supply**) and the commodity-specific demand by the world total consumption (**demand**), drawn from World Bureau of Metal

Statistics (2021).⁶ Moreover, we use the end-of-month price (**price**), drawn from Thomson Reuters Eikon, standardized to U.S. Dollar per metric ton, following Chen (2010).

Further, we account for the impact of the common factor on commodity markets by including macroeconomic variables, representing the economic activity, exchange rates and monetary policy. Therefore, we add the vector of exogenous variables to the MS-VAR models, which includes the seasonally unadjusted world industrial production (IP) as proxy for economic activity, drawn from The World Bank (2022),⁷ the U.S. Dollar index (FX) as exchange rate, drawn from ICE Futures U.S. (2022), as well as the effective federal funds rate (FFR) as interest rate, drawn from Board of Governors of the Federal Reserve System (U.S.) (2022).

In order to satisfy the central assumption of stationarity in VAR models, we apply the augmented Dickey Fuller (ADF) test to each of the attributes and calculate logarithmic returns in case of non-stationary data, based on the five percent significance level. All time series were non-stationary at first, therefore, we calculate the logarithmic returns of each variable which are stationary.⁸ Moreover, we seasonally adjust and standardize them to have mean zero and standard deviation one, but use the original variable names unadjusted, i.e. supply, demand and price.

Descriptive statistics of the stationary, seasonally adjusted, but non-standardized variables are given in Table 10 of Appendix A. Overall, most variables show a non-normal behavior, especially the metal prices exhibit fat tails and are negatively skewed, indicating time-varying models might fit the data, as Ang and Timmermann (2012) emphasize the usefulness of regime switching models for non-normal data. Hereby, the regime analysis allows to reflect time-varying correlations, which are present in metal commodity prices, see Fig. 1.

⁶ We appreciate the reviewer's suggestion regarding the limitations of using world total production and consumption, as it may not fully capture regional supply-demand dynamics and inventory changes that influence price fluctuations. Regional disparities, such as differences in production costs, trade policies, and geopolitical factors, can impact industrial metal markets. While our model does not account for short-term regional imbalances that may directly affect prices, it captures broader global supply and demand trends, where regional disruptions might be offset by adjustments in other areas. As a result, our findings may underestimate the impact of localized supply and demand shocks on metal prices. However, our approach provides a comprehensive perspective on macroeconomic influences and effectively considers global supply and demand shocks, which are less likely to be offset and can have more profound effects on international metal markets.

⁷ For a robustness check, we include the global economic activity index by Kilian (2009) and obtain similar results.

⁸ As logarithmic prices were non-stationary as well, we apply our models on the logarithmic returns of the prices.

Demand relations between industrial metals

To integrate the individual commodity markets into a comprehensive commodity-market model, we establish connections between commodity-specific markets using a weight matrix $(w_{i,\tilde{i}})_{i,\tilde{i}=1,\dots,N}$, based on co-consumption patterns rather than the trade weights originally proposed by Pesaran et al. (2004) for linking individual economies, following the approach of Schischke et al. (2024). Therefore, we analyze the sectors in which industrial metals are co-consumed, while approximating the economy by the five industries Automotive/ Transportation, Chemistry/ Pharmaceuticals, Electrics, Construction and Mechanical Engineering, which in summary account for up to 90% of the worldwide demand.⁹

Table 1 displays the proportional consumption per commodity and industry. We aggregate these values to a demand-side information matrix using the following formula:

$$\hat{w}_{i,\tilde{i}} = \sum_h ind_{h,i} \cdot ind_{h,\tilde{i}}, \text{ for } i, \tilde{i} = 1, \dots, N, i \neq \tilde{i} \quad (11)$$

where $\hat{w}_{i,\tilde{i}}$ represents the weight between commodity i and commodity \tilde{i} and $ind_{h,i}$ denotes the proportion of commodity i belonging to industry $h = \{\text{Automotive/ Transportation, Chemistry/ Pharmaceuticals, Electrics, Construction, Mechanical Engineering}\}$. Finally, we convert this information table into a weight matrix for the MS-GVAR model, by scaling the values to row sums of 1 and display the resulting weight matrix in Table 2.¹⁰

Model specification and estimation

The objective of this study is the analysis of the spillover effects within and between commodity markets over time. Therefore, we consider two states in the Markov-switching models such that calm as well as volatile periods are captured. Moreover, we apply a slightly adjusted model selection procedure of Li and Kwok (2021), using the information criterion of Hannan and Quinn (1979), to determine the optimal lag length as well as model specification. Hereby, we estimate the optimal lag length, up to the predefined number of lags $P_{max} = 2$, as well as the specification out of all considered specifications, which allow for regime-varying intercept, coefficients and/or covariance matrices, $spec \in \{MSI, MSIH, MSH, MSA, MSAH\}$, and conclude the MSH(2)-VAR(1) model, with regime-dependent covariance matrix, but regime-invariant intercept as well as regime-invariant parameters for the endogenous and exogenous variables, performs best. The results of the Durbin-

Watson (DW) test indicate neither of the commodity-specific MSH(2)-VAR(1) model suffers from autocorrelation, indicating the lag length of one chosen by the model selection procedure is feasible from a statistical point of view.

Empirical results

The objective of this study is to examine whether the interdependencies within and between the commodity markets change over time, especially between calm and volatile periods. Therefore, we apply the time-dependent Markov-switching global vector autoregression (MS-GVAR) model on the industrial metal markets, which disentangles single-market effects from inter-market effects, while controlling for macroeconomic factors.

First, we simultaneously estimate individual, commodity-specific Markov-switching VAR models, accounting for the aggregated impact of other commodity markets alongside exogenous variables, and investigate the regime inference of each market. Subsequently, we extend the analysis by integrating industrial metal markets into a unified MS-GVAR model, enabling the assessment of interdependencies among commodities. Through regime-dependent generalized impulse response functions (GIRFs), we analyze spillover effects within and between the commodity markets via regime-dependent GIRFs and underline the importance across markets. Furthermore, we highlight the necessity of a time-varying analysis by evaluating the out-of-sample forecasting performance of the MS-GVAR model in comparison to its time-invariant counterpart.

Regime inference

Since the MS-GVAR model aggregates the individual, commodity-specific MS-VAR models to one global commodity market model, the transition probabilities, i.e. the probabilities to switch from state one to state two and vice versa, displayed in Table 3, as well as the smoothed probabilities, indicating in which state a commodity is at a specific point in time, differs across the markets. Therefore, we briefly discuss the transition and regime probabilities of each industrial metal market in the following.

The transition probabilities indicate it is more likely to stay in the present state for aluminum, lead, tin and zinc, whereas the copper market exhibits a strong tendency to remain in, or move to, state one. Moreover, the probability to switch between the regimes is almost equal to the probability to stay, in case of the nickel market. Due to the comparably high probabilities to switch the regimes, the nickel market often switches its states, whereas the other metal markets show only brief periods in regime two,

⁹ Please refer to Schischke et al. (2024) for detailed information.

¹⁰ Table 2 shows rounded values, whereas further calculations in the model use the true values without rounding.

Table 1 Consumption of commodities across industries

Industry	Al	Cu	Ni	Pb	Sn	Zn
Automotive/ Transportation	0.36	0.10	0.32	0.00	0.00	0.63
Chemistry/ Pharmaceuticals	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

Note: This table presents the distribution of consumption for aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn) across major industrial sectors: Automotive/Transportation, Chemistry/Pharmaceuticals, Electronics, Construction, and Mechanical Engineering. The data illustrate the relevance of each metal to specific end-use applications, providing context for their demand dynamics

see Figs. 2, 3, 4, 5, 6 and 7,¹¹ indicating the industrial metal markets are stable, except the nickel market.

Overall, the metal markets are mainly located in regime one until 2004, the beginning of the financialization of commodity markets, see Tang and Xiong (2012), with only few and brief periods in regime two, indicating the increase in index investment changed the industrial metal markets. Thereafter, the markets show longer periods in regime two, especially in the years 2006/07, 2009, 2011, and 2015, corresponding to the boom in commodity prices, the financial crisis, the European debt crisis, and the sharp drop in the oil price. In the following, we turn to a commodity-specific perspective and examine each commodity market and its regimes separately, whereby we exemplary focus on the aluminum market. However, the regime switches are similar in the copper, lead, tin and zinc markets, whereas the regimes in nickel market fluctuate more.

While at the beginning of the considered time period, the aluminum market shows longer periods in state one, with only brief periods in state two, the market switches to state two at the end of 2008, during the financial crisis, and remains almost four years in this regime. Moreover, the aluminum market is located in state two in 2015 as well as 2017 for almost two years each. Hereby, aluminum's variables, especially the aluminum price, fluctuate widely within these periods.

After the significant price increase from 2004 to mid-2008, caused by a strong demand growth partly driven by the emerging countries, the physical as well as speculative demand dropped, due to the financial crisis, at the end of the year 2008, resulting in rising inventories and declining prices, probably provoking the observed switch in aluminum's regimes. While the prices were recovered in 2010, due to the increase in Chinese demand, see U.S. Geological Survey (2013a), the supply side of the aluminum market

¹¹ These figures show the returns of each individual supply, demand and price variable over the entire sample period. Shaded areas indicate the smoothed probability to be in state two exceeds 50%, hence, it is more likely for the commodity market to be in state two at these points in time.

remained turbulent. The production from U.S. primary aluminum smelters increased during the first half of 2011, whereas the leading U.S. aluminum producer announced to close permanently several smelters, at the beginning of 2012, see U.S. Geological Survey (2012). However, caused by new capacity in China, India, and Qatar, the world production increased in 2012, see U.S. Geological Survey (2013b).

Fluctuations in aluminum supply and price likely contributed to the market being in regime two between 2009 and 2012. Similarly, the decline in aluminum inventories held by LME-bonded warehouses, coupled with continued demand growth, may explain why the market remained in state two in 2015, as noted by U.S. Geological Survey (2016). In contrast, the volatile price in the years 2017 and 2018, caused by supply concerns, inter alia due to regulation problems of the world's largest alumina refinery, Alunorte, sanctions on the Russian aluminum producer Rusal as well as labour strike at Alcoa, might be the reason for the market being in state two during the years 2017 and 2018, see U.S. Geological Survey (2020).

The copper market rarely changes its regimes and exhibits only brief periods in regime two, indicating its stability. While it is located longer periods in state two in 2006, just before the onset of the financial crisis, and corresponding to periods of a more volatile copper price, probably caused by the financialization, the periods in state one reflect calmer markets. In general, U.S. Geological Survey (2013a) state

Table 2 Weight matrix

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.18	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

Note: Demand-side weight matrix of the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn)

Table 3 Transition probability matrices for the commodity-specific MS-VAR models

	Al	Cu	Ni	Pb	Sn	Zn
0.92	0.08	0.82	0.18	0.50	0.50	0.92
0.16	0.84	0.50	0.50	0.56	0.44	0.16
0.08	0.90	0.10	0.82	0.18	0.10	0.82
0.12	0.88	0.23	0.77	0.12	0.88	0.23

Note: This table reports the estimated transition probabilities for each commodity-specific Markov-switching VAR (MS-VAR) model, covering aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn). The first row of each matrix shows the probability of remaining in regime one or switching to regime two. The second row displays the probability of transitioning to regime one or staying in regime two. These values reflect the stability and switching behavior of each commodity market over time

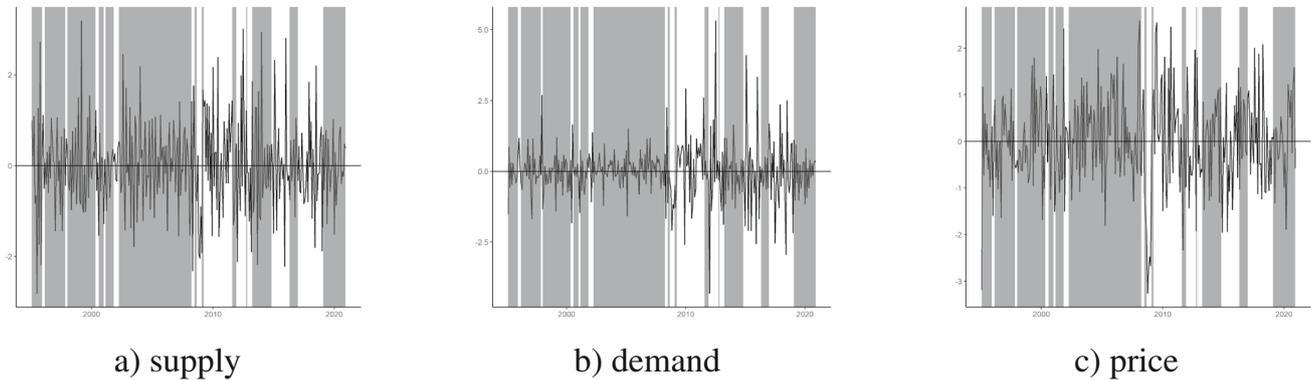


Fig. 2 Aluminum (Al) time series plots for supply, demand, and price, with shaded areas indicating periods where the regime probability of the crisis state exceeds 0.5

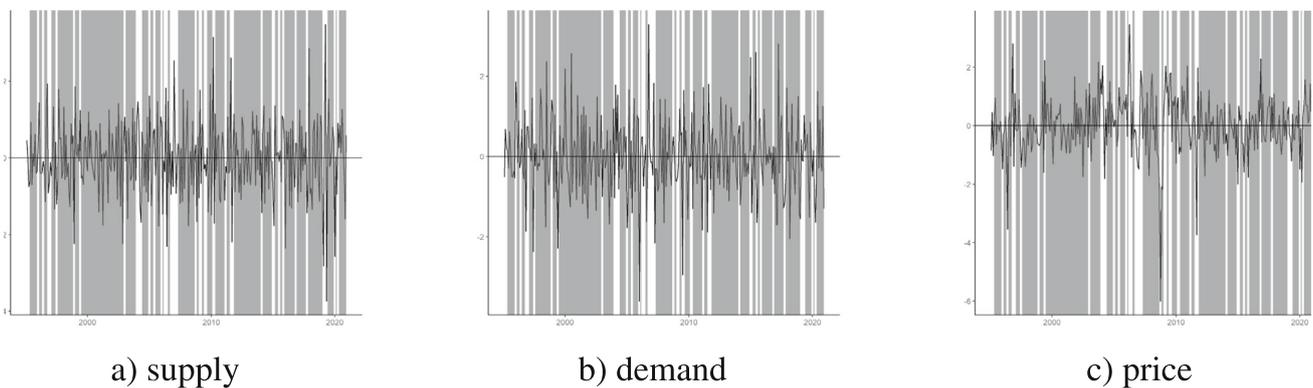


Fig. 3 Copper (Cu) time series plots for supply, demand, and price, with shaded areas indicating periods where the regime probability of the crisis state exceeds 0.5

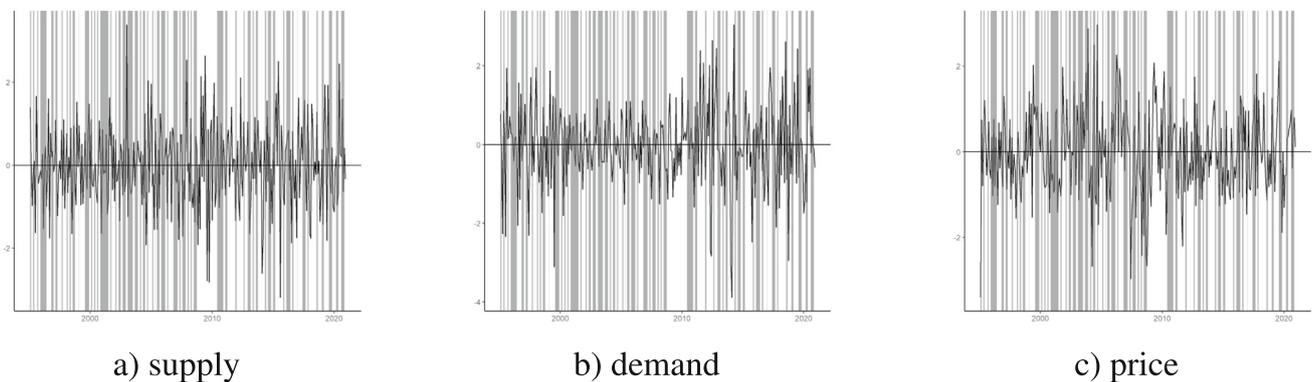


Fig. 4 Nickel (Ni) time series plots for supply, demand, and price, with shaded areas indicating periods where the regime probability of the crisis state exceeds 0.5

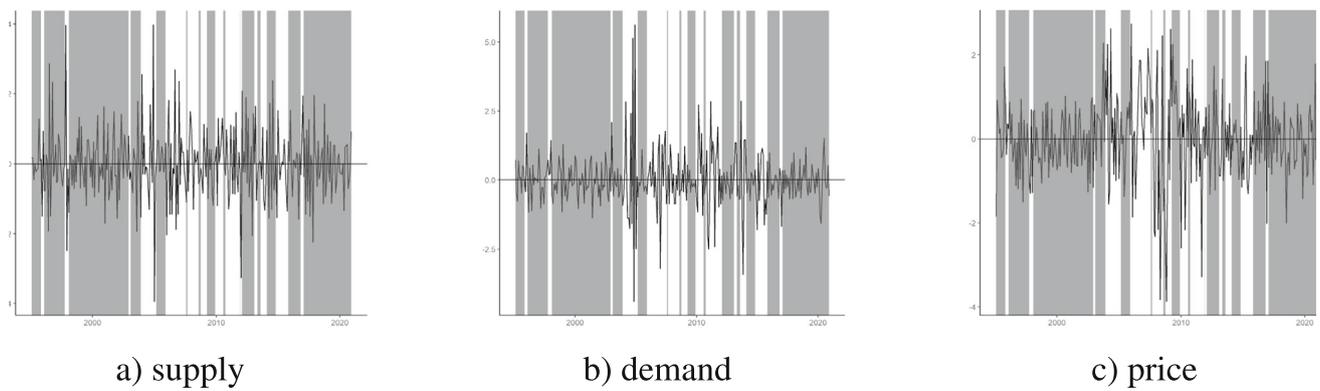


Fig. 5 Lead (Pb) time series plots for supply, demand, and price, with shaded areas indicating periods where the regime probability of the crisis state exceeds 0.5

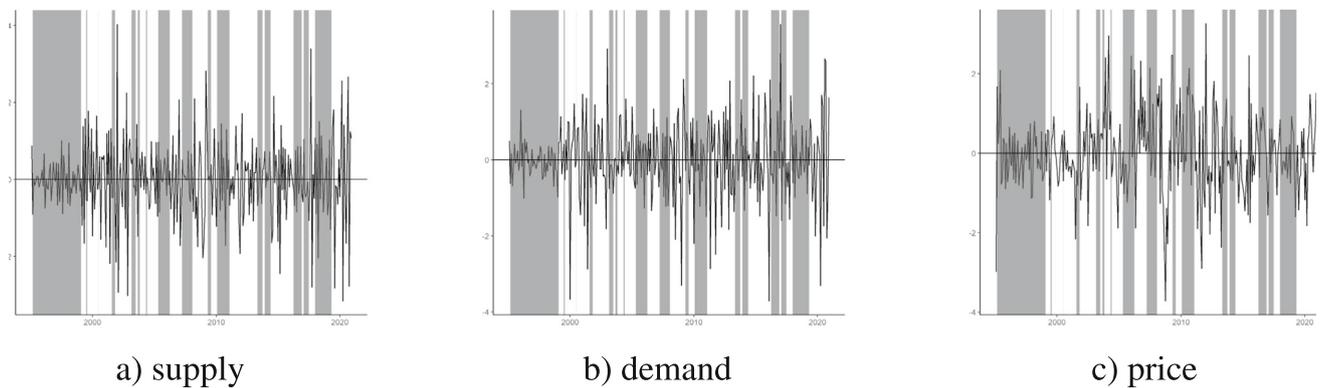


Fig. 6 Tin (Sn) time series plots for supply, demand, and price, with shaded areas indicating periods where the regime probability of the crisis state exceeds 0.5

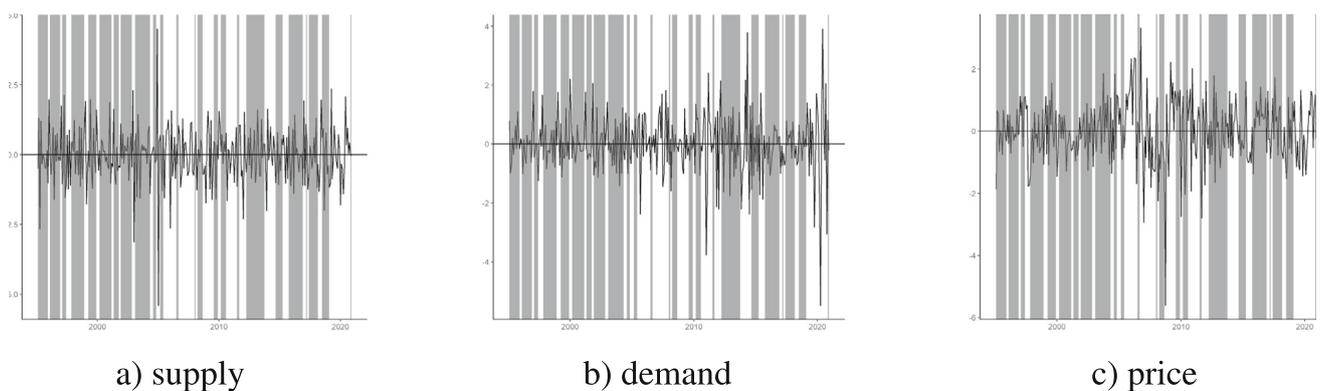


Fig. 7 Zinc (Zn) time series plots for supply, demand, and price, with shaded areas indicating periods where the regime probability of the crisis state exceeds 0.5

copper prices react to disturbances to production at any given large mine, due to copper's close balance between production and consumption. For example, the pit wall failure in Indonesia and a mine strike in Mexico in the year 2006, combined with the growth in global consumption during this period, resulted in a price increase, which might explain the longer lasting period of the copper market in state two.

As indicated by the transition probabilities, the nickel market experiences the most frequent regime switches, often with brief but recurring periods in state two, highlighting its relative instability. This heightened volatility can be attributed to several structural imbalances in the market. First, the global nickel market is highly concentrated, with a few key producers, primarily Indonesia and the Philippines, dominating production, see U.S. Geological Survey (2020). Policy changes, export bans, or geopolitical tensions in these regions can rapidly disrupt supply and trigger market shifts. Second, nickel's diverse industrial applications contribute to its instability. Unlike other industrial metals primarily used in construction and manufacturing, nickel has experienced surging demand for lithium-ion batteries in electric vehicles (EVs), see Sun et al. (2022). Shifts in EV market expectations, battery technology advancements, or policy-driven incentives can further amplify market volatility. Additionally, when nickel prices rise, manufacturers can opt for lower-nickel alloys in stainless steel production, causing fluctuations in demand, following Sverdrup and Olafsdottir (2019). These supply and demand imbalances make nickel inherently less stable than other industrial metals. Notably, the slightly longer lasting period in regime two around 2009 is probably caused by the financial crisis, whereas the period in state two at the end of 2013 to the beginning of 2014 corresponds to a period of weak prices associated with an oversupply of nickel.

In periods of high price volatility, during the beginning of the financialization of commodity markets in 2004, the commodity price boom and the financial crisis, the lead market is situated in state two. Hereby, the price increase between 2004 and 2007 is mainly driven by the strong demand for lead in China, see U.S. Geological Survey (2013a), while the surplus in the lead market might explain why the market is situated in state two in 2011, see U.S. Geological Survey (2012). In addition, the decline in the average London Metal Exchange (LME) cash lead price by about 13% in 2015 from that in 2014 caused the switch to regime two in 2015, see U.S. Geological Survey (2016).

In contrast to the other metal markets, tin is in both regimes for almost equal length of time, which might be explained by the corresponding transition probabilities, in particular, it is equally probable to remain in the states, see Table 3. While the tin market is only situated in state one until 1999, tin remains longer periods in regime two at the beginning of the recent century, during the beginning of the financialization

of commodity markets, during the financial crisis, between 2011 to 2013, 2014 to 2016 and 2019 to 2020. Hereby, the increase in the tin price around 2008, leading to a more volatile period, was caused by supply disruptions in China as well as Indonesia, a demand growth of emerging economies, the decrease in U.S. inventories as well as the increasing role of investment funds, see U.S. Geological Survey (2013a). Additionally, the tin price increased around 2012, as major tin-consuming countries aim to lead-free solders that usually contain larger amounts of tin, probably causing the switch of the market to regime two, see U.S. Geological Survey (2012). In contrast, the volatile price, due to the price decline in response to the increased tin production in Burma in 2014, as well the reduced consumption of tin in the United States, probably caused the tin markets staying in regime two in 2015, see U.S. Geological Survey (2016).

Similar to the copper market, the zinc market shows longer periods in state one, with only brief periods in state two. Given that zinc, as a key alloying element in steel production, is highly consumption-dependent, fluctuations in industrial demand may contribute to these regime changes. In particular, the zinc market switches to and remains in state two for several years during the commodity price boom from 2005 to 2008, corresponding to the period of financialization, and the financial crisis starting in 2009. Moreover, the production-to-consumption surplus in 2015, see U.S. Geological Survey (2016), and the increase in global zinc mine production, see U.S. Geological Survey (2020), both periods of higher price volatility, probably caused the switch of the zinc market to regime two.

Overall, we observe the commodity markets are mostly situated in regime one, while the markets remain in regime two during periods with high fluctuations in supply, demand, and price. For an in-depth analysis of the commodity markets, we report distinct descriptive statistics for each regime in Table 11, where we assume the commodities are either located in state one or state two, depending on their respective smoothed probability exceeding 50%. While copper is rarely located in state two, the tin market is situated in this state half of the time. Overall, the minimum, quantiles as well as maximum values show the markets take on more extreme values in the second state. Moreover, the commodity variables exhibit a higher volatility in state two, indicating periods of more fluctuations, which is why we refer in the following to the state two as *volatile* and the state one as *calm* period.

Impulse response analysis of the final MS-GVAR model

The analysis of the regime inferences in the industrial metal markets indicate the commodity markets change their regimes in more volatile periods. Hereby, the metal markets

exhibit calm periods until the financialization, while inter alia the boom in commodity prices, and the financial crisis lead to more fluctuations and a regime switch. However, the regimes between the markets differ, as for example nickel changes its regimes more often than aluminum. To disentangle whether the interdependencies between the commodity markets change between the regimes, we artificially attribute all industrial metal markets to either the calm or volatile regime and examine how shocks to the commodity variables transmit to the commodity markets under the calm or volatile regime.

In particular, we initially assume the commodity markets are all simultaneously in their calm (volatile) state, and we calculate the corresponding regime-dependent generalized impulse response functions, according to Ehrmann et al. (2003), based on the 68% confidence bounds, obtained by the bootstrap procedure of Ehrmann et al. (2001), which we slightly adjust for the MS-GVAR framework.

Hereby, we shock each commodity-specific variable by one standard deviation and examine the direct as well as the indirect effects of this shock to the remaining variables, in the individual, commodity-specific, as well as in the cross-commodity dimension.

First of all, we examine the spillover effects within and between the industrial metal markets under the calm regime. To condense the GIRF results and to facilitate the comparison to the GIRFs of the volatile results later on, we provide an overview of the results in Table 4. Hereby, we indicate significant positive or negative, responses of the column variables, to a shock in the row variables, by a (+) or (-).

The diagonal shows significantly positive responses for all variables, which is rather unsurprising, as they capture the effect of a shock to the response variable itself. Despite the concerns of false negatives within GIRF analyses in general, see Runkle (1987); Lütkepohl (1990) and Galesi and Lombardi (2009), we obtain numerous significant responses in the cross-commodity dimension, underlining the importance of jointly modeling commodity markets, as discussed in Schischke et al. (2024).

To start, we examine the spillover effects within the individual commodity markets, before we focus on the effects in the cross-commodity dimension. In particular, the copper market is affected most by its own shocks. Hereby, an increase in the copper consumption or price leads to significantly rising production volume, indicating the supply of copper increases in response to a higher demand and price. Moreover, the consumption of copper (price of tin) reduces in case of increasing production (consumption) volume, which is rather counterintuitive, since we would expect a synchronous reaction. However, the GIRF methodology investigates direct as well as indirect effects on the attributes to an innovation of one standard deviation in a certain variable, therefore, the observed responses may be caused by

unobservable, indirect effects. In addition, the aluminum price positively affects its consumption, whereas zinc's production and consumption significantly react to a shock in the price of zinc. While these results indicate the MS-GVAR model reflects the spillover effects in the individual markets of aluminum, copper, tin, and zinc, the nickel and lead market do not exhibit any significant responses to shocks in their own production, consumption and price, however, we observe various spillover effects in the cross-commodity dimension.

In general, the majority of the spillover effects is between the supply and supply, demand and demand, as well as price and price variables, indicating a concurrent behavior between the metal markets. The interactions between production variables are less pronounced, whereas prices emerge as the primary driver, reinforcing the presence of common patterns across commodity markets.

Overall, we observe strong interdependencies between the prices themselves, except for tin, the smallest metal in terms of its trading volume, as its price does not influence and is not influenced by the other commodity prices. However, an increase in the price of aluminum, copper, nickel, lead, or zinc leads to rising prices of the other commodities, indicating a common behavior in the metals' prices. The only exception is zinc, as its price reduces in response to a positive shock in the aluminum, copper, and nickel price. This decrease in the zinc price might be caused by a disproportionally increase in its supply, compared to the demand increase, also caused by rising prices. Moreover, shocks to the copper price affect the other commodities, whereas the copper price itself does not react to changes in the other prices, indicating a strong impact of copper on the other commodity markets.

While the prices influence each other, production and consumption volumes, reflecting supply and demand, are also highly affected by rising prices. The positive reactions of the supply in response to price shocks can be explained by indirect effects due to the co-production relation. A higher price of one commodity cause an increase in its production volume, and therefore also in the production volume of a co-produced metal. Thereafter, the consumption might adjust in response to the increase in the overall supply, leading to a demand increase. Further, the inverse relation between zinc's and the other metals' prices cause the positive response of consumption to price shocks. In particular, an increase in one metal's price leads to a decline in another metal's price and, ultimately, results in higher demand.

Turning to a commodity perspective, lead, which was largely banned from many applications in the previous decades, is least connected to the other markets. In contrast, we observe the majority of the spillover effects between the aluminum, copper, nickel, tin, and zinc markets, whereby especially copper and tin significantly react to shocks in the other markets. Moreover, aluminum and copper are related most. Hereby, the strong interdependencies between these

Table 4 Generalized impulse response function (GIRF) results of the MS-GVAR model in the calm regime

	Al			Cu			Ni			Pb			Sn			Zn		
	supply	demand	price															
Al supply	+																	
Al demand		+																
Al price			+															
Cu supply				+														
Cu demand					+													
Cu price						+												
Ni supply							+											
Ni demand								+										
Ni price									+									
Pb supply										+								
Pb demand											+							
Pb price												+						
Sn supply													+					
Sn demand														+				
Sn price															+			
Zn supply																+		
Zn demand																	+	
Zn price																		+
Al supply																		
Al demand																		
Al price																		
Cu supply																		
Cu demand																		
Cu price																		
Ni supply																		
Ni demand																		
Ni price																		

Table 4 continued

	Al		Cu		Ni		Pb		Sn		Zn	
	supply	demand	price									
Pb supply							+					
Pb demand	+		+	+	+							+
Pb price		+							+			
Sn supply	-									+		
Sn demand	+		+	+	+						+	
Sn price		+		+								+
Zn supply	-											+
Zn demand	+		+	+	+							+
Zn price		+		+								+

Note: Results of the GIRF analysis of the MS-GVAR model under the assumption each commodity market is in its calm regime. We analyze the response of the column variables to a shock of the row variables supply (**supply**), demand (**demand**) and price (**price**) 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. Note: This table displays the generalized impulse response function (GIRF) results for the MS-GVAR model under the assumption that all commodity markets operate in a calm regime. Each cell shows the effect of a one-standard-deviation shock to the supply, demand, or price of the row commodity on the column commodity. Significant positive (+) or negative (-) spillovers at the 68% confidence level are indicated, highlighting cross-commodity interdependencies in stable periods

two metals can be explained by their common applications in electrical conduction, automotive and aerospace industries. However, the GIRF analysis generally detects strong interrelations, emphasizing the importance of jointly modeling commodity markets.

The objective of this study is to disentangle how the commodity market structure change over time. Therefore, we estimate the spillover effects under the volatile regime and examine the differences in the spillover effects, see Tables 4 and 5 for the effects under the calm and volatile regime, respectively. Hereby, we do not observe any differences in the significant responses between the two regimes, indicating a shock to one variable either leads to a significant response or not, independent of the underlying regime.

However, the magnitude of the spillover effects differs between the states. Hereby, we apply the one-sided Wilcoxon-test¹²

on the absolute value of the median GIRFs, to examine whether the responses of a shock to a variable is stronger under the volatile regime, compared to the calm regime in absolute terms, see Table 12 for the test statistics. In particular, apart from shocks to the aluminum and nickel price as well as to the lead and tin market, the responses are significantly stronger under the volatile regime, at least at the 10% level, indicating the spillover effects are stronger in more volatile periods. Thereby, shocks to the aluminum, copper, nickel, and zinc market cause significantly stronger reactions in the commodity markets, especially the prices are affected to a larger extent.

Due to the stronger reactions in the commodity markets, the spillover effects may lead to higher risks in volatile periods, compared to calm periods. For that reason, we further investigate the conditional value at risk (CoVaR)¹³ of the variables, a risk measure which represents the expected return in the worst 10% of cases. In particular, the conditional value at risk indicates the average maximum increase in the variables and therefore, provides an indication of the increases in the commodity markets, especially the price, in response to shocks. In this context, we focus on the difference between the conditional value at risk under the volatile and calm regime of the prices for shocks to each variable in Fig. 8.

Overall, we observe shocks to the aluminum, copper, nickel, and zinc market cause an increased price risk under the volatile regime, indicating the prices react stronger to

changes in the other markets in periods of more fluctuations. Moreover, the production and consumption variables exhibit higher risks in response to these spillover effects. However, the conditional value at risk is higher under the calm period in response to changes in the lead and tin market, confirming the reactions to changes in the lead and tin market and the corresponding risks are not stronger in the volatile periods, in line with the Wilcoxon-test results.

Although the comparison of the significance of the GIRFs under the calm and volatile regime indicate the spillover effects equal under the calm and volatile regime, the impact of fundamentals as well as the effects between prices are stronger in the volatile regime, as the magnitude is generally larger, implying stronger spillover effects. These larger effects in terms of the magnitude cause higher risks of the spillover effects for shocks in the aluminum, copper, nickel, and zinc markets under the volatile regime.

Therefore, the commodity markets react stronger to any changes in the market in periods of high fluctuations, whereas under the calm period they only slightly respond to shocks. This finding underlines the stability of the markets under the calm regime, whereas the responses are more pronounced in volatile periods, suggesting the risk is even higher under the volatile regime, due to possible reactions in response to shocks in other commodity markets. However, while the magnitude of the responses is higher for almost all shocks under the volatile regime, the significance does not change, indicating neither the impact of fundamentals nor spillover effects between prices affect commodity markets more in calm or volatile regime. In contrast, the markets react more sensitive to both, shocks in the supply and demand as well as to prices, under the volatile regime.

Out-of-sample forecast performance

To underline the importance of a time-varying analysis, we assess the out-of-sample forecast performance of the MS-GVAR model and compare our results against the time-invariant GVAR model as benchmark model. Therefore, we forecast the commodity-specific variables with a rolling window approach and compare the predictability using the out-of-sample test of Clark and West (2007). Hereby, we split our dataset into a rolling in-sample window starting with data from January 1995 to December 2013 and an out-of-sample window covering the period from January 2014 to December 2020. For each step in time of the out-of-sample window, we estimate the (MS-)GVAR¹⁴ model based on the in-sample

¹² Since generalized impulse responses (GIRFs) are not normally distributed, we apply the non-parametric Wilcoxon signed-rank test to assess median differences between regimes. For robustness, we also computed results using a t-test, which yield qualitatively similar conclusions.

¹³ As all original variables were non-stationary, we base the entire analysis on the logarithmic return data and hence, also the forecasts are forecasts of logarithmic returns.

¹⁴ The model selection of the MS-GVAR model, based on the in-sample data, indicates the model which allows for regime-switches in the covariance matrix performs best. Therefore, we apply this model specification throughout the analysis.

Table 5 Generalized impulse response function (GIRF) results of the MS-GVAR model in the volatile regime

	Al			Cu			Ni			Pb			Sn			Zn		
	supply	demand	price															
Al	+			-		+	-											
supply		+		+														
demand			+		+													
price																		
Cu		-																
supply		+		+														
demand		+		+														
price		+		+														
Ni																		
supply																		
demand		+		+														
price		+		+														
Pb																		
supply																		
demand		+																
price		+		+														
Sn																		
supply																		
demand		+																
price		+		+														
Zn																		
supply																		
demand		+																
price		+		+														

Note: Results of the GIRF analysis of the MS-GVAR model under the assumption each commodity market is in its volatile regime. We analyze the response of the column variables to a shock of the row variables supply (**supply**), demand (**demand**) and price (**price**) of fAl, fCu, fNi, fPb, fSn, and fZn. Significant positive (+) or negative (-) effects on the 68%-level are displayed. Note: This table displays the generalized impulse response function (GIRF) results for the MS-GVAR model under the assumption that all commodity markets operate in a volatile regime. Each cell shows the effect of a one-standard-deviation shock to the supply, demand, or price of the row commodity on the column commodity. Significant positive (+) or negative (-) spillovers at the 68% confidence level are indicated, highlighting cross-commodity interdependencies during market turbulence

Table 6 Results of the out-of-sample (Clark and West 2007) test

Al	Cu		Ni		Pb		Sn		Zn									
	demand	price																
0.12	-0.81	1.38*	0.72	1.27	1.27	1.43*	0.56	1.58*	1.3*	2.18**	0.7	0.75	0.06	-0.01	-0.01	0.57	1.22	2.31**

Note: This table presents the out-of-sample forecast performance of the MS-GVAR model compared to the GVAR model based on the statistic of the Clark and West (2007) test with corresponding significance level (1% (***), 5% (**), and 10% (*)). Hereby, the forecasts are estimated for the out-of-sample window from January 2014 to December 2020 for each individual variable supply, demand, and price of the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn)

Table 7 Correlation matrix of spot prices

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.48	0.46	0.46	0.21	0.51
Cu	0.48	1.00	0.47	0.50	0.25	0.63
Ni	0.46	0.47	1.00	0.41	0.23	0.43
Pb	0.46	0.50	0.41	1.00	0.13	0.60
Sn	0.21	0.25	0.23	0.13	1.00	0.24
Zn	0.51	0.63	0.43	0.60	0.24	1.00

Note: Correlation matrix of adjusted spot prices, between 2014 and 2020

data and forecast all commodities’ annual prices one-step ahead. Hereby, we estimate and solve the (MS-)GVAR model repeatedly and we also re-evaluate the regime-probabilities in each step in the out-of-sample period.

The results of the Clark and West (2007) test are displayed in Table 6. Hereby, we compare the predictability of each commodity-specific variable. Overall, the MS-GVAR model significantly outperforms the time-invariant GVAR model in 6 of the 18 variables at the 10% significance level. In particular, the MS-GVAR model outperforms the predictions of the aluminum, copper, nickel, and zinc price, whereas the time-varying analysis barely improves the predictions of the production and consumption volumes.

To highlight the MS-GVAR model is able to forecast commodity prices, but also represents the co-movement between the prices, we compare the predicted price correlations of the MS-GVAR model with the dependencies observed in the markets. Therefore, we use the predicted prices of the (MS-)GVAR model, calculate the corresponding Pearson correlation matrices and compare them with the observed correlations in the period from January 2014 to December 2020, see Tables 7, 8, and 9. Hereby, we recognize the GVAR model overestimates the true correlations. This might be caused by the high correlations in the period until 2013, whereas the dependencies decreased around 2015, see Fig. 1.

Table 8 Correlation matrix of predicted prices based on the GVAR model

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.77	0.70	0.81	0.63	0.83
Cu	0.77	1.00	0.71	0.95	0.85	0.89
Ni	0.70	0.71	1.00	0.70	0.67	0.81
Pb	0.81	0.95	0.70	1.00	0.82	0.87
Sn	0.63	0.85	0.67	0.82	1.00	0.83
Zn	0.83	0.89	0.81	0.87	0.83	1.00

Note: Correlation matrix of predicted prices, using the GVAR framework, in an out-of-sample rolling window forecast from 2014 to 2020

Table 9 Correlation matrix of predicted prices based on the MSGVAR model

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.48	0.45	0.45	0.22	0.49
Cu	0.48	1.00	0.44	0.49	0.24	0.61
Ni	0.45	0.44	1.00	0.39	0.23	0.43
Pb	0.45	0.49	0.39	1.00	0.14	0.59
Sn	0.22	0.24	0.23	0.14	1.00	0.23
Zn	0.49	0.61	0.43	0.59	0.23	1.00

Note: Correlation matrix of predicted prices, using the MS-GVAR framework, in an out-of-sample rolling window forecast from 2014 to 2020

In contrast, the MS-GVAR model is able to reflect the dependency between the prices exceptionally well, with differences in the correlations for the predicted and observed prices being smaller than 5%.

Overall, the results indicate the MS-GVAR model reproduces the fluctuations as well as the relations between the prices. Moreover, the time-varying properties allow an in-depth analysis of the commodity market structure. In particular, the spillover effects and the associated risks can be analyzed in more detail. Hereby, the application of the MS-GVAR model on the industrial metal markets show the spillover effects are stronger during volatile periods, implying higher risks.

Discussion

In this study, we analyze the evolution of commodity markets, focusing on how fundamentals influence price dynamics and how co-movement between commodity prices changes over time. Therefore, we propose a new framework, the Markov-switching global vector autoregressive model for commodity markets, which allows to simultaneously investigate the time-varying spillover effects within and between commodity markets, contrary to previous studies which either examine the common behavior in prices, see Le Pen and Sévi (2017); Nicola et al. (2016); Ohashi and Okimoto (2016) and Pindyck and Rotemberg (1990) among others, or the influence of the individual supply and demand on prices, see Chen et al. (2019); Lutzenberger et al. (2017); Stuermer (2018) and Thomas et al. (2010). While accounting for the common impact of the economy on commodity markets, we also reflect the commodity-specific supply and demand by the world production and consumption and examine their impact on the commodity prices (in the cross-commodity dimension), whereas previous studies mostly neglect the impact of commodity-specific supply and demand factors on commodity prices probably due to data constraints. Our analysis

reveals commodity-specific production and consumption still significantly affect commodity prices in the individual markets, confirming the results of Chen et al. (2019); Lutzenberger et al. (2017), and Thomas et al. (2010). Additionally, the results suggest that fundamentals influence prices across commodities, indicating that supply and demand contribute to common market patterns. This effect is particularly evident as supply and demand dynamics also interact across different commodities, further reinforcing their interdependencies. Moreover, the spillover effects from prices to the supply and demand variables indicate the production as well as the consumption respond to changes in the price (in the cross-commodity dimension). In addition, we observe strong interdependencies between the prices themselves, confirming the co-movement between commodity prices observed in several studies, see Ciner et al. (2020); Fernandez (2015), and Tang and Xiong (2012) among others. Hereby, our results reveal the commodity markets react stronger to any changes in the markets in periods of high fluctuations, in accordance with the findings of Ciner et al. (2020), implying higher risks of increasing prices. Moreover, the out-of-sample forecasting analysis confirms the superiority of the time-varying MS-GVAR model over its time-invariant counterpart in price prediction. In particular, the MS-GVAR framework more accurately captures both fluctuations and interdependencies among metal prices, demonstrating its exceptional ability to reflect market dynamics. This finding strongly underscores the importance of time-varying analyses, further supporting the insights of Peersman et al (2021).

Conclusion

While the classical fundamental theory states supply and demand determine the commodity price, empirical studies reveal a common pattern in price movements, particularly since the financialization of commodity markets and the financial crisis. Therefore, we aim to analyze whether the commodity market structure and the interrelations between commodity markets changes over time. For that reason, we jointly investigate the impact of fundamentals on prices, the co-movement and the time-varying spillovers in the individual commodity markets as well as in the cross-commodity dimension, by applying a Markov-switching Global Vector Autoregression (MS-GVAR) model.

Hereby, we model each industrial metal market separately using Markov-switching Vector Autoregression (MS-VAR) models with the commodity-specific microeconomic variables supply, demand and price, as well as a vector of exogenous variables consisting of an interest rate, an exchange rate and an economic activity proxy, based on monthly data in the period of January 1995 to December 2020.

Analyzing the regime inference of each commodity market, we observe the nickel market exhibits numerous fluctuations between the regimes, while the aluminum, copper, lead, tin and zinc markets are more stable, with long periods in the calm regime and only few (brief) periods in the volatile regime, corresponding to the commodity price boom, the financial crisis, the European debt crisis as well as the oil price drop. Moreover, we investigate the dynamic properties of commodity markets using regime-dependent generalized impulse response functions, assuming that markets operate in either a calm or volatile state. In particular, we observe under both regimes various spillover effects of supply and demand, within and especially across commodity markets, as well as significant spillover effects between prices, underlining the importance of jointly modeling commodity markets, see Schischke et al. (2024). However, we do not observe differences in the significance of the responses between the calm and volatile regime, whereas the magnitude of almost all spillover effects is significantly larger under the volatile regime, indicating if shocks to fundamentals or prices affect the commodity markets, the effect increases in volatile periods. Albeit the significance in responses do not change across the regimes in our case of the industrial metal markets, the out-of-sample forecast analysis underlines the importance of a time-varying consideration of commodity markets, as the MS-GVAR model significantly outperforms the time-invariant GVAR model. Hereby, the MS-GVAR model reproduces the correlation structure in the commodity prices exceptionally well.

Overall, our results carry important implications for both policymakers and market participants. The identification of stronger spillover effects during volatile periods underscores the need for robust risk monitoring frameworks, especially when markets are under stress. Regulators should be aware that price shocks or supply disruptions in one commodity can have amplified effects on related markets, particularly during crises. This highlights the importance of coordinated policy responses and transparent market data to reduce contagion effects. For investors and portfolio managers, our findings reinforce the value of time-varying risk models in anticipating cross-market dynamics.

Appendix A: Data description

Descriptive statistics of the stationary variables included in our empirical analysis are given in Table 10. For our analysis, we seasonally adjust and standardize these returns such that they have mean zero and standard deviation one, but use the original variable names unadjusted, i.e. supply, demand and price.

Table 10 Descriptive statistics of the commodity-specific variables

	Minimum	5% Quantile	25% Quantile	Median	Mean	75% Quantile	95% Quantile	Maximum	St. Dev.	Skewness	Kurtosis	ADF	SW
Al													
supply	-0.10	-0.04	-0.01	0.00	0.00	0.01	0.03	0.13	0.02	0.45	4.51	-23.96**	0.94***
demand	-0.11	-0.06	-0.02	-0.00	-0.00	0.02	0.07	0.13	0.04	0.29	0.51	-25.88**	0.99*
price	-0.18	-0.08	-0.03	-0.00	-0.00	0.03	0.09	0.14	0.05	-0.08	0.35	-17.24**	0.99
Cu													
supply	-0.09	-0.04	-0.01	-0.00	0.00	0.02	0.04	0.09	0.03	0.17	0.93	-23.11**	0.99*
demand	-0.18	-0.07	-0.03	-0.00	-0.00	0.03	0.07	0.16	0.05	-0.02	0.83	-25.01**	0.99
price	-0.43	-0.11	-0.04	0.00	-0.00	0.04	0.11	0.25	0.07	-0.68	4.59	-15.59**	0.95***
Ni													
supply	-0.24	-0.10	-0.03	0.00	0.00	0.03	0.10	0.19	0.06	-0.33	1.46	-19.94**	0.97***
demand	-0.25	-0.13	-0.05	0.00	0.00	0.05	0.13	0.27	0.08	0.03	0.43	-22.05**	1.00
price	-0.33	-0.14	-0.07	-0.00	-0.00	0.06	0.15	0.29	0.10	-0.06	0.33	-16.98**	0.99
Pb													
supply	-0.25	-0.08	-0.03	-0.00	0.00	0.02	0.08	0.32	0.06	0.74	6.55	-23.53**	0.91***
demand	-0.19	-0.07	-0.02	-0.00	0.00	0.02	0.08	0.19	0.05	0.31	2.05	-26.35**	0.97***
price	-0.31	-0.12	-0.05	-0.00	-0.00	0.05	0.14	0.22	0.08	-0.27	1.38	-17.87**	0.98***
Sn													
supply	-0.27	-0.12	-0.03	-0.00	0.00	0.04	0.11	0.26	0.07	-0.34	1.97	-22.79**	0.97***
demand	-0.27	-0.14	-0.04	-0.00	-0.00	0.05	0.12	0.34	0.08	-0.01	1.72	-27.41**	0.97***
price	-0.24	-0.10	-0.04	-0.01	-0.00	0.03	0.11	0.21	0.06	0.05	1.06	-15.85**	0.98***
Zn													
supply	-0.24	-0.07	-0.02	-0.00	0.00	0.02	0.07	0.17	0.04	-0.43	4.21	-20.83**	0.95***
demand	-0.27	-0.08	-0.03	0.00	0.00	0.03	0.08	0.23	0.05	-0.28	3.35	-25.53**	0.97***
price	-0.41	-0.11	-0.05	0.00	-0.00	0.05	0.11	0.24	0.07	-0.53	2.83	-17.13**	0.97***
IP	-0.13	-0.03	-0.01	-0.00	-0.00	0.01	0.03	0.07	0.02	-0.61	4.87	-25.66**	0.96***
FX	-0.07	-0.04	-0.01	0.00	-0.00	0.01	0.04	0.07	0.02	0.02	0.48	-16.63**	0.99
FFR	-2.48	-0.18	-0.03	0.01	0.00	0.06	0.19	0.69	0.20	-6.68	75.99	-12.10**	0.54***

Note: This table displays the descriptive statistics (minimum, 5%, 25%, 75%, 95% quantile, median, mean, maximum, standard deviation (St. Dev.), skewness and excess kurtosis) of the stationary, commodity-specific variables supply, demand and price for the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), platinum (Pt), tin (Sn), and zinc (Zn), and the exogenous variables world Industrial Production (IP), U.S. Dollar index (FX), Federal Funds Effective Rate (FFR), as well as 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% (.)

Appendix B: Data description under regimes

Table 11 Descriptive statistics of the commodity-specific variables being either in state one (calm) or in state two (volatile)

		Minimum	5% Quantile	25% Quantile	Median	Mean	75% Quantile	95% Quantile	Maximum	St. Dev.	Nr. Obs.
Al	supply	1	-0.04	-0.03	-0.01	0.00	-0.00	0.01	0.04	0.01	215
		2	-0.10	-0.05	-0.02	0.00	0.00	0.02	0.13	0.04	97
	demand	1	-0.11	-0.06	-0.02	0.00	0.00	0.02	0.13	0.04	215
		2	-0.09	-0.08	-0.02	-0.00	-0.00	0.02	0.12	0.05	97
	price	1	-0.18	-0.07	-0.03	-0.00	0.00	0.04	0.14	0.05	215
		2	-0.18	-0.11	-0.04	-0.00	-0.00	0.03	0.14	0.07	97
Cu	supply	1	-0.06	-0.04	-0.01	-0.00	0.00	0.01	0.07	0.02	260
		2	-0.09	-0.06	-0.02	-0.00	0.00	0.02	0.09	0.04	52
	demand	1	-0.11	-0.06	-0.02	0.00	0.00	0.03	0.13	0.04	260
		2	-0.18	-0.11	-0.05	-0.01	-0.01	0.04	0.16	0.07	52
	price	1	-0.16	-0.08	-0.03	0.00	0.00	0.03	0.16	0.05	260
		2	-0.43	-0.19	-0.09	-0.00	-0.00	0.10	0.25	0.13	52
Ni	supply	1	-0.09	-0.05	-0.01	0.00	0.01	0.03	0.12	0.03	198
		2	-0.24	-0.16	-0.08	-0.03	-0.01	0.07	0.19	0.09	114
	demand	1	-0.14	-0.11	-0.04	0.00	0.00	0.05	0.16	0.06	198
		2	-0.25	-0.15	-0.08	-0.00	-0.00	0.06	0.27	0.10	114
	price	1	-0.33	-0.15	-0.07	0.00	0.00	0.07	0.29	0.10	198
		2	-0.26	-0.14	-0.07	-0.01	-0.00	0.06	0.22	0.10	114
Pb	supply	1	-0.09	-0.05	-0.02	-0.00	-0.00	0.02	0.09	0.03	217
		2	-0.25	-0.14	-0.05	0.01	0.01	0.07	0.32	0.09	95
	demand	1	-0.11	-0.07	-0.02	-0.00	-0.00	0.02	0.14	0.04	217
		2	-0.19	-0.08	-0.04	-0.00	0.00	0.04	0.19	0.06	95
	price	1	-0.19	-0.09	-0.04	-0.00	0.00	0.04	0.18	0.06	217
		2	-0.31	-0.18	-0.08	0.00	-0.00	0.06	0.22	0.11	95
Sn	supply	1	-0.11	-0.09	-0.03	-0.01	-0.01	0.02	0.09	0.04	150
		2	-0.27	-0.15	-0.04	0.01	0.01	0.07	0.26	0.09	162
	demand	1	-0.17	-0.08	-0.03	-0.00	-0.00	0.03	0.13	0.05	150
		2	-0.27	-0.18	-0.06	-0.00	0.00	0.07	0.34	0.11	162
	price	1	-0.10	-0.05	-0.03	0.00	0.01	0.04	0.16	0.05	150
		2	-0.24	-0.12	-0.05	-0.01	-0.01	0.03	0.21	0.07	162

Table 11 (Continued)

		Minimum	5% Quantile	25% Quantile	Median	Mean	75% Quantile	95% Quantile	Maximum	St. Dev.	Nr. Obs.
Zn	supply	1	-0.08	-0.05	-0.02	-0.00	0.01	0.04	0.06	0.03	196
		2	-0.24	-0.10	-0.03	0.01	0.05	0.09	0.17	0.06	116
	demand	1	-0.13	-0.06	-0.02	0.00	0.03	0.06	0.11	0.04	196
		2	-0.27	-0.09	-0.04	0.00	0.04	0.10	0.23	0.06	116
	price	1	-0.21	-0.09	-0.04	0.00	0.04	0.09	0.14	0.06	196
		2	-0.41	-0.13	-0.06	0.01	0.07	0.13	0.24	0.09	116

Note: This table displays the descriptive statistics (Minimum, 5%, 25%, 75%, 95% quantiles, median, mean, maximum, standard deviation (Nr. Obs.)) of the stationary, commodity-specific variables supply, demand and price for the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn), either in state one or in state two, when assuming the markets are in state two if the smoothed probability to be in state two exceeds 50%

Appendix C: Empirical results

C.1 Differences in the spillover effects

Table 12 Results of the Wilcoxon-test for the assessment of differences in the magnitude of spillover effects under the calm and volatile regime

	Al			Cu			Ni			Pb			Sn			Zn		
	supply	demand	price															
Al	81***	91***	91***	89***	86***	91***	74**	91***	91***	85***	88***	81***	91***	87***	91***	91***	89***	91***
supply	91***	82***	81***	91***	85***	70**	91***	77**	86***	89***	90***	80***	91***	71**	88***	88***	91***	87***
demand	25	15	15	13	3	23	18	20	15	28	4	42	13	5	24	9	20	20
price																		
Cu	38	53	52	71**	62	73**	41	66*	64*	58	67*	36	51	34	64*	66*	55	55
supply	74**	70**	66*	71**	49	59	65*	62	52	69*	86***	51	69*	71**	59	47	51	51
demand	90***	87***	91***	91***	88***	91***	91***	91***	91***	82***	90***	91***	89***	79***	73**	85***	84***	84***
price																		
Ni	89***	88***	91***	62	83***	73**	91***	89***	87***	78**	78**	57	91***	45	84***	87***	84***	84***
supply	59	61	61	71**	72**	59	64*	65*	70**	67*	80***	41	91***	68*	70**	72**	73**	73**
demand	86***	68*	63	84***	42	45	84***	60	74**	53	51	79***	52	45	48	71**	71**	71**
price																		
Pb	1	1	2	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0
supply	10	7	0	0	0	0	0	0	0	0	0	0	1	1	7	0	0	7
demand	0	1	18	3	0	2	4	0	0	1	2	0	0	0	0	0	0	11
price																		
Sn	29	19	31	64*	0	4	36	5	14	18	22	41	13	5	46	12	30	30
supply	28	11	39	55	46	52	42	51	29	58	20	24	26	29	33	34	65*	65*
demand	29	37	24	34	12	38	17	31	2	18	29	31	36	25	33	28	47	47
price																		
Zn	91***	91***	81***	81***	91***	80***	87***	85***	74**	84***	86***	91***	79***	73**	82***	86***	81***	81***
supply	91***	84***	91***	82***	91***	91***	89***	89***	74**	89***	88***	81***	67*	83***	82***	86***	91***	91***
demand	78**	66*	78**	80***	79***	69*	85***	77**	89***	63	72**	76**	88***	72**	83***	84***	83***	83***
price																		

Note: This table displays the statistics with corresponding significance level (0.1% (***), 1% (**), 5% (*) and 10% (.)) of the Wilcoxon test to assess whether the magnitude of the spillover effects are stronger in absolute terms under the volatile regime than under the calm regime. Hereby, we investigate the differences in the spillover effects of the column variables to shocks in the row variables (**supply**), demand (**demand**) and price (**price**) of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and Zinc (Zn). Note: This table displays the statistics with corresponding significance level (1% (***), 5% (**), and 10% (.)) of the Wilcoxon test to assess whether the magnitude of the spillover effects are stronger in absolute terms under the volatile regime than under the calm regime. Hereby, we investigate the differences in the spillover effects of the column variables to shocks in the row variables (**supply**), demand (**demand**) and price (**price**) of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and Zinc (Zn).

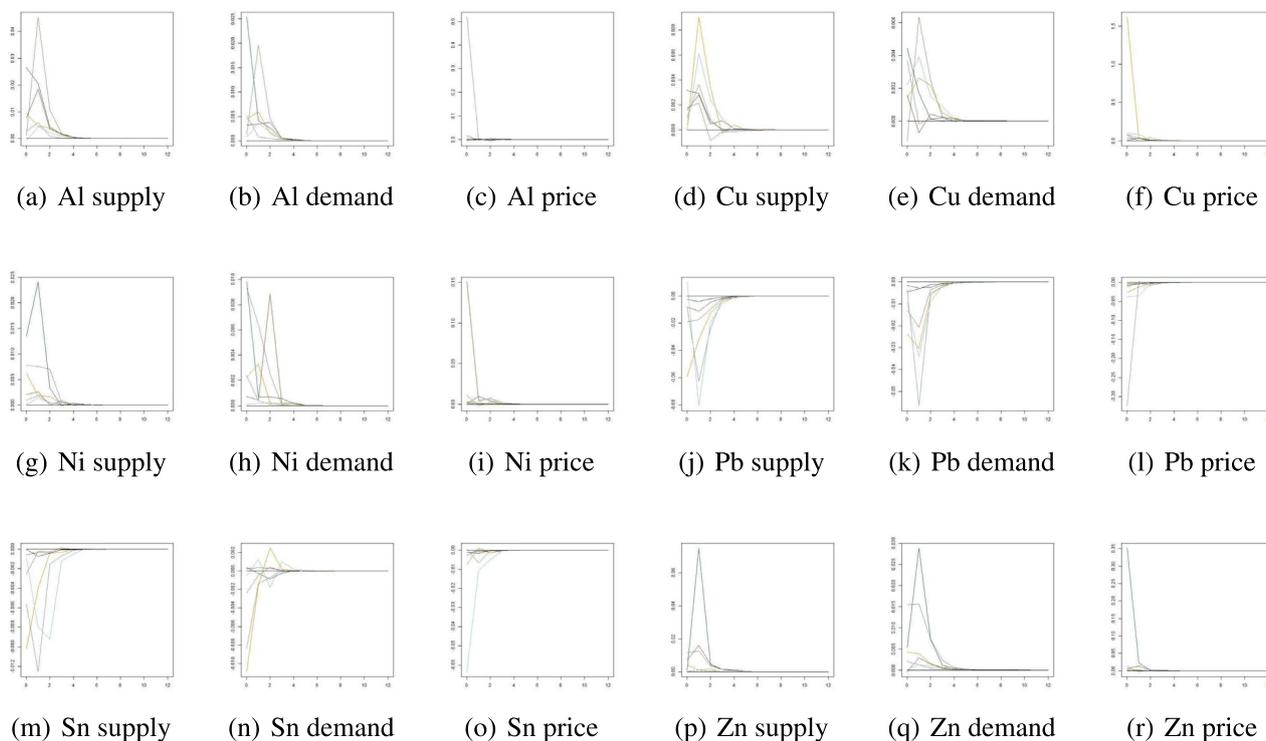


Fig. 8 Differences in the risk of the spillover effects on prices between the MS-GVAR model under the volatile vs. the calm regime. The plots illustrate the differences in the conditional value at risk between spillover effects from the supply, demand, and price of individual com-

modities to the commodity prices of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn), under the volatile vs. the calm regime.

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Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

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References

- Aepli MD, Füss R, Henriksen TES et al (2017) Modeling the multivariate dynamic dependence structure of commodity futures portfolios. *J Commodity Markets* 6:66–87. <https://doi.org/10.1016/j.jcomm.2017.05.002>
- Ahumada H, Cornejo M (2014) Explaining commodity prices by a cointegrated time series-cross section model. *Empirical Econ* 48:1667–1690. <https://doi.org/10.1007/s00181-014-0827-5>
- Akram QF (2009) Commodity prices, interest rates and the dollar. *Energy Econ* 31(6):838–85. <https://doi.org/10.1016/j.eneco.2009.05.016>
- Andersson S (2014) On the specification of local models in a global vector autoregression: a comparison of markov-switching alternatives. <https://www.diva-portal.org/smash/get/diva2:727669/FULLTEXT01.pdf>
- Ang A, Timmermann A (2012) Regime changes and financial markets. *Annual Rev Financ Econ* 4(1):313–337. <https://doi.org/10.1146/annurev-financial-110311-101808>
- Anzuini A, Lombardi MJ, Pagano P (2013) The impact of monetary policy shocks on commodity prices. *Int J Central Bank* 9(3):125–150. <https://doi.org/10.2139/ssrn.2030797>

- Baffes J, Savescu C (2014) Monetary conditions and metal prices. *Appl Econ Lett* 21(7):447–452. <https://doi.org/10.1080/13504851.2013.864029>
- Basak S, Pavlova A (2016) A model of financialization of commodities. *J Financ* 71(4):1511–155. <https://doi.org/10.1111/jofi.12408>
- Bigerna S, Campbell G (2025) The impact of by-product production on the availability of critical metals for the transition to renewable energy. *Energy Pol* 198:11451. <https://doi.org/10.1016/j.enpol.2025.114515> <https://www.sciencedirect.com/science/article/pii/S0301421525000229>
- Binder M, Gross M (2013) Regime-switching global vector autoregressive models. Tech. rep., ECB Working Paper. <https://doi.org/10.2139/ssrn.2302510>
- Board of Governors of the Federal Reserve System (U.S.) (2022) Federal funds effective rate (FEDFUNDS). <https://fred.stlouisfed.org/series/FEDFUNDS>
- Bollerslev T (1990) Modelling the coherence in short-run nominal exchange rates: a multivariate generalized arch model. *Rev Econ Stat* 498–505
- Borensztein E, Reinhart C (1994) The Macroeconomic Determinants of Commodity Prices. *IMF Staff Papers* 41(2):236–261. <https://doi.org/10.2307/3867508>
- Büyüksahin B, Robe MA (2014) Speculators, commodities and cross-market linkages. *J Int Money Financ* 42:38–70. <https://doi.org/10.1016/j.jimonfin.2013.08.004>
- Byrne JP, Fazio G, Fiess N (2013) Primary commodity prices: co-movements, common factors and fundamentals. *J Develop Econ* 101:16–2. <https://doi.org/10.1016/j.jdeveco.2012.09.002>
- Chen MH (2010) Understanding world metals prices — returns, volatility and diversification. *Resour Pol* 35(3):127–140. <https://doi.org/10.1016/j.resourpol.2010.01.001>
- Chen SL, Jackson J, Kim H et al (2014) What drives commodity prices? *Am J Agric Econ* 96:1455–1468. <https://doi.org/10.1093/ajae/aa014>
- Chen J, Zhu X, Zhong M (2019) Nonlinear effects of financial factors on fluctuations in nonferrous metals prices: a Markov-switching VAR analysis. *Resour Pol* 61:489–500. <https://doi.org/10.1016/j.resourpol.2018.04.015>
- Ciner C, Lucey B, Yarovaya L (2020) Spillovers, integration and causality in LME non-ferrous metal markets. *J Commodity Markets* 17. <https://doi.org/10.1016/j.jcomm.2018.10.001>
- Clark TE, West KD (2007) Approximately normal tests for equal predictive accuracy in nested models. *J Econ* 138(1):291–311. <https://doi.org/10.1016/j.jeconom.2006.05.023>
- Deaton A, Laroque G (2003) A model of commodity prices after sir arthur lewis. *J Develop Econ* 71(2):289–310. [https://doi.org/10.1016/S0304-3878\(03\)00030-0](https://doi.org/10.1016/S0304-3878(03)00030-0)
- Deb P, Trivedi PK, Varangis P (1996) The excess co-movement of commodity prices reconsidered. *J Appl Econ* 11(3):275–291. [https://doi.org/10.1002/\(SICI\)1099-1255\(199605\)11:3<275::AID-JAE392>3.0.CO;2-3](https://doi.org/10.1002/(SICI)1099-1255(199605)11:3<275::AID-JAE392>3.0.CO;2-3)
- Dées S, di Mauro F, Pesaran MH et al (2007) Exploring the international linkages of the euro area: a global VAR analysis. *J Appl Econ* 22:1–3. <https://doi.org/10.1002/jae.932>
- Dempster AP, Laird NM, Rubin DB (1977) Maximum likelihood from incomplete data via the EM algorithm. *J R Stat Soc Ser B (Methodological)* 39(1):1–22. <https://doi.org/10.1111/j.2517-6161.1977.tb01600.x>
- Ehrmann M, Ellison M, Valla N (2003) Regime-dependent impulse response functions in a Markov-switching vector autoregression model. *Econ Lett* 78(3):295–29. [https://doi.org/10.1016/S0165-1765\(02\)00256-2](https://doi.org/10.1016/S0165-1765(02)00256-2)
- Ehrmann M, Ellison M, Valla N (2001) Regime-dependent impulse response functions in a Markov-switching vector autoregression model. *Bank of Finland Discussion Paper* (11). <http://hdl.handle.net/10419/211889>
- Engle R (2002) Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J Bus Econ Stat* 20(3):339–350
- Fernandez V (2015) Commodity price excess co-movement from a historical perspective: 1900–2010. *Energy Econ* 49:698–710. <https://doi.org/10.1016/j.eneco.2015.04.003>
- Frankel JA (2008) The Effect of Monetary Policy on Real Commodity Prices. In: *Asset Prices and Monetary Policy*. National Bureau of Economic Research, Inc, pp 291–333. <https://doi.org/10.3386/w12713>
- Frankel JA, Rose AK (2010) Determinants of agricultural and mineral commodity prices. HKS faculty research working paper series, vol RWP10, no. 38, pp 1–48. <https://ideas.repec.org/p/ecl/harjfk/rwp10-038.html>
- Galesi A, Lombardi MJ (2009) External shocks and international inflation linkages: a global VAR analysis. ECB working paper series (1062). <https://ideas.repec.org/p/ecb/ecbwps/20091062.html>
- Guzmán JI, Silva E (2018) Copper price determination: fundamentals versus non-fundamentals. *Mineral Econ* 31(3):283–300. <https://doi.org/10.1007/s13563-017-0130-y>
- Hamilton JD (1989) A new approach to the economic analysis of non-stationary time series and the business cycle. *Econ J Econ Soc* 357–384. <https://doi.org/10.2307/1912559>
- Hamilton JD (1990) Analysis of time series subject to changes in regime. *J Econ* 45(1):39–70. [https://doi.org/10.1016/0304-4076\(90\)90093-9](https://doi.org/10.1016/0304-4076(90)90093-9)
- Hammoudeh S, Nguyen DK, Sousa RM (2015) US monetary policy and sectoral commodity prices. *J Int Money Financ* 57:61–85. <https://doi.org/10.1016/j.jimonfin.2015.06.003>
- Hannan EJ, Quinn BG (1979) The Determination of the Order of an Autoregression. *J R Stat Soc Ser B (Methodological)* 41(2):190–195. <http://www.jstor.org/stable/2985032>
- Helbling T, Mercer-Blackman V, Cheng K (2008) Riding a wave - soaring commodity prices may have a lasting impact. *Financ Dev* 45(1):10–15. <https://www.imf.org/external/pubs/ft/fandd/2008/03/helbling.htm>
- Hotelling H (1931) The economics of exhaustible resources. *J Pol Econ* 39:137–17. <https://doi.org/10.1086/254195>
- ICE Futures U.S. (2022) US Dollar INDEX DXY - PRICE INDEX (.DXY). Data retrieved from Investing.com. <https://de.investing.com/indices/usdollar-historical-data>
- Issler J, Rodrigues C, Burjack R (2014) Using common features to understand the behavior of metal-commodity prices and forecast them at different horizons. *J Int Money Financ* 42:310–335. <https://doi.org/10.1016/j.jimonfin.2013.08.017>
- Kagraoka Y (2016) Common dynamic factors in driving commodity prices: implications of a generalized dynamic factor model. *Econ Model* 52:609–61. <https://doi.org/10.1016/j.econmod.2015.10.005>
- Kang W, Tang K, Wang N (2023) Financialization of commodity markets ten years later. *J Commodity Markets* 30:100313. <https://doi.org/10.1016/j.jcomm.2023.100313> <https://www.sciencedirect.com/science/article/pii/S240585132300003X>
- Keyvani B, Aghayari R, Yosefi F et al (2025) Synthesis of copper oxide nanoparticles and their efficiency in automotive radiator heat transfer systems. *Powder Technol* 457:120887. <https://doi.org/10.1016/j.powtec.2025.120887> <https://www.sciencedirect.com/science/article/pii/S0032591025002827>
- Kilian L (2009) Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *Am Econ Rev* 99(3):1053–106. <https://doi.org/10.1257/aer.99.3.1053>
- Koop G, Pesaran MH, Potter SM (1996) Impulse response analysis in nonlinear multivariate models. *J Econ* 74(1):119–147. <https://ideas.repec.org/a/eee/econom/v74y1996i1p119-147.html>
- Kozian LL, Machado MR, Osterrieder JR (2025) Modeling commodity price co-movement: building on traditional time series models and

- exploring applications of machine learning algorithms. *Decisions in economics and finance* pp 1–44
- Krolzig HM (1997) Markov-switching vector autoregressions: modelling, statistical inference, and application to business cycle analysis. Springer, Berlin Heidelberg, Berlin, Heidelberg. <https://doi.org/10.1007/978-3-642-51684-9>
- Kupabado MM, Kaehler J (2025) Price effects of commodity financialization: review of the evidence. *J Econ Surv* 39(1):352–374. <https://doi.org/10.1111/joes.12619>
- Le Pen Y, Sévi B (2017) Futures trading and the excess co-movement of commodity prices. *Rev Finance* 22(1):381–418. <https://doi.org/10.1093/rof/rfx039>
- Lescaroux F (2009) On the excess co-movement of commodity prices—a note about the role of fundamental factors in short-run dynamics. *Energy Pol* 37(10):3906–391. <https://doi.org/10.1016/j.enpol.2009.05.013>
- Li N, Kwok SS (2021) Jointly determining the state dimension and lag order for Markov-switching vector autoregressive models. *J Time Ser Anal* 42(4):471–49. <https://doi.org/10.1111/jtsa.12587>
- Liao W, Ma J, Zhang C (2024) Commodity returns co-movement, uncertainty shocks, and the us dollar exchange rate. *J Int Money Financ* 143:10305. <https://doi.org/10.1016/j.jimonfin.2024.103056><https://www.sciencedirect.com/science/article/pii/S0261560624000433>
- Lombardi MJ, Osbat C, Schnatz B (2012) Global commodity cycles and linkages: a FAVAR approach. *Empir Econ* 43(2):651–670. <https://doi.org/10.1007/s00181-011-0494-8>
- Lübbers J, Posch PN (2016) Commodities' common factor: an empirical assessment of the markets' drivers. *J Commodity Markets* 4(1):28–4. <https://doi.org/10.1016/j.jcomm.2016.10.002>
- Lütkepohl H (1990) Asymptotic distributions of impulse response functions and forecast error variance decompositions of vector autoregressive models. *Rev Econ Stat* 72(1). <https://EconPapers.repec.org/RePEc:tpr:restat:v:72:y:1990:i:1:p:116-25>
- Lutzenberger F, Gleich B, Mayer HG et al (2017) Metals: resources or financial assets? A multivariate cross-sectional analysis. *Empir Econ* 53(3):927–95. <https://doi.org/10.1007/s00181-016-1162-9>
- Nassar NT, E. T, Graedel, et al (2015) By-product metals are technologically essential but have problematic supply. *Sci Adv* 1(3). <https://doi.org/10.1126/sciadv.1400180>
- Nicola F, Pace PD, Hernandez M (2016) Co-movement of major energy, agricultural, and food commodity price returns: a time-series assessment. *Energy Econ* 5. <https://doi.org/10.1016/j.eneco.2016.04.012>
- Ohashi K, Okimoto T (2016) Increasing trends in the excess comovement of commodity prices. *J Commodity Markets* 1(1):48–64. <https://doi.org/10.1016/j.jcomm.2016.02.001>
- Papenfuß P, Schischke A, Rathgeber A (2025) Factors of predictive power for metal commodities. *North Am J Econ Financ* 76:10230. <https://doi.org/10.1016/j.najef.2024.102309><https://www.sciencedirect.com/science/article/pii/S1062940824002341>
- Peersman G, Rùth SK, Van der Veken W (2021) The interplay between oil and food commodity prices: has it changed over time? *J Int Eco* 13. <https://doi.org/10.1016/j.jinteco.2021.103540>
- Pesaran M, Shin Y (1998) Generalized impulse response analysis in linear multivariate models. *Econ Lett* 58(1):17–29. [https://doi.org/10.1016/S0165-1765\(97\)00214-0](https://doi.org/10.1016/S0165-1765(97)00214-0)
- Pesaran M, Schuermann T, Weiner S (2004) Modeling regional interdependencies using a global error-correcting macroeconomic model. *J Bus Econ Stat* 22(2):129–162. <https://doi.org/10.1198/073500104000000019>
- Pindyck R, Rotemberg J (1990) The excess co-movement of commodity prices. *Econ J* 100(403):1173–1189. <https://EconPapers.repec.org/RePEc:ecj:conjl:v:100:y:1990:i:403:p:1173-89>
- Poncela P, Senra E, Sierra LP (2014) Common dynamics of nonenergy commodity prices and their relation to uncertainty. *Appl Econ* 46(30):3724–3735. <https://doi.org/10.1080/00036846.2014.939377>
- Reller A (2011) Criticality of metal resources for functional materials used in electronics and microelectronics. *Phys Stat Solid (RRL) – Rapid Res Lett* 5(9):309–311. <https://doi.org/10.1002/pssr.201105126>
- Runkle DE (1987) Vector autoregressions and reality. *J Bus Econ Stat* 5(4):437–442. <https://doi.org/10.1080/07350015.1987.10509609>
- Schischke A, Papenfuß P, Rathgeber A (2024) *Empir Econ*. pp 883–92. <https://doi.org/10.1007/s00181-023-02471-1>
- Schischke A, Rathgeber A (2023) Commodities and monetary policy - the role of interest rates revisited. <https://www.ssrncom/abstract=4365481>
- Shahani R, Singhal U (2023) Do efficient commodity markets co-move: evidence from Indian base metals market. *Miner Econ* 36(3):413–425. <https://doi.org/10.1007/s13563-022-00353-z>
- Shojaeinia S (2023) Metal market analysis: an empirical model for copper supply and demand in US market. *Miner Econ* 36(3):509–517
- Sivanur K, Umananda KV, Pai D (2021) Advanced materials used in automotive industry—a review. *AIP Conf Proc* 2317(1):020032
- Stuermer M (2018) 150 Years of boom and bust: what drives mineral commodity prices? *Macroecon Dyn* 22(3):702–717. <https://doi.org/10.1017/S136510051600050X>
- Sun X, Ouyang M, Hao H (2022) Surging lithium price will not impede the electric vehicle boom. *Joule* 6(8):1738–1742
- Su H, Wu Q, Zhou N, et al (2024) Dynamic spillover of upstream primary metals and by-product metals market and its impact from the downstream new energy vehicles market. *Miner Econ* 1–19. <https://doi.org/10.1007/s13563-024-00456-9>
- Sverdrup HU, Olafsdottir AH (2019) Assessing the long-term global sustainability of the production and supply for stainless steel. *Bio-Phys Econ Resour Qual* 4(2):8
- Tang K, Xiong W (2012) Index investment and the financialization of commodities. *Financ Anal J* 68(6):54–74. <https://doi.org/10.2469/faj.v68.n6.5>
- Tang K, Xiong W (2012) Index investment and the financialization of commodities. *Financ Anal J* 68(6):54–74. <https://doi.org/10.2469/faj.v68.n6.5>
- The World Bank (2022) World industrial production (IPTOTNSKD), seasonally unadjusted. [https://databank.worldbank.org/source/global-economic-monitor-\(gem\)](https://databank.worldbank.org/source/global-economic-monitor-(gem))
- Thomas AH, Mùhleisen M, Pant M (2010) Peaks, spikes, and barrels: modeling sharp movements in oil prices. *IMF Working Papers* pp 1–17. <https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Peaks-Spikes-and-Barrels-Modeling-Sharp-Movements-in-Oil-Prices-24133>
- U.S. Geological Survey (2012) Mineral commodity summaries 2012. <http://pubs.er.usgs.gov/publication/mcs2012>
- U.S. Geological Survey (2013a) Metal prices in the United States through 2010: U.S. geological survey scientific investigations report 2012–5188. <https://pubs.usgs.gov/sir/2012/5188/>
- U.S. Geological Survey (2013b) Mineral commodity summaries 2013. <http://pubs.er.usgs.gov/publication/mcs2013>
- U.S. Geological Survey (2016) Mineral commodity summaries 2023. <http://pubs.er.usgs.gov/publication/mcs2016>
- Vansteenkiste I (2009) How important are common factors in driving non-fuel commodity prices? A dynamic factor analysis. *ECB Working Paper Series* (1072). <https://doi.org/10.2139/ssrn.1433332>
- West K, Wong KF (2014) A factor model for co-movements of commodity prices. *J Int Money Financ* 42(C):289–309. <https://EconPapers.repec.org/RePEc:eee:jimfin:v:42:y:2014:i:c:p:289-309>
- World Bureau of Metal Statistics (2021) Bespoke production and consumption report 1995-2021. <https://world-bureau.co.uk/>

- Yin L, Han L (2015) Co-movements in commodity prices: global, sectoral and commodity-specific factors. *Econ Lett* 126:96–100. <https://doi.org/10.1016/j.econlet.2014.11.027>
- Zapp P, Rombach G, Kuckshinrichs W (2002) The future of automotive aluminium. https://www.researchgate.net/publication/290772721_The_future_of_automotive_aluminium
- Zaremba A, Umar Z, Mikutowski M (2021) Commodity financialisation and price co-movement: lessons from two centuries of evidence. *Financ Res Lett* 3. <https://doi.org/10.1016/j.frl.2020.101492>
- Zhang Y, Ding S, Scheffel EM (2019) A key determinant of commodity price Co-movement: the role of daily market liquidity. *Econ Model* 81:170–180. <https://doi.org/10.1016/j.econmod.2019.01.004>
- Zhang D, Broadstock DC (2020) Global financial crisis and rising connectedness in the international commodity markets. *Int Rev Financ Anal* 6. <https://doi.org/10.1016/j.irfa.2018.08.003>
- Zhou L (2023) Towards sustainability in mineral resources. *Ore Geol Rev* 160:10560. <https://doi.org/10.1016/j.oregeorev.2023.105600> <https://www.sciencedirect.com/science/article/pii/S0169136823003165>
- Zhu X, Chen J, Zhong M (2015) Dynamic interacting relationships 1556 among international oil prices, macroeconomic variables and pre- 1557 ciousmetalprices. *Trans Nonferr Metals Soc China* 25(2):669–676. 1558. [https://doi.org/10.1016/S1003-6326\(15\)63651-2](https://doi.org/10.1016/S1003-6326(15)63651-2)

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