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Macro-financial conditions and volatility connectedness across industrial and precious metal markets

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ABSTRACT

This study investigates the intensity and structure of volatility spillovers between industrial and precious metal markets from 2000 to 2024. Using the standard generalized Diebold–Yilmaz connectedness framework within a rolling-window setting, we estimate total and directional connectedness and decompose volatility transmission into within- and between-group components. In addition, this study relates the time-varying volatility spillovers to macro-financial conditions using regression models.

The full-sample total connectedness index amounts to 39%, whereby 73% of volatility transmission occurs within the industrial- and precious-metal groups and 27% between them. We find that metal market interconnectedness has increased substantially since the early 2000s, with volatility spillovers intensifying during periods of systemic stress. Directional analysis reveals that copper, zinc, gold, silver, and platinum act as net transmitters of volatility on average, while aluminum, nickel, lead, tin, and palladium are typically net receivers, although these roles change across subperiods.

The regression results identify crisis conditions as the most consistent predictors of subsequent changes in connectedness. The evidence is strongest for COVID-19, which is associated with increases in total, within-group, between-group, and directional connectedness. By contrast, evidence for the global financial crisis is weaker and concentrated mainly in total and within-group transmission. At the individual-metal level, additional macro-financial associations are concentrated primarily in received volatility. By contrast, net transmitter and receiver positions are largely characterized by persistence. Overall, macro-financial conditions are more closely associated with changes in the gross intensity of volatility transmission than with persistent changes in the relative network positions of individual metals.

1. Introduction

Metal markets are structurally interconnected through their supply, demand, and trading relationships. Metals may be co-produced as joint outputs, co-consumed in common industrial applications, and co-traded by overlapping market participants, creating channels through which shocks can propagate across markets, see Schischke et al. (2024). These structural linkages coexist with important differences in the economic functions of industrial and precious metals. Industrial metals are closely linked to manufacturing, construction, infrastructure investment, and expectations about future economic activity, see Ciner et al. (2020), whereas precious metals combine industrial applications with financial-market functions as investment assets and potential safe havens, see, for example, Mensi et al. (2020) and Mokni et al. (2021). At the same time, both groups respond to common conditions

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such as global demand, energy costs, exchange rates, monetary policy, and broader financial-market developments, according to Balli et al. (2019). The coexistence of structural interdependencies and heterogeneous exposures means that volatility shocks may remain concentrated within one metal group or spread across group boundaries, while also changing the relative roles of individual metals as transmitters and receivers. Understanding whether volatility transmission occurs predominantly within or between metal groups is therefore important for portfolio diversification, hedging, and the management of metal-price risk by investors, producers, processors, and other market participants with substantial metal exposure.

A growing literature documents substantial and time-varying volatility transmission across metal markets. Hereby, some studies examine connectedness within either industrial or precious metal markets, see, for example, Chen and Tongurai (2022), Ciner et al. (2020), Gong et al. (2022), Mokni et al. (2021), and Uddin et al. (2019), whereas others directly analyze the net spillover positions of the individual industrial and precious metals, including Al-Yahyaee et al. (2020), Batten et al. (2015), and Liu et al. (2021). More recent contributions extend this perspective to critical or battery metals, see Cagli (2023) and Wei et al. (2025). Despite differences in the markets, sample periods, and empirical approaches considered, two broad findings emerge from this literature. First, metal-market connectedness changes substantially over time and frequently intensifies during periods of economic uncertainty, financial stress, and market disruption. Second, individual metals occupy heterogeneous and time-varying positions within the connectedness network, with some markets acting predominantly as transmitters of volatility and others primarily absorbing shocks.

What remains less understood is which economic and financial conditions account for these changes in the intensity and structure of metal-market connectedness. A smaller strand of the literature relates total commodity-market spillovers to macroeconomic conditions, financial-market stress, economic policy uncertainty, transportation conditions, or commodity-specific shocks. For example, Bouri et al. (2021) examine several macroeconomic determinants of spillovers across a broad commodity system, while Padhan and Kocoglu (2025) analyze the role of transportation indicators, economic policy uncertainty, and oil demand and supply shocks in connectedness among energy, metal, and grain markets. Focusing more directly on metals, Al-Yahyaee et al. (2020) and Mokni et al. (2021) consider the impact of economic policy uncertainty and financial-market volatility on spillovers, while Ijaz et al. (2025) additionally examines climate risk. Overall, the resulting evidence nevertheless remains fragmented because existing studies frequently analyze broad commodity systems, focus on a limited set of explanatory factors, or concentrate primarily on aggregate connectedness. Consequently, it remains unclear through which economic channels macro-financial conditions are associated with volatility transmission and whether they primarily alter its overall intensity or also reshape the underlying structure of the metal-market network. This distinction is economically important because co-production, co-consumption, and co-trading may generate different transmission patterns within and across metal groups. Similar changes in total connectedness may therefore originate from stronger transmission within industrial or precious metals, greater spillovers between the two groups, or changing transmitter and receiver roles of individual metals.

Against this background, we ask which macro-financial conditions are associated with changes in the intensity and structure of volatility transmission across industrial and precious metal markets? More specifically, we investigate whether these conditions are associated primarily with changes in system-wide connectedness or also with changes in within- and between-group transmission and in the relative roles of individual metals as net transmitters and receivers. To address these questions, we analyze weekly volatility connectedness across six industrial and four precious metals over the period from 2000 to 2024. We apply the generalized connectedness framework of Diebold and Yilmaz (2012) within a rolling-window setting and estimate total as well as metal-specific transmitted, received, and net volatility spillovers. We further apply the group-based decomposition of total connectedness of Gabauer and Gupta (2018) to distinguish transmission within the industrial and precious metal groups from transmission between them. Finally, we relate these measures to macro-financial conditions representing global and regional demand, energy costs, financial risk and uncertainty, monetary and exchange-rate conditions, and broader commodity-market developments. In doing so, we build on previous studies that use regression-based approaches to explain connectedness, such as Al-Yahyaee et al. (2020) and Mokni et al. (2021), while extending their typically more limited explanatory sets and predominantly aggregate focus to within-group, between-group, and directional transmission. This multi-level design allows us to distinguish conditions associated with general changes in system-wide volatility transmission from those associated with changes in the internal structure of the metal-market network.

Our results indicate a total volatility spillover index of approximately 40%, suggesting that nearly half of future volatility in metal markets originates from cross-market transmission. The dynamic analysis reveals a substantial increase in connectedness from the mid-2000s, with a peak around the end of 2010 and comparatively elevated values until approximately 2013. Connectedness subsequently declined before increasing sharply during the initial phase of the COVID-19 pandemic, confirming that volatility transmission across metal markets varies considerably over time.

The group-level decomposition shows that 73% of total connectedness occurs within the industrial- and precious-metal segments on average, whereas spillovers between the two groups account for the remaining 27%. Although within-group transmission remains dominant throughout the sample, the relative contributions of industrial and precious metals vary over time. Cross-group transmission is largely bidirectional, with precious metals acting as modest net transmitters toward industrial metals on average, although the direction temporarily reverses in some periods. At the individual-market level, copper, zinc, silver, gold, and platinum are net transmitters on average, whereas aluminum, nickel, lead, tin, and palladium are net receivers on average. The dynamic results nevertheless show that these transmitter and receiver positions vary over time and are not temporally invariant.

The regression results show that crisis conditions provide the most consistent predictive information for subsequent changes in connectedness. Both the global financial crisis and the COVID-19 period are associated with increases in total and aggregate within-group connectedness, while only the COVID-19 period is significantly associated with stronger aggregate between-group transmission. Moreover, the group-specific results indicate that the crisis-related increase in within-group connectedness originates

primarily from industrial metals. In addition, COVID-19 is associated with stronger volatility transmission in both directions between industrial and precious metals. Although cross-group spillovers increase bidirectionally, the negative crisis coefficients in the net specification indicate that both crises shift the directional balance toward precious metals as net transmitters.

The metal-level panel results likewise show that both crisis periods are associated with increases in transmitted and received connectedness. Received connectedness exhibits additional associations with broader macro-financial conditions: higher lagged oil-price returns and an appreciation of the U.S. dollar are followed by increases in volatility received from other metal markets, whereas stronger emerging-market equity performance and higher long-term interest rates are associated with subsequent declines. By contrast, the net transmitter and receiver positions of individual metals are explained predominantly by their own persistence and are not systematically associated with the remaining macro-financial variables. Overall, the results indicate that macro-financial conditions are more closely related to changes in the gross intensity of volatility transmission than to persistent changes in the relative network positions of individual metals. To assess whether our findings depend on specific modeling choices, we conduct several robustness checks involving alternative forecast horizons, rolling-window lengths, VAR lag orders and estimators, including a conventional VAR and a time-varying parameter VAR, as well as an alternative volatility measure and alternative explanatory-variable specifications, with the main qualitative findings remaining broadly robust.

This study contributes to the literature in three respects. First, this study complements the predominantly descriptive evidence on time-varying metal-market connectedness by examining how lagged macro-financial conditions are associated with subsequent changes in connectedness. Second, this study applies the group-based decomposition of connectedness of Gabauer and Gupta (2018) to distinguish within-industrial, within-precious, and cross-group volatility transmission. Third, this study combines system-wide, group-level, and metal-specific evidence to assess whether macro-financial conditions contain predictive information for specific components of the metal-market network even when their association with aggregate connectedness is limited.

The remainder of this paper is structured as follows. Section 2 provides the theoretical fondaition, while Section 3 outlines the methodological framework employed in the analysis. Section 4 describes the data, and Section 5 presents the empirical findings. Finally, Section 6 offers concluding remarks and discusses implications for future research.

2. Theoretical framework

Volatility connectedness across metal markets can arise from both common exposure to macro-financial shocks and the transmission of shocks through economic and financial linkages between individual markets, see, for example, Al-Yahyaee et al. (2020) and Balli et al. (2019). While common macro-financial conditions may increase the overall intensity of volatility transmission, the distinct economic functions and market characteristics of industrial and precious metals may cause their effects to differ across individual markets and metal groups, thereby altering the structure of the connectedness network.

One important transmission channel operates through changes in real economic activity and expected metal demand, as common shifts in economic conditions can simultaneously affect several commodity markets, see Bouri et al. (2021) and Padhan and Kocoglu (2025). Industrial metals are closely linked to manufacturing, construction, infrastructure investment, and other metal-intensive activities, whereas demand for precious metals additionally reflects investment and hedging motives. Broad and synchronized changes in economic conditions may consequently generate common volatility across several metal markets and strengthen transmission both within and between the two groups. More geographically or sectorally concentrated demand developments may instead affect particular metals more strongly and thereby alter their relative positions as transmitters or receivers of volatility. For example, demand growth related to electrification and renewable-energy infrastructure may affect copper more strongly than other metals and thereby alter its role within the volatility-transmission network.

Production conditions provide a second channel through which volatility may propagate across metals. Mining, refining, processing, and transportation require substantial energy inputs, creating a production-cost channel through which energy-market shocks may propagate across industrial and precious metals, see Oliyide et al. (2021) and Umar et al. (2021). The resulting cost shocks may strengthen connectedness when they influence multiple metals through similar production processes. At the same time, differences in energy intensity, supply structures, and production locations imply heterogeneous exposure, which may shift the direction of volatility transmission across individual markets and metal groups.

Financial conditions and uncertainty constitute a further source of connectedness, as changes in perceived risk and risk aversion may induce investors to rebalance portfolio weights and adjust their commodity positions. During periods of heightened uncertainty or market stress, such reallocations may occur simultaneously across markets and thereby affect inventories, and financial exposures, see Al-Yahyaee et al. (2020) and Mokni et al. (2021). Such adjustments can transmit volatility even when the underlying physical supply and demand conditions of individual metals remain unchanged. The effects may nevertheless differ between industrial and precious metals because precious metals also serve as financial assets and potential stores of value. Financial shocks may therefore increase system-wide connectedness while simultaneously changing the relative transmitter and receiver roles of the two metal groups.

Broader commodity-market developments may additionally capture common changes in global demand, inflation conditions, and portfolio allocations toward commodities as an asset class, see Bouri et al. (2021), Ordu-Akkaya and Soytas (2020) and Tian and Hamori (2016). These common factors may increase volatility transmission across metal markets, whereas heterogeneous exposure to them may change the relative transmitter and receiver positions of individual metals.

Monetary and exchange-rate conditions may create common repricing across metal markets while affecting industrial and precious metals through different channels. Because internationally traded metals are predominantly denominated in U.S. dollars, exchange-rate movements alter their effective prices for consumers outside the United States, see Antonakakis and Kizys (2015).

At the same time, mining and processing costs are often incurred in the local currencies of producing countries. Changes in the U.S. dollar may therefore affect demand, producer margins, and supply incentives differently across metals and production regions, potentially altering both the intensity and direction of volatility transmission. Interest-rate changes may likewise generate heterogeneous responses across the two metal groups. Precious metals may react relatively directly through changes in the opportunity cost of holding non-interest-bearing assets, inflation expectations, and safe-haven demand in their role as an inflation hedge. Industrial metals may respond more gradually through financing conditions, inventory-carrying costs, investment activity, and cyclical demand. Such differences in timing and transmission channels may weaken or strengthen synchronized repricing across industrial and precious metals.

Taken together, these channels do not imply a uniform response of all connectedness measures. Macro-financial conditions that operate as broad common shocks should be associated primarily with changes in total connectedness. Conditions that affect particular metals or metal groups asymmetrically may additionally change transmitted, received, and net connectedness and hence the structure of the network. Moreover, the theoretical direction of these relationships is not always unambiguous, as the same development may increase common exposure while simultaneously reducing market activity or improving liquidity. The influence of macro-financial conditions on both the intensity and structure of metal-market connectedness therefore remains an empirical question.

3. Methodology

The objective of this study is to examine the association between macroeconomic and financial market variables and volatility spillovers between industrial and precious metals. To this end, we first apply the Diebold–Yilmaz spillover index, following Diebold and Yilmaz (2012), to quantify the volatility transmission across these markets. In a second step, we employ regression analysis to examine how key macroeconomic and financial variables are associated with the magnitude and direction of volatility spillovers.

3.1. Volatility spillovers in metal markets

To analyze volatility spillovers within metal markets, this study employs the Diebold–Yilmaz (DY) spillover index. Originally introduced by Diebold and Yilmaz (2009) and subsequently refined in Diebold and Yilmaz (2012, 2014), the index utilizes variance decomposition techniques based on vector autoregressive (VAR) models to quantify market interconnectedness. Specifically, it measures the share of forecast error variance in variable i that is attributable to shocks originating from variable j. In particular, this framework allows for the computation of both total and directional spillovers, offering a comprehensive perspective on the dynamics of volatility transmission and interdependence among markets.

To examine volatility spillovers within metal markets, we specify a vector autoregressive (VAR) model for the vector of volatility series $\mathbf{V}_t = (V_{1,t}, V_{2,t}, \dots, V_{N,t})'$, where N denotes the number of metals. The model takes the form of a covariance-stationary VAR(P) process of order P:

$$\mathbf{V}_t = \sum_{p=1}^{P} \boldsymbol{\Phi}_p \mathbf{V}_{t-p} + \boldsymbol{\epsilon}_t, \tag{1}$$

where $\boldsymbol{\Phi}_p$ are the $N \times N$ parameter matrices capturing the influence of lagged values $\mathbf{V}_{t-p}$, and $\boldsymbol{\epsilon}_t$ represents the innovation vector. The innovations are assumed to follow a white noise process with zero mean and constant covariance matrix $\boldsymbol{\Sigma}$, i.e., $\boldsymbol{\epsilon}_t \sim$ iid $(\mathbf{0}, \boldsymbol{\Sigma})$. Hereby, we address the estimation challenges posed by the high dimensionality of the parameter space by applying the least absolute shrinkage and selection operator (LASSO) method, in line with the recommendations by Demirer et al. (2018).

According to the Wold representation theorem, any stable VAR process can be equivalently expressed as an infinite-order vector moving average (VMA) process. Accordingly, the VAR can be rewritten as:

$$\mathbf{V}_t = \sum_{p=0}^{\infty} \mathbf{A}_p \boldsymbol{\epsilon}_{t-p}, \tag{2}$$

where $\mathbf{A}_p$ are $N \times N$ matrices computed recursively using the VAR coefficients:

$$\mathbf{A}_p = \boldsymbol{\Phi}_1 \mathbf{A}_{p-1} + \boldsymbol{\Phi}_2 \mathbf{A}_{p-2} + \cdots + \boldsymbol{\Phi}_P \mathbf{A}_{p-P} \tag{3}$$

with the initial condition $\mathbf{A}_0 = \mathbf{I}_N$ (the identity matrix), and $\mathbf{A}_p = \mathbf{0}$ for $p < 0$.

The Diebold–Yilmaz framework builds on the moving average representation by utilizing the VAR coefficient matrices to compute forecast error variance decompositions. These decompositions quantify the proportion of the forecast error variance of variable i, at horizon H, that is attributable to shocks in variable j, where $i \neq j$ and $i, j = 1, 2, \dots, N$. To ensure invariance to variable ordering, we follow Diebold and Yilmaz (2012) and adopt the generalized forecast error variance decomposition approach proposed by Koop et al. (1996). For a given forecast horizon H, the contribution of shocks from variable j to the H-step-ahead forecast error variance of variable i, denoted $\theta_{ij}^{g}(H)$, is defined as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{A}_h \boldsymbol{\Sigma} \mathbf{e}_j)^2}{\sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{A}_h \boldsymbol{\Sigma} \mathbf{A}_h' \mathbf{e}_i)}, \tag{4}$$

where $\boldsymbol{\Sigma}$ denotes the covariance matrix of the residuals $\boldsymbol{\varepsilon}$, $\sigma_{jj} = [\boldsymbol{\Sigma}]_{jj}$ denotes its jth diagonal element, i.e., the variance of the innovation in variable j, and $\mathbf{e}_i$ and $\mathbf{e}_j$ are selection vectors with one in the ith and jth positions, respectively, and zeros elsewhere.

Since generalized variance decompositions do not assume orthogonal shocks, the row sums of $\theta^g_{ij}(H)$ are not constrained to equal one. To address this, we normalize each row by its respective sum, yielding the normalized variance shares:

$$\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}, \tag{5}$$

such that $\sum_{j=1}^{N} \tilde{\theta}^g_{ij}(H) = 1$ and the total sum over all variables satisfies $\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H) = N$. The normalized off-diagonal elements $\tilde{\theta}^g_{ij}(H)$, where $i \neq j$, capture pairwise directional volatility spillovers from metal j to metal i over the forecast horizon H. These metrics provide a powerful tool to assess the dynamic interdependence of markets by quantifying how shocks in one metal influence the forecast uncertainty in another.

Following the framework proposed by Diebold and Yilmaz (2014), we compute directional volatility spillovers using the normalized generalized forecast error variance decomposition (GFEVD) matrix. The total directional spillovers received by variable i, denoted as "from others", are calculated as the row sum of all off-diagonal elements in row i, capturing the share of forecast error variance in variable i attributable to shocks from all other variables:

$$S_{i\leftarrow}(H) = \sum_{j=1, j\neq i}^{N} \tilde{\theta}^g_{ij}(H) \tag{6}$$

where N denotes the number of variables included and H is the chosen forecast horizon. This measure reflects the degree to which variable i is influenced by volatility originating from the rest of the system.

Conversely, the directional spillovers transmitted by variable i to all other markets, termed "to others", are obtained by summing the off-diagonal elements in column i:

$$S_{\leftarrow i}(H) = \sum_{j=1, j\neq i}^{N} \tilde{\theta}^g_{ji}(H). \tag{7}$$

To assess the relative importance of variable i as a net transmitter or receiver of volatility, we calculate net directional spillovers as the difference between the volatility transmitted to others and the volatility received from others:

$$S_i(H) = S_{\leftarrow i}(H) - S_{i\leftarrow}(H). \tag{8}$$

This metric helps identify the role of each individual metal within the spillover network, indicating whether it predominantly acts as a transmitter or receiver of volatility.

Finally, the total spillover index measures the overall degree of connectedness within the system by quantifying the share of the forecast error variance in all variables that is attributable to shocks arising from other variables in the system. It is computed as the normalized sum of all off-diagonal elements in the generalized forecast error variance decomposition (GFEVD) matrix:

$$S_g(H) = \frac{\sum_{i\neq j} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j} \tilde{\theta}^g_{ij}(H)} \times 100, \tag{9}$$

where $\tilde{\theta}^g_{ij}(H)$ denotes the normalized contribution of shocks from variable j to the H-step-ahead forecast error variance of variable i, and H is the forecast horizon. The total spillover index provides a system-wide measure of volatility transmission and reflects the overall extent of integration and interdependence among the markets under consideration.

The total and directional connectedness measures characterize the overall intensity of volatility transmission and the roles of individual metals as transmitters or receivers, but they do not reveal whether spillovers occur mainly within or between the industrial- and precious-metal groups. Following Gabauer and Gupta (2018), who extend the connectedness framework to distinguish internal from external transmission across predefined groups, we apply this decomposition to separate within-industrial, within-precious, and cross-group volatility spillovers.

Hereby, we assign the N metal markets to either the industrial-metal group or the precious-metal group. Let $\gamma \in \{\mathrm{IM}, \mathrm{PM}\}$ index the two groups and let $\mathcal{I}_\gamma$ denote the set of metals belonging to group γ. Within-group connectedness is obtained from the diagonal blocks of the normalized generalized forecast error variance decomposition matrix and captures volatility transmission among metals belonging to the same group. For group γ, it is defined as

$$C^{\mathrm{WITHIN}}_{\gamma}(H) = \frac{100}{N} \sum_{i\in\mathcal{I}_\gamma} \sum_{\substack{j\in\mathcal{I}_\gamma \\ j\neq i}} \tilde{\theta}^g_{ij}(H). \tag{10}$$

Volatility may also propagate between industrial and precious metals. These cross-group linkages are captured by the off-diagonal blocks of the connectedness matrix. Directed between-group connectedness from group η to group γ is generally defined as

$$C^{\mathrm{BETWEEN}}_{\gamma\leftarrow\eta}(H) = \frac{100}{N} \sum_{i\in\mathcal{I}_\gamma} \sum_{j\in\mathcal{I}_\eta} \tilde{\theta}^g_{ij}(H), \qquad \gamma \neq \eta. \tag{11}$$

Since metal i belongs to the receiving group γ and metal j belongs to the shock-originating group η, the measure captures volatility transmission from group η to group γ. Accordingly, $C^{\mathrm{BETWEEN}}_{\mathrm{PM}\leftarrow\mathrm{IM}}(H)$ measures spillovers from industrial to precious metals, whereas $C^{\mathrm{BETWEEN}}_{\mathrm{IM}\leftarrow\mathrm{PM}}(H)$ captures transmission in the opposite direction.

Aggregating the two group-specific within components yields total within-group connectedness:

$$C^{\text{WITHIN}}(H) = C^{\text{WITHIN}}_{\text{IM}}(H) + C^{\text{WITHIN}}_{\text{PM}}(H). \tag{12}$$

Total between-group connectedness is correspondingly given by

$$C^{\text{BETWEEN}}(H) = C^{\text{BETWEEN}}_{\text{IM}\leftarrow\text{PM}}(H) + C^{\text{BETWEEN}}_{\text{PM}\leftarrow\text{IM}}(H). \tag{13}$$

Together, the two components provide an additive decomposition of total connectedness:

$$S_g(H) = C^{\text{WITHIN}}(H) + C^{\text{BETWEEN}}(H). \tag{14}$$

This decomposition reveals whether changes in system-wide connectedness originate primarily from stronger transmission within the two metal groups or from greater interdependence between industrial and precious metals.

With only two groups, the directed between-group measures also directly determine their external transmitter and receiver positions. For group γ and the respective other group η, these measures are given by

$$C^{\text{EXT,TO}}_{\gamma}(H) = C^{\text{BETWEEN}}_{\eta\leftarrow\gamma}(H), \tag{15}$$

$$C^{\text{EXT,FROM}}_{\gamma}(H) = C^{\text{BETWEEN}}_{\gamma\leftarrow\eta}(H), \tag{16}$$

$$C^{\text{EXT,NET}}_{\gamma}(H) = C^{\text{BETWEEN}}_{\eta\leftarrow\gamma}(H) - C^{\text{BETWEEN}}_{\gamma\leftarrow\eta}(H). \tag{17}$$

A positive external net position identifies group γ as a net transmitter of volatility to the other metal group, whereas a negative value indicates a net receiver position. By construction, the external net positions of the two groups are equal in magnitude and opposite in sign.

Because the industrial- and precious-metal groups contain different numbers of markets, their group-specific within-connectedness measures comprise different numbers of possible links and are therefore interpreted as aggregate contributions rather than as average bilateral transmission intensities. This does not affect the additive comparison between total within- and total between-group connectedness, while the two directed between-group measures are based on the same number of possible cross-group links.

3.2. Regression analysis of volatility spillovers

To analyze the relationship between macro-financial conditions and volatility spillovers across metal markets, this study employs both linear and panel regression approaches. The linear regression model captures average associations between macroeconomic and financial conditions and overall, within-group, and between-group connectedness, while the panel regression framework additionally accounts for time-invariant and metal-specific heterogeneity. The explanatory variables comprise a broad set of macroeconomic and financial factors that may contain predictive information for subsequent changes in the intensity and direction of volatility spillovers across metal markets.

The linear regression model is specified as follows:

$$S_t = \beta_0 + \rho S_{t-1} + \beta_1 x_{1,t-1} + \beta_2 x_{2,t-1} + \cdots + \beta_K x_{K,t-1} + \varepsilon_t, \tag{18}$$

where the dependent variable S_t denotes either total connectedness, aggregate within- or between-group connectedness, group-specific within-group connectedness, directed between-group connectedness, or net directional connectedness between industrial and precious metals at time $t = 1, 2, \ldots, T$, as defined in Section 3.1. To ensure stationarity, all connectedness measures except net directional connectedness enter the regressions in logarithmic first differences, while net connectedness enters in levels. The K explanatory variables $x_{1,t-1}, x_{2,t-1}, \ldots, x_{K,t-1}$ represent several macroeconomic and financial factors at time $t-1$, see Section 4. The coefficients $\beta_1, \beta_2, \ldots, \beta_K$ capture the marginal association between each factor and the spillover index. The error term ε_t is assumed to be independently and identically distributed with zero mean and constant variance, i.e., $\varepsilon_t \sim \text{iid}(0, \sigma^2)$.

To examine how macroeconomic and financial factors are associated with net, received, and transmitted spillovers, we estimate a random-effects panel regression model,[1] accounting for unobserved metal-specific heterogeneity. The panel regression model is specified as follows:

$$S_{i,t} = \beta_0 + \rho S_{i,t-1} + \beta_1 x_{1,i,t-1} + \beta_2 x_{2,i,t-1} + \cdots + \beta_K x_{K,i,t-1} + u_i + \varepsilon_{i,t}, \tag{19}$$

where $S_{i,t}$ denotes the spillover measure for metal $i = 1, 2, \ldots, N$ at time t, corresponding to net spillovers, spillovers from others, or spillovers to others. To ensure stationarity, spillovers from and to others enter the regressions in logarithmic first differences, whereas net spillovers enter in levels. The explanatory variables $x_{1,i,t-1}, x_{2,i,t-1}, \ldots, x_{K,i,t-1}$ comprise both common macro-financial variables and, where applicable, metal-specific variables. The term u_i captures unobserved metal-specific effects that are assumed to be random and uncorrelated with the regressors, while $\varepsilon_{i,t}$ denotes the idiosyncratic error term. As a robustness check, we additionally estimate the dynamic panel specifications with metal fixed effects, thereby relaxing the random-effects orthogonality assumption.

[1] The Hausman test does not reject the random-effects specification in favor of fixed effects. However, because the inclusion of a lagged dependent variable may violate the standard random-effects orthogonality assumption, we do not rely on the Hausman test alone and additionally estimate metal fixed-effects specifications as a robustness check; see Appendix B.

Table 1
Descriptive statistics for the log volatility per country.

	Min.	Median	Mean	Max.	St.Dev.	Skewn.	Kurt.	ADF
Al	−4.81	−0.01	0.00	2.30	0.69	−0.15	4.63	−60.94***
Cu	−2.80	−0.03	0.00	2.90	0.68	0.15	3.44	−59.15***
Ni	−4.32	0.00	0.00	4.52	0.80	0.08	5.89	−62.12***
Pb	−4.10	0.00	0.00	4.03	0.76	−0.05	5.21	−63.67***
Sn	−3.60	−0.02	0.00	4.91	0.82	0.39	4.39	−60.02***
Zn	−4.28	0.02	0.00	4.24	0.77	−0.16	5.40	−61.90***
Ag	−1.68	0.01	0.00	1.78	0.49	0.10	3.10	−57.32***
Au	−1.43	−0.01	0.00	1.78	0.48	0.06	3.04	−58.09***
Pd	−2.39	−0.03	0.00	2.06	0.53	0.22	3.66	−56.38***
Pt	−1.43	−0.02	0.00	1.46	0.48	0.15	2.88	−60.24***

This table displays the minimum (Min.), median, mean, maximum (Max.), standard deviation (St.Dev.), skewness (Skewn.) and kurtosis (Kurt.) of the logarithmized volatility of the industrial metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zind (Zn), as well as the precious metals silver (Ag), gold (Au), palladium (Pd) and platinum (Pt). Moreover, the test statistics of the Augmented Dickey Fuller (ADF) test are reported, whereby *** indicate significance at the 1% level.

Table 2
Assignment of macro-financial variables to transmission channels.

Channel	Variables
Global and regional demand channel	S&P 500, MSCI Emerging markets, CSI 300, NIFTY 50
Cost channel	WTI crude-oil spot price
Asset management channel	VIX, Economic Policy Uncertainty index, global financial crisis dummy, COVID-19 dummy
Market-specific trading activity	Futures trading volume, included in the metal-level panel analysis
Broad commodity-market conditions	GSCI; CRB Commodity Index as robustness measure
Monetary and exchange-rate conditions	U.S. Treasury yields with maturities of one and thirty years, Chinese ten-year government bond yield, U.S. Dollar index

4. Data

This study investigates weekly volatility spillover effects across precious and industrial metal markets over the period from January 2000 to December 2024. We consider spot prices for the six industrial metals, aluminum, copper, nickel, lead, tin, and zinc, and four precious metals, silver, gold, palladium, and platinum, sourced from Bloomberg (2025). In this context, we build on the approach of Liu et al. (2021), who highlight that the volatility of these metal prices has attracted considerable attention from both financial investors and industrial enterprises.

Following Diebold and Yilmaz (2012), we estimate price volatility based on high and low price ranges. However, instead of daily frequencies, we compute weekly volatilities to better capture persistent, economically meaningful spillover patterns and to mitigate the influence of short-term noise and microstructure effects.[2] For metal i in week t, the volatility is defined as:

$$\hat{V}_{it} = 100\sqrt{\left(\ln(P_{it}^{\max}) - \ln(P_{it}^{\min})\right)^2}, \tag{20}$$

where $P_{it}^{\max}$ and $P_{it}^{\min}$ denote the weekly maximum and minimum spot prices, respectively.

Following Liu et al. (2021), we apply the natural logarithm transformation to the estimated volatility to address the non-negativity constraint and improve the statistical properties of the series. Descriptive statistics for the weekly volatility estimates are presented in Table 1. Interestingly, tin exhibits the highest average volatility and range among the considered metals, while the precious metals show lower variability compared to the industrial metals. Augmented Dickey–Fuller (ADF) tests confirm the stationarity of all logarithmized volatility series.

4.1. Macro-financial variables

To examine which macro-financial conditions are associated with changes in the intensity and structure of volatility transmission, we relate the different connectedness measures to a channel-based set of lagged explanatory variables. The market variables are generally obtained from Datastream (2024). In line with the theoretical framework, the variables capture global and regional demand conditions, energy-market conditions, risk and uncertainty, monetary and exchange-rate conditions, broader commodity-market developments, and market-specific trading activity. Table 2 summarizes their assignment to these channels.

First of all, global and regional demand conditions are represented by four different equity-market indices. The S&P 500 captures market expectations concerning economic conditions in the United States, while the MSCI Emerging markets index reflects broader developments across emerging economies. The CSI 300 and NIFTY 50 are included to capture economic developments in China and

[2] In contrast to Diebold and Yilmaz (2012), we do not annualize the volatility estimates. Since the annualization factor is merely a constant scaling term, it does not affect the relative dynamics or the computation of spillover indices.

India, whose relevance for global metal demand differs across market segments. China is the leading consumer of many base metals, whereas India represents an important source of precious-metal demand, particularly for gold and silver (Chen & Tongurai, 2022; Metals Focus, 2017; Mukherjee et al., 2017). Rather than serving as direct measures of realized economic output, these indices are interpreted as forward-looking, market-based indicators of regional economic conditions and expected demand.

In addition, energy costs are represented by the WTI crude-oil spot price, as mining, refining, processing, and transportation are energy intensive. Moreover, for the asset management channel, risk and uncertainty are captured by the VIX and the U.S. Economic Policy Uncertainty index developed by Baker et al. (2016), with the corresponding series obtained from the Federal Reserve Economic Data database (Baker et al., 2026). We further include two crisis indicators. The global financial crisis dummy equals one from September 2008 to June 2009, while the COVID-19 dummy equals one from March to May 2020 and captures the initial phase of widespread lockdowns and severe disruptions to economic activity.

Furthermore, we include futures trading volume in the metal-specific panel analysis to capture differences in trading activity and market participation across individual metals. Although connectedness is estimated from spot-market prices, futures volume provides a market-specific measure of trading activity in the principal venue for commodity risk transfer and price discovery. Because consistent trading-volume data for industrial metals are available only from 2004 onward, the panel analysis covers the period from 2004 to 2024. Additionally, broader commodity-market conditions are measured by the GSCI. As a robustness check, we replace the GSCI with the CRB Commodity Index to assess whether the results depend on the selected broad commodity benchmark.

Finally, monetary and exchange-rate conditions are captured by short- and long-term U.S. government bond yields, represented by the one-year and thirty-year Treasury yields, respectively. We additionally include the Chinese ten-year government bond yield to reflect financing conditions and longer-term economic expectations in China. Exchange-rate conditions are measured by the U.S. Dollar index, given the dominant role of the U.S. dollar in international commodity pricing.

All explanatory variables are aligned to the weekly frequency of the connectedness measures and enter the regressions in lagged form. Moreover, based on the results of the unit-root tests, continuous variables found to be non-stationary in levels are transformed into logarithmic first differences to ensure stationarity. Finally, pairwise correlations and variance inflation factors are reported in Tables A.8 and A.9 in the Appendix. Neither diagnostic indicates problematic multicollinearity among the explanatory variables.

5. Empirical results

This section presents the empirical results on volatility spillovers across industrial and precious metal markets and their associations with macroeconomic and financial conditions. To construct the spillover measures, we estimate first-order vector autoregressions (VAR(1)), selected based on the Bayesian Information Criterion, using LASSO regularization techniques. Following Liu et al. (2021), we set the forecast horizon to 20 steps.

The results are structured as follows: we begin by examining both the static and time-varying connectedness among the selected metal markets. Subsequently, we analyze the associations between macroeconomic and financial variables and the observed spillover dynamics.

5.1. Static analysis

Table 3 reports the static volatility spillover estimates across metal markets, based on the Diebold–Yilmaz framework calculated over the full sample period. The table presents the pairwise directional volatility spillovers from market j to market i, as defined in Eq. (5). Each entry in row i and column j reflects the contribution of volatility shocks originating in market j to the forecast error variance of market i. In addition, the table includes aggregate spillover measures: "from others" captures the total volatility transmitted to each market by all others, while "to others" reflects the total volatility spillovers a market transmits to the system. Net spillover values, computed as the difference between transmitted and received volatility, allow us to identify whether a market acts as a net transmitter or receiver within the network of metal markets.

Overall, the total spillover index of 39.19% indicates that around two-fifths of the forecast error variance across the ten metal markets is on average attributable to volatility shocks originating in other markets. This points to a substantial degree of interconnectedness within the metal-market system and is broadly consistent with the findings of Liu et al. (2021).

To determine whether this system-wide connectedness originates primarily from transmission within the industrial- and precious-metal segments or from spillovers between them, we decompose the total connectedness index into four components. The corresponding results are reported in Table 4.

The decomposition shows that volatility connectedness is predominantly concentrated within the two metal groups. Hereby, within-industrial-metal spillovers contribute 16.83 index points, corresponding to 42.93% of total connectedness, while within-precious-metal spillovers account for 11.95 points, or 30.49%. Taken together, within-group transmission represents 73.42% of total connectedness.

This concentration suggests that industrial and precious metals retain partially distinct transmission structures despite forming part of the same broader metal-market system. Within-industrial connectedness is consistent with common exposure to manufacturing activity, infrastructure investment, and metal-intensive technologies, whereas within-precious connectedness may reflect shared exposure to investment demand, financial-market conditions, and overlapping industrial applications. The larger aggregate contribution of industrial metals must nevertheless be interpreted in light of the different group sizes. Since the industrial-metal group contains six markets and the precious-metal group only four, the former comprises a larger number of possible within-group

Table 3
Static volatility spillovers.

	Al	Cu	Ni	Pb	Sn	Zn	Ag	Au	Pd	Pt	From
Al	66.94	8.42	3.92	3.10	3.23	7.12	3.38	0.57	1.80	1.51	33.06
Cu	6.43	50.49	6.48	6.39	5.46	8.60	6.82	4.09	2.18	3.04	49.51
Ni	3.71	8.56	67.57	5.22	3.83	5.60	2.44	1.13	0.53	1.42	32.43
Pb	3.06	7.66	5.03	64.61	2.93	9.56	3.83	2.12	0.44	0.76	35.39
Sn	2.86	7.39	4.16	2.75	67.60	4.42	4.33	2.44	1.84	2.22	32.40
Zn	6.05	9.58	4.95	8.52	3.27	59.33	3.60	1.54	1.48	1.69	40.67
Ag	2.57	5.44	2.07	2.75	4.27	3.18	48.87	20.56	3.27	7.04	51.13
Au	0.44	3.76	0.95	1.41	1.64	1.37	23.84	54.90	3.44	8.25	45.10
Pd	1.80	2.78	0.57	0.35	1.93	1.71	4.66	4.40	67.62	14.19	32.38
Pt	1.30	3.26	1.29	0.50	1.95	1.67	8.53	8.97	12.35	60.18	39.82
To	28.21	56.83	29.42	31.00	28.50	43.23	61.42	45.83	27.33	40.12	
Net	−4.85	7.32	−3.00	−4.39	−3.90	2.56	10.28	0.73	−5.04	0.30	**39.19**

This table presents the volatility spillover estimates among a set of industrial metals, aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn), and precious metals, silver (Ag), gold (Au), palladium (Pd), and platinum (Pt). Each cell reports the pairwise directional spillover transmitted from the market listed in the column to the market listed in the row. The "to others" row shows the aggregate spillovers a market transmits to all others, while the "from others" column captures the total spillovers a market receives from the rest of the system. The "net" row reflects the difference between spillovers transmitted and received, indicating whether a market is a net transmitter or net receiver of volatility. Bold values in the "from others" column and "net" row highlight the total spillover contribution of the system.

Table 4
Within- and between-group volatility spillovers.

Component	Contribution to TCI	Share of TCI (%)
Within-industrial	16.83	42.93
Within-precious	11.95	30.49
Industrial-to-precious	4.89	12.49
Precious-to-industrial	5.52	14.09
Total connectedness	39.19	100.00
Net industrial-to-precious	−0.63	−1.60

This table decomposes the total volatility spillover index reported in Table 3 into within-group and between-group components for the industrial and precious metal segments. Each of the first four rows reports the contribution of the respective transmission block to the total connectedness index. The four components sum to the total connectedness index, subject to rounding. "Net industrial-to-precious" is defined as the industrial-to-precious contribution minus the precious-to-industrial contribution and does not constitute an additional component of the total index.

links. The aggregate components therefore measure each group's contribution to total connectedness rather than the average strength of its bilateral relationships.

Between-group spillovers account for the remaining 26.58% of total connectedness. Transmission from industrial to precious metals contributes 4.89 index points, or 12.49% of total connectedness, whereas spillovers in the opposite direction amount to 5.52 points, or 14.09%. The external net position of the industrial-metal group therefore equals −0.63 index points, corresponding to −1.60% of total connectedness. Industrial metals are thus modest net receivers of volatility from precious metals at the aggregate group level. However, the small net balance indicates that cross-group transmission is largely bidirectional rather than dominated by a persistent one-way channel. Overall, the group-level decomposition reveals strong within-group clustering alongside economically meaningful and comparatively symmetric spillovers between industrial and precious metals.

The group-level decomposition provides the broader context for the market-specific directional spillovers reported in Table 3. At the individual-market level, silver and copper emerge as the principal transmitters of volatility, as reflected in their comparatively high "to others" measures. Zinc, gold, and platinum also transmit substantial volatility, although to a somewhat lesser extent. At the same time, these markets exhibit relatively high "from others" measures and therefore occupy central positions in the network as both transmitters and receivers of volatility. Conversely, aluminum, nickel, lead, tin and palladium exhibit weaker connections with the broader system, with less than one-third of their volatility attributable to spillovers either received or transmitted. These metals appear more segmented in terms of cross-market volatility dynamics.

The bilateral estimates are consistent with the predominance of within-group transmission. Among industrial metals, copper exhibits particularly strong linkages with zinc, aluminum, nickel, lead, and tin. Nevertheless, copper also maintains meaningful connections with precious metals and therefore represents an important link between the two segments. Silver similarly combines strong relationships with other precious metals with non-negligible connections to industrial metals, consistent with its dual role as both an investment asset and an industrial input.

However, the strongest bilateral volatility transmission occurs between silver and gold, in line with the findings of Batten et al. (2015), reflecting their shared monetary and investment characteristics and their common sensitivity to global financial conditions. Similarly, the directional spillovers between platinum and palladium are relatively high, which is consistent with their overlapping industrial applications, particularly in the automotive and electronics sectors. These strong silver-gold and platinum-palladium

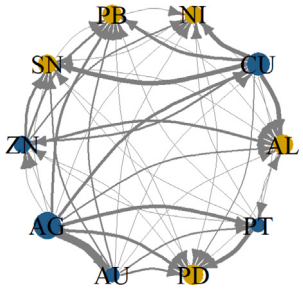


Fig. 1. Volatility spillover network between the industrial and precious metal markets.
This figure depicts the network graphs of the pairwise directional volatility connectedness across the set of industrial metals, aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn), and precious metals, silver (Ag), gold (Au), palladium (Pd), and platinum (Pt), computed using the approach of Diebold and Yilmaz (2012) over the full sample period. The blue nodes represent net transmitters, while the yellow nodes indicate net receivers of risk.

relationships explain why individual bilateral links within the precious-metal segment can be particularly intensive even though its aggregate within-group contribution is smaller than that of industrial metals.

Turning to net directional spillovers, copper, zinc, silver, gold, and platinum are identified as net transmitters of volatility on average, with copper, zinc, and silver standing out as the most dominant contributors, see Fig. 1. Aluminum, nickel, lead, tin, and palladium instead act as net receivers on average. These patterns are broadly consistent with previous evidence on volatility transmission across metal markets, including Cagli (2023), Chen and Tongurai (2022), Ciner et al. (2020), Gong et al. (2022), Liu et al. (2021), and Uddin et al. (2019).

However, some divergence from the existing literature is observed, as Al-Yahyaee et al. (2020) identify aluminum as a net transmitter of volatility, whereas in our sample it appears to absorb more risk than it emits. This difference may reflect the distinct sample periods, as their analysis covers 1997–2018, whereas ours extends from 2000 to 2024. More generally, it highlights the limitations of interpreting full-sample network positions as temporally invariant characteristics.

The static results therefore establish the average intensity and structure of volatility transmission over the full sample. The following dynamic analysis examines whether total connectedness, the relative importance of within- and between-group transmission, and the net positions of individual metals remain stable over time.

5.2. Dynamic analysis

A key limitation of the static spillover index is its implicit assumption that volatility spillovers among metal markets remain constant over time. This assumption overlooks the fact that market interconnectedness is likely to evolve in response to short-term shocks or structural changes in global economic conditions. As noted by Liu et al. (2021), time-invariant approaches may fail to capture significant shifts in spillover dynamics, particularly during periods of heightened uncertainty or macroeconomic transition.

To account for potential time variation in volatility transmission, we estimate dynamic spillover indices using a rolling window approach. Specifically, we employ a 104-week (two-year) rolling window as the baseline because it provides sufficient observations for estimating the ten-variable VAR while retaining the ability to capture medium-term changes in metal-market connectedness. This technique enables us to track how the degree of interconnectedness among metal markets changes over time.

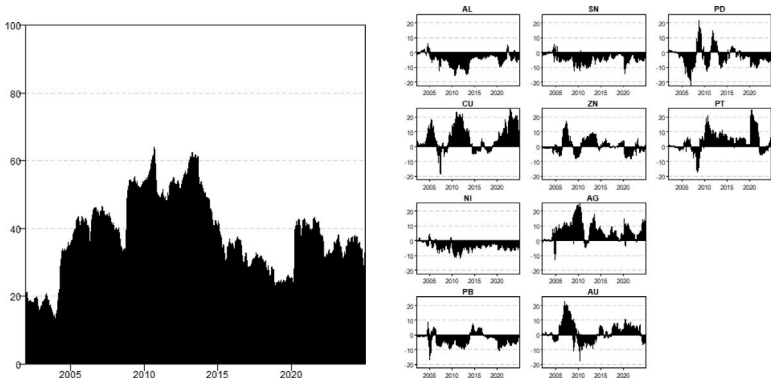
Fig. 2(a) displays the evolution of the total volatility spillover index from January 2002 to December 2024. The index exhibits substantial fluctuations, ranging between approximately 13% and 64%, indicating considerable time variation in the extent of volatility transmission across metal markets.

At the beginning of the 2000s, metal markets exhibited comparatively low levels of volatility transmission. Starting in 2004, however, connectedness increased steadily, coinciding with the growing financialization of commodity markets and strong metal demand from emerging economies, particularly China.

Connectedness peaked at the end of 2010 and remained at comparatively elevated levels until approximately 2013. This period coincides with the later phase of the commodity boom and strong global demand for metals. A temporary decline is visible around the onset of the global financial crisis, potentially reflecting the initial contraction in industrial activity during the onset of the global financial crisis.

Following 2013, the spillover index gradually declined before increasing sharply during the initial phase of the COVID-19 pandemic. The latter increase coincides with widespread supply-chain disruptions and heightened uncertainty concerning industrial demand.

Overall, the dynamic total spillover index confirms that volatility connectedness across metal markets varies substantially over time, consistent with findings in Al-Yahyaee et al. (2020), Ciner et al. (2020), Gong et al. (2022), Liu et al. (2021), Mokni et al. (2021), Uddin et al. (2019), and Wei et al. (2025). Several periods of elevated connectedness coincide with episodes of pronounced macroeconomic or financial stress, including the global financial crisis, the later phase of the commodity boom, and the COVID-19 pandemic. However, the timing and magnitude of these increases differ across episodes, and the use of a 104-week rolling window



(a) Total volatility spillovers. (b) Net volatility spillovers.

Fig. 2. Dynamic total and net volatility spillovers.
These figures show the total volatility spillover index and net spillover indices by metal over time, calculated using a 104-week rolling window technique based on the approach of Diebold and Yilmaz (2012).

implies that individual peaks reflect persistent changes over the preceding observation window rather than immediate responses to a single event. Moreover, changes in the total index alone do not reveal whether stronger connectedness originates within the industrial and precious metal segments or from increased transmission between them. We therefore extend the static group-level decomposition to the dynamic rolling-window setting.

To assess whether the group structure identified in the static analysis persists over time, we apply the within- and between-group decomposition to each rolling-window connectedness estimate. Fig. 3 reports connectedness within industrial metals, within precious metals, the two directed cross-group components, and the resulting net industrial-to-precious transmission.

The dynamic decomposition confirms that within-group transmission remains the dominant component throughout the sample, with its combined contribution consistently exceeding between-group connectedness. The group-specific clustering observed in the static analysis is therefore not solely a consequence of averaging across the full sample. Nevertheless, the between-group share increases around 2012–2013, during 2020–2021, and toward the end of the sample. These higher shares largely reflect declines in within-group connectedness rather than similarly pronounced increases in the absolute level of cross-group transmission. The level and relative contribution of between-group connectedness therefore provide complementary information.

The relative importance of the two within-group components also changes over time. Within-industrial connectedness is comparatively elevated from approximately 2005 onward, except for a temporary decline around 2009, and rises again after 2021. The earlier increase coincides with strong global economic growth and rising industrial-commodity demand, whereas the decline around 2009 corresponds to the contraction in economic activity during the global financial crisis. Within-precious connectedness becomes particularly pronounced during several periods of market stress, including the global financial crisis and the COVID-19 pandemic, and exceeds within-industrial connectedness through much of the second half of the 2010s. Thus, while within-group transmission remains dominant, the metal segment contributing most strongly to it is not constant.

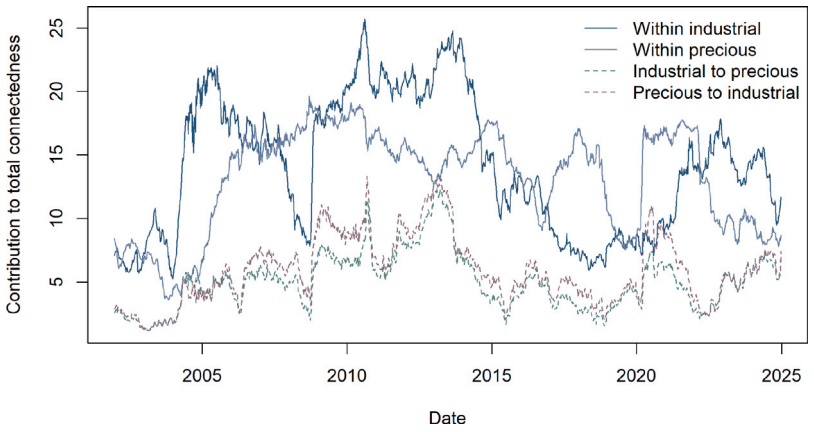
The two directed cross-group components generally move closely together and remain smaller than the within-group components. However, transmission from precious to industrial metals exceeds transmission in the opposite direction during much of the sample. Accordingly, net industrial-to-precious connectedness is predominantly negative from approximately 2006 onward, with particularly pronounced negative values around the global financial crisis and during 2020–2021. Temporary positive values around 2004–2005 and 2022 indicate periods in which industrial metals instead become net transmitters toward precious metals.

Despite these directional changes, the net balance remains small relative to gross between-group connectedness. Cross-group transmission is therefore predominantly bidirectional, with precious metals assuming only a modest net-transmitter position during much of the sample. Overall, the dynamic decomposition confirms the persistent predominance of within-group connectedness while revealing substantial variation in both the composition and direction of volatility transmission.

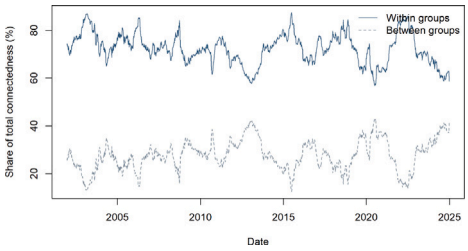
The group-level results describe how volatility transmission is distributed within and between the two broad metal segments. We next examine which individual markets account for these changing transmission patterns. The dynamic "to others", "from others", and net spillover measures are displayed in Figs. 4(a), 4(b), and 2(b).

The dynamic "to others" and "from others" measures broadly co-move with the total connectedness index, although their magnitudes and relative importance differ across metals and over time. Copper, silver, gold, and platinum frequently exhibit comparatively high directional connectedness, but the decomposition also shows that their contributions cannot be interpreted independently of the changing structure of within- and between-group transmission. The market-level results therefore complement the group analysis by identifying the individual metals underlying the broader shifts in network connectedness.

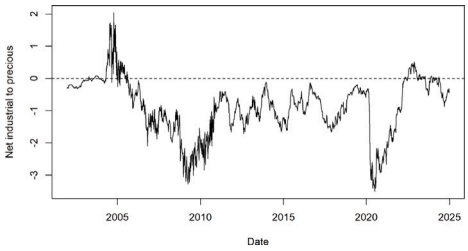
Turning to the directional dynamics, the time-varying net spillover analysis reveals persistent asymmetries in the roles of individual metal markets. Aluminum, nickel, lead, tin, and palladium predominantly act as net receivers over the sample period,



(a) Within- and between-group components.

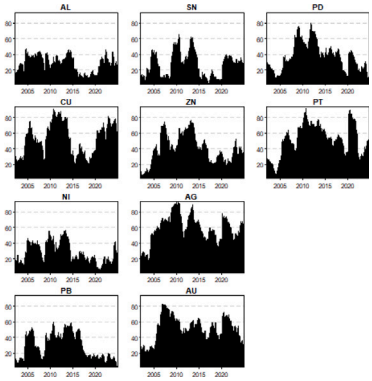


(b) Relative within- and between-group contributions.

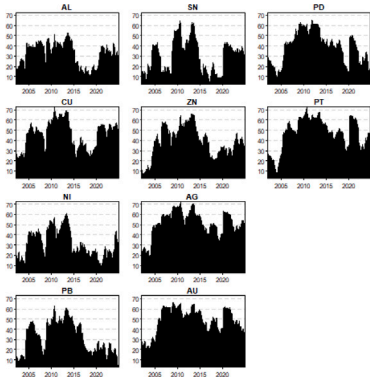


(c) Net industrial-to-precious spillovers.

Fig. 3. Dynamic within- and between-group volatility connectedness.
Panel (a) presents the contributions of within-industrial, within-precious, industrial-to-precious, and precious-to-industrial volatility transmission to total connectedness. Panel (b) reports the shares of total connectedness attributable to within-group and between-group transmission. Panel (c) presents net industrial-to-precious connectedness, defined as industrial-to-precious spillovers minus precious-to-industrial spillovers. Positive values in Panel (c) identify industrial metals as net transmitters toward precious metals, whereas negative values identify precious metals as net transmitters toward industrial metals. All connectedness measures are estimated using a 104-week rolling window based on the approach of Diebold and Yilmaz (2012).



(a) Volatility spillover index "to others".



(b) Volatility spillovers "from others".

Fig. 4. Dynamic volatility spillover indices "to others" and "from others".
These figures show the volatility spillover indices "to others" and "from others" by metal over time, calculated using a 104-week rolling window technique based on the approach of Diebold and Yilmaz (2012).

broadly reinforcing the static results, see Fig. 2(b). In contrast, copper, zinc, silver, gold, and platinum emerge as the primary net transmitters, although their specific roles fluctuate across subperiods in response to changing market conditions.

First of all, silver maintains a relatively stable position as a net transmitter throughout the sample period, consistent with its dual role as both an industrial metal and a financial asset. Moreover, copper stands out as a dominant transmitter of volatility in recent years, reflecting its pivotal role in global industrial production, particularly in the context of the energy transition. However, during the global financial crisis, copper temporarily shifted into a net receiver role, suggesting that the direction of spillovers is shaped by broader crisis dynamics and investor behavior. Platinum likewise changes from a net receiver during the financial crisis to a net transmitter during the COVID-19 period before returning to a receiver position around 2022. Zinc also functions predominantly as a net transmitter, yet it was a net receiver both at the beginning of the sample period and temporarily during the pandemic.

Gold exhibits a more variable net position. It acts as a net transmitter during several intermediate periods, including around the global financial crisis, but becomes a net receiver at the beginning and end of the sample and during much of 2010–2013. These changes emphasize that gold's position within the metal-market network is time varying and cannot be characterized by a stable transmitter or receiver role.

Taken together, the dynamic results show that both the intensity and the internal structure of metal-market connectedness change over time. Within-group transmission remains the dominant component throughout the sample, but its relative importance varies and cross-group linkages become more prominent during selected periods. At the same time, the identities of individual net transmitters and receivers are not temporally invariant, and the direction of aggregate cross-group transmission also reverses in some subperiods. These findings motivate the subsequent regression analysis, which examines whether macro-financial conditions predict changes in total connectedness, group-level transmission, and market-specific directional spillovers.

5.3. Macro-financial conditions and volatility connectedness

The dynamic analysis reveals substantial variation in volatility connectedness across metal markets over time. Periods of comparatively high connectedness coincide with major commodity-market and macroeconomic disruptions, including the later phase of the previous commodity boom and the onset of the COVID-19 pandemic. These patterns motivate an examination of whether broader macro-financial conditions contain predictive information for subsequent changes in the intensity and structure of volatility transmission.

To empirically assess these relationships, we estimate regression models using the macro-financial variables described in Section 4. All explanatory variables enter the models with a one-period lag to establish a temporal ordering between macro-financial conditions and subsequent connectedness and to mitigate concerns regarding contemporaneous endogeneity.

We begin by estimating linear regression models for total connectedness and the different within- and between-group connectedness measures. All connectedness measures except net connectedness are non-stationary in levels and therefore enter the regressions in logarithmic first differences. Accordingly, these specifications explain proportional changes in connectedness rather than its absolute level. Net connectedness is stationary in levels and is therefore included without transformation. Moreover, the models are estimated using Ordinary Least Squares (OLS) with Newey–West standard errors to account for potential heteroscedasticity and autocorrelation. The regression results are reported in Tables 5 and 6.

The results for total connectedness provide evidence of short-run persistence in changes in system-wide volatility transmission. The positive and statistically significant coefficient of lagged total connectedness indicates that increases in connectedness tend to be followed by further increases in the subsequent period.

Among the macro-financial variables, the crisis indicators are the only statistically significant predictors. Most notably, the COVID-19 dummy variable yields a positive and statistically significant coefficient, indicating an increase in total market connectedness during the pandemic period. This finding reinforces the results of the dynamic spillover analysis and is consistent with previous dynamic spillover studies that report intensified interconnectedness during periods of systemic crisis, such as Al-Yahyaee et al. (2020), Ciner et al. (2020), Gong et al. (2022), Liu et al. (2021), Mokni et al. (2021), and Uddin et al. (2019).

The coefficient of the global financial crisis dummy is also positive, although statistically significant only at the 10% level. This provides weaker evidence that the financial crisis was followed by an increase in system-wide volatility transmission. The smaller statistical precision may reflect the fact that the crisis occurred during a broader period of rising metal-market connectedness rather than constituting an isolated shift in its dynamics. None of the remaining macro-financial variables is statistically significant in the total-connectedness specification. However, the aggregate model may conceal heterogeneous associations across different parts of the metal-market network. We therefore repeat the analysis using aggregate within- and between-group connectedness, group-specific within connectedness, directed cross-group transmission, and the net position of the two metal groups as dependent variables.

The decomposition reveals important differences between within- and between-group transmission. For aggregate within-group connectedness, the coefficient on the lagged dependent variable is positive and statistically significant at the 5% level, indicating persistence in proportional changes in volatility transmission within the two metal groups. The global financial crisis and COVID-19 dummies are likewise positive and significant at the 5% and 10% levels, respectively. Thus, both crisis periods are associated with subsequent increases in volatility transmission within the industrial- and precious-metal segments.

Aggregate between-group connectedness also exhibits some persistence. Moreover, the COVID-19 dummy is positive and statistically significant, whereas the global financial crisis dummy is not significant. This suggests that the pandemic was associated not only with stronger transmission within the two metal groups but also with a pronounced increase in volatility propagation between industrial and precious metals. By contrast, the increase associated with the global financial crisis appears to have been concentrated primarily within the two groups.

Table 5
Macro-financial conditions and aggregate connectedness.

Variable	Total connectedness		Within total		Between total		Net (Industrial to Precious)	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	−0.0009	(0.0006)	−0.0010.	(0.0006)	−0.0005	(0.0018)	−0.0478 ***	(0.0118)
Total connectedness$_{t-1}$	0.1194 **	(0.0372)						
Within total$_{t-1}$			0.0789 *	(0.0402)				
Between total$_{t-1}$					0.0723	.	(0.0388)	
Net (Industrial to Precious)$_{t-1}$							0.9497 ***	(0.0102)
MSCI Emerging markets$_{t-1}$	−0.0942	(0.0616)	−0.0716	(0.0493)	−0.1690	(0.1558)	−0.1083	(0.5643)
CSI 300$_{t-1}$	−0.0011	(0.0256)	0.0084	(0.0220)	−0.0379	(0.0851)	0.1405	(0.2356)
NIFTY 50$_{t-1}$	0.0046	(0.0450)	0.0050	(0.0392)	0.0013	(0.1044)	−0.2368	(0.5394)
S&P 500$_{t-1}$	−0.0396	(0.0790)	0.0275	(0.0639)	−0.2345	(0.2161)	1.1493.	(0.6279)
Oil price$_{t-1}$	0.0304	(0.0311)	−0.0116	(0.0222)	0.1314	(0.0919)	−0.3725	(0.3246)
VIX$_{t-1}$	−0.0031	(0.0106)	0.0030	(0.0078)	−0.0290	(0.0303)	0.0876	(0.0569)
EPU$_{t-1}$	0.0010	(0.0026)	0.0023	(0.0021)	−0.0045	(0.0072)	0.0043	(0.0176)
COVID-19$_{t-1}$	0.0321 *	(0.0129)	0.0205.	(0.0119)	0.0588 **	(0.0194)	−0.2481 ***	(0.0525)
Golbal financial crisis$_{t-1}$	0.0093.	(0.0050)	0.0082 *	(0.0040)	0.0141	(0.0101)	−0.0897 ***	(0.0216)
U.S. Dollar index$_{t-1}$	0.0868	(0.1023)	0.0037	(0.0904)	0.2613	(0.2324)	−0.4677	(0.6734)
Chinese 10y bond yield$_{t-1}$	−0.0503	(0.0454)	−0.0438	(0.0386)	−0.0461	(0.1043)	−0.3723	(0.4283)
U.S. 1y bond yield$_{t-1}$	0.0066	(0.0137)	0.0034	(0.0098)	0.0033	(0.0324)	0.1349	(0.0870)
U.S. 30y bond yield$_{t-1}$	−0.0286	(0.0433)	−0.0051	(0.0378)	−0.1089	(0.0717)	0.2735	(0.1834)
GSCI$_{t-1}$	−0.0487	(0.0527)	0.0245	(0.0394)	−0.2060	(0.1528)	0.4385	(0.4867)

This table reports OLS estimates for total connectedness, aggregate within-group connectedness, aggregate between-group connectedness, and net connectedness from industrial to precious metals. All explanatory variables enter the regressions with a one-period lag. Total, within-group, and between-group connectedness are expressed in logarithmic first differences, while net connectedness is included without transformation. Newey–West standard errors accounting for heteroscedasticity and serial correlation are reported in parentheses. Statistical significance is indicated by *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and . $p < 0.10$.

Table 6
Macro-financial conditions and group-specific connectedness.

Variable	Within industrial		Within precious		Industrial to precious		Precious to industrial	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	−0.0016	(0.0010)	−0.0005	(0.0010)	−0.0005	(0.0019)	−0.0004	(0.0019)
Within industrial$_{t-1}$	0.0869.	(0.0453)						
Within precious$_{t-1}$			0.0428	(0.0584)				
Industrial to precious$_{t-1}$					0.0458	(0.0390)		
Precious to industrial$_{t-1}$							0.0573	(0.0416)
MSCI Emerging markets$_{t-1}$	−0.1208	(0.0773)	−0.0458	(0.0579)	−0.1589	(0.1553)	−0.1669	(0.1669)
CSI 300$_{t-1}$	−0.0117	(0.0327)	0.0184	(0.0274)	−0.0437	(0.0890)	−0.0392	(0.0868)
NIFTY 50$_{t-1}$	0.0025	(0.0600)	0.0085	(0.0535)	−0.0462	(0.1012)	0.0264	(0.1195)
S&P 500$_{t-1}$	0.0353	(0.0954)	0.0491	(0.0894)	−0.2250	(0.2195)	−0.2472	(0.2234)
Oil price$_{t-1}$	0.0180	(0.0631)	−0.0106	(0.0347)	0.1522	(0.1003)	0.1243	(0.0936)
VIX$_{t-1}$	0.0112	(0.0142)	0.0013	(0.0099)	−0.0282	(0.0308)	−0.0295	(0.0301)
EPU$_{t-1}$	0.0009	(0.0033)	0.0034	(0.0023)	−0.0045	(0.0074)	−0.0047	(0.0072)
COVID-19$_{t-1}$	0.0131 *	(0.0058)	0.0251	(0.0169)	0.0539 ***	(0.0159)	0.0639 **	(0.0224)
Golbal financial crisis$_{t-1}$	0.0188.	(0.0097)	0.0009	(0.0017)	0.0159	(0.0115)	0.0133	(0.0094)
U.S. Dollar index$_{t-1}$	−0.0027	(0.1393)	0.0041	(0.1106)	0.2692	(0.2324)	0.2516	(0.2421)
Chinese 10y bond yield$_{t-1}$	−0.1220	(0.0861)	0.0092	(0.0376)	−0.0670	(0.1109)	−0.0374	(0.1072)
U.S. 1y bond yield$_{t-1}$	0.0143	(0.0201)	−0.0060	(0.0083)	0.0119	(0.0346)	−0.0048	(0.0319)
U.S. 30y bond yield$_{t-1}$	0.0053	(0.0543)	−0.0350	(0.0371)	−0.0795	(0.0691)	−0.1313.	(0.0744)
GSCI$_{t-1}$	−0.0377	(0.0929)	0.0598	(0.0705)	−0.2493	(0.1712)	−0.1882	(0.1506)

This table reports OLS estimates for connectedness within industrial metals, within precious metals, from industrial to precious metals, and from precious to industrial metals. All explanatory variables enter the regressions with a one-period lag. The dependent variables are expressed in logarithmic first differences. Newey–West standard errors accounting for heteroscedasticity and serial correlation are reported in parentheses. Statistical significance is indicated by *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and . $p < 0.10$.

The group-specific within-connectedness models further show that these aggregate results are mainly attributable to industrial metals. Hereby, within-industrial connectedness exhibits weak persistence. The COVID-19 and global financial crisis dummies are also positive and statistically significant at the 5% and 10% levels, respectively. For within-precious connectedness, by contrast, none of the lagged macro-financial variables is statistically significant. In particular, the absence of a significant global financial crisis coefficient may reflect heterogeneous responses among precious metals during periods of stress. Their roles as investment assets and potential safe havens may induce market-specific portfolio reallocations, such that crisis-related volatility does not necessarily translate into stronger transmission within the precious-metal group. The crisis-related increase in aggregate within-group transmission therefore appears to originate predominantly from stronger connectedness among industrial metals.

The directed between-group regressions provide additional evidence on the structure of cross-group transmission. The COVID-19 dummy is positive and highly significant in both directions, indicating that the pandemic was followed by increases in volatility

transmission from industrial to precious metals and from precious to industrial metals. The pandemic-related strengthening of cross-group connectedness was therefore bidirectional rather than confined to a single transmission channel. For spillovers from precious to industrial metals, the lagged thirty-year U.S. Treasury yield has a negative coefficient that is significant at the 10% level, providing limited evidence that higher long-term interest rates are associated with lower subsequent growth in this transmission component. One possible interpretation is that interest-rate changes affect the two metal groups through different channels and at different speeds, see Schischke and Rathgeber (2025). Precious metals may respond more immediately through changes in opportunity costs, inflation expectations, and safe-haven demand, whereas industrial metals may react more gradually through financing conditions, inventory-carrying costs, and cyclical demand. Such asymmetric responses may reduce synchronized repricing and thereby weaken volatility transmission from precious to industrial metals.

Finally, the regression for net industrial-to-precious connectedness examines whether macro-financial conditions are associated with changes in the relative transmitter and receiver positions of the two groups. The strongly positive coefficient on lagged net connectedness indicates substantial persistence in the directional balance between industrial and precious metals. The lagged S&P 500 coefficient is also positive and significant at the 10% level, suggesting a weak shift toward a stronger net-transmitter position of industrial metals following improvements in the U.S. equity market, probably due the dominance of industrial demand.

Both crisis dummies, however, are negative and statistically significant at the 0.1% level. Because net connectedness is defined as transmission from industrial to precious metals minus transmission in the opposite direction, the negative coefficients indicate that both crises shifted the directional balance toward precious metals as net transmitters. In the case of COVID-19, this result complements the positive coefficients in both directed between-group regressions: although transmission increased in both directions, the increase from precious to industrial metals was comparatively stronger.

Overall, the group-level regressions show that the limited evidence obtained from the total-connectedness model conceals substantial heterogeneity in the structure of volatility transmission. The global financial crisis is associated mainly with stronger within-group connectedness, particularly among industrial metals, whereas the COVID-19 period is characterized by increases in both within- and between-group transmission. Moreover, the negative crisis coefficients in the net specification indicate that periods of systemic stress shift the relative transmission balance toward precious metals.

The preceding time-series regressions examine changes in system-wide and group-level connectedness. To assess whether macro-financial conditions are also associated with the relative positions of individual metals, we subsequently estimate panel regressions for metal-specific transmitted, received, and net connectedness.

The dependent variables comprise the directional connectedness measures “to others”, “form others”, and “net”. Since the transmitted and received connectedness measures are non-stationary in levels, they enter the regressions in logarithmic first differences. The net connectedness measure is stationary and is therefore retained in levels.

We estimate random-effects panel models that account for unobserved time-invariant heterogeneity across metals under the assumption that the individual effects are uncorrelated with the explanatory variables.[3] All macro-financial variables enter the models with a one-period lag to establish temporal ordering and mitigate concerns regarding contemporaneous endogeneity. Standard errors are calculated using the heteroscedasticity- and autocorrelation-consistent covariance estimator proposed by Arellano (1987).

In addition to the macro-financial variables used in the previous analyses, the panel models include lagged metal-specific futures trading volume. This variable serves as a proxy for market activity and participation and may provide additional predictive information on whether individual metals act as transmitters or receivers of volatility. Higher trading volumes may reflect greater liquidity or speculative activity, both of which can amplify a metal’s exposure to external shocks or its capacity to propagate volatility across markets. Because consistent trading-volume data for industrial metals are available only from 2004 onward, the panel analysis covers the period from 2004 to 2024. The results are reported in Table 7.

The panel regression results reveal notable differences between the directional and net spillover measures. While several macro-financial conditions are associated with subsequent changes in the “to others” and “from others” measures, the net positions of individual metals are explained almost exclusively by their own persistence, implying a certain stability in the net positions of individual metals.

For transmitted connectedness to others, higher lagged returns of the MSCI Emerging markets index are associated with a subsequent decline in the volatility transmitted to other metal markets. Both the global financial crisis and COVID-19 dummies exhibit positive coefficients that are statistically significant at the 1% level, indicating stronger subsequent growth in transmitted connectedness during the two crisis periods. Increases in the Chinese ten-year government bond yield and the U.S. thirty-year Treasury yield are additionally associated with lower transmitted connectedness, although both relationships are significant only at the 10% level. This finding is consistent with the within- and between-group results, as interest-rate changes represent common macro-financial shocks that may affect industrial and precious metals through different channels and at different speeds. While precious metals may respond more directly through opportunity costs, inflation expectations, and safe-haven demand, industrial metals may react more gradually through financing conditions, inventory costs, and cyclical demand. Such asymmetric responses may weaken synchronized volatility transmission across metal markets.

Furthermore, the results for received connectedness show a broader set of statistically significant associations. The positive and highly significant coefficient on the lagged dependent variable indicates persistence in proportional changes in volatility received from other metal markets. As in the “to others” specification, higher lagged MSCI Emerging markets returns are associated with

[3] The Hausman test does not reject the random-effects specification in favor of fixed effects.

Table 7
Regression results for spillover indices "from others", "to others" and "net".

Variable	To others		From others		Net	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	−0.0013 ***	(0.0003)	−0.0012 ***	(0.0003)	0.0000	(0.0420)
Spillover_{t-1}	−0.0200	(0.0257)	0.0609 ***	(0.0084)	0.9685 ***	(0.0043)
$\text{MSCI Emerging markets}_{t-1}$	−0.1404 ***	(0.0365)	−0.1300 ***	(0.0253)	0.0016	(1.1513)
CSI 300_{t-1}	−0.0188	(0.0274)	−0.0093	(0.0220)	0.0027	(0.5721)
NIFTY 50_{t-1}	−0.0006	(0.0183)	0.0070	(0.0118)	−0.0016	(0.5574)
$\text{S\&P 500}_{t-1}$	−0.0095	(0.0446)	−0.0292	(0.0313)	−0.0024	(1.1025)
Oil price_{t-1}	0.0516	(0.0363)	0.0519 *	(0.0214)	−0.0042	(1.6298)
VIX_{t-1}	0.0025	(0.0073)	0.0007	(0.0059)	−0.0016	(0.1711)
EPU_{t-1}	0.0016	(0.0018)	0.0010	(0.0011)	−0.0001	(0.0559)
COVID-19_{t-1}	0.0327 **	(0.0108)	0.0351 ***	(0.0075)	0.0002	(0.2462)
$\text{Global financial crisis}_{t-1}$	0.0142 ***	(0.0037)	0.0123 ***	(0.0028)	−0.0001	(0.0848)
$\text{U.S. Dollar index}_{t-1}$	0.1138	(0.0713)	0.1110 *	(0.0506)	−0.0040	(0.9652)
Chinese 10y bond yield	−0.0628.	(0.0344)	−0.0563 **	(0.0176)	−0.0001	(1.3965)
U.S. 1y bond yield	0.0102	(0.0099)	0.0086	(0.0063)	−0.0004	(0.2874)
U.S. 30y bond yield	−0.0355.	(0.0214)	−0.0424 **	(0.0154)	0.0028	(0.3319)
GSCI_{t-1}	−0.0949	(0.0638)	−0.0823.	(0.0449)	0.0016	(2.4647)
$\text{Trading volume}_{t-1}$	−0.0002	(0.0002)	−0.0002	(0.0002)	0.0023	(0.0071)

This table reports results from a panel regression on the spillover index "to others", "from others" and "net" with heteroscedasticity and serial correlation consistent standard errors (Std. E.) by Arellano (1987). Statistical significance is indicated by *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and . $p < 0.10$.

a subsequent decline in received connectedness, whereas both crisis indicators are positive and statistically significant at the 0.1% level. These findings indicate that the global financial crisis and the COVID-19 period were followed by stronger volatility transmission in both directions.

Several additional variables are associated specifically with received connectedness. Higher lagged oil-price returns and an appreciation of the U.S. Dollar index are followed by increases in the volatility received from other metals. By contrast, increases in the Chinese ten-year government bond yield and the U.S. thirty-year Treasury yield are associated with lower received connectedness. By contrast, increases in the Chinese ten-year government bond yield and the U.S. thirty-year Treasury yield are associated with lower received connectedness. Similar to the results for transmitted connectedness and the within- and between-group specifications, this finding may reflect asymmetric responses of industrial and precious metals to changes in long-term interest rates, which reduce synchronized volatility transmission. The GSCI coefficient is likewise negative, although significant only at the 10% level. Overall, the greater number of significant coefficients in the "from others" model suggests that received volatility is more closely associated with changes in the considered macro-financial conditions than transmitted volatility.

For net connectedness, the lagged dependent variable is positive and statistically significant at the 0.1% level. This result indicates substantial persistence in the relative transmitter or receiver positions of individual metals. None of the remaining macro-financial variables, including metal-specific trading volume, is statistically significant in the net specification. Thus, although crisis conditions and several financial-market variables predict changes in the gross amount of volatility transmitted and received, they do not systematically alter the balance between these two components at the individual-metal level.

Taken together, the panel results suggest that macro-financial conditions are primarily associated with changes in gross directional connectedness rather than with the relative network positions of individual metals. The crisis indicators are the most consistent predictors of transmitted and received volatility, while the net transmitter and receiver roles exhibit considerable persistence and remain largely unrelated to the remaining lagged explanatory variables.

5.4. Robustness and sensitivity analyses

To evaluate the stability and reliability of our findings, we conduct several robustness checks. The full results are presented in Appendix B. First, we test the sensitivity of our results to alternative specifications of the Diebold–Yilmaz spillover framework. Specifically, we increase the VAR lag order to 2, shorten the forecast horizon to 10 steps, decrease and increase the rolling window length to 52, 156 and 208 weeks, and estimate a standard VAR model and a time-varying parameter VAR model, as proposed by Antonakakis et al. (2020), following the approach of Gong et al. (2022). Second, building on Liu et al. (2021) and Xiao et al. (2019), we recalculate volatility using weekly realized variances based on the standard deviation of daily returns. Third, to assess whether the results depend on the highly saturated baseline specification, we implement two complementary parsimonious approaches based on the economic channels developed in the theoretical framework. First, we estimate separate regressions for demand conditions, uncertainty and financial stress, energy and production-cost conditions, monetary and exchange-rate conditions, and broader commodity-market conditions. Second, starting from the full specification, we apply a channel-guided backward-selection procedure in which the variable with the highest robust p-value above 0.10 is iteratively removed within each channel and the complete model is re-estimated after each elimination step. The procedure cycles across all channels until no further variable exceeds the 10% significance threshold. Variable selection is based on Newey–West inference in the time-series regressions and Arellano-type heteroskedasticity- and serial-correlation-consistent standard errors in the panel regressions. Fourth, we assess robustness with

respect to the choice of explanatory variables by replacing the GSCI index with the CRB commodity index. Fifth, to address potential concerns regarding the random-effects assumption in the dynamic panel specifications, we re-estimate the panel regressions using metal fixed effects.

Overall, our main conclusions remain robust across all model variations. In terms of total connectedness dynamics, the main patterns remain consistent across the alternative specifications. As expected, the TVP-VAR and the longer 208-week rolling window produce smoother connectedness paths, whereas the shorter 52-week window displays greater short-term variation. The 156-week specification lies between these two cases, while the timing of the major connectedness episodes remains broadly unchanged. Using realized volatility leads to higher total spillover values, especially in the early 2000s, suggesting that market connectedness may have begun increasing even before the commonly cited onset of commodity market financialization. In addition, net spillover roles remain broadly consistent when adjusting the lag length, forecast horizon, or volatility specification. However, switching to the standard VAR model produces some divergence in the static net spillover index, identifying only silver and aluminum as net transmitters. By contrast, the dynamic analysis confirms our previous findings that gold, platinum, and zinc play shifting roles over time. The TVP-VAR model, for instance, highlights copper, gold, and silver as transmitters in the static setting, while showing also zinc and platinum emerging as risk transmitters more prominently in recent years. Similarly, under the realized volatility specification, platinum appears as a net transmitter only in the dynamic setting.

Turning to the regression results for the different alternative specifications of the spillover indices, the alternative specifications broadly support the main conclusions while revealing additional statistically significant associations for several macro-financial variables. In particular, the COVID-19 indicator remains positively associated with a range of aggregate, within-group, between-group, and directional connectedness measures. The evidence for the global financial crisis continues to be concentrated mainly in total and within-group transmission, whereas the net positions of individual metals remain primarily characterized by persistence.

Furthermore, the parsimonious analyses broadly confirm the main substantive conclusions of the baseline specification. The separate channel-specific regressions continue to identify crisis conditions, particularly COVID-19, as an important source of predictive information for subsequent changes in gross connectedness. The complementary channel-guided model-selection exercise reinforces this result at a broader level: variables from the uncertainty and financial-stress channel are retained most frequently across the final specifications, with COVID-19 selected for several aggregate, group-specific, and directional connectedness measures. The global financial crisis is retained less systematically and is concentrated mainly in net and metal-specific directional connectedness. At the same time, the reduced specifications reveal additional associations that are less apparent in the saturated baseline model. Equity-market conditions are selected for total and metal-specific directional connectedness, while energy, monetary, exchange-rate, and broader commodity-market variables remain relevant for selected dimensions of the network. In particular, the GSCI is retained for between-group and cross-group transmission, while oil prices and several interest-rate measures are selected primarily for received spillovers. Overall, the parsimonious specifications suggest that uncertainty and crisis conditions provide the most consistent predictive information across connectedness dimensions, whereas the remaining macro-financial channels are more specific to particular components of the metal-market network.

The remaining robustness checks likewise support the main conclusions, although individual coefficient estimates vary across alternative variable definitions and model specifications. Although the statistical significance and magnitude of individual coefficients vary across specifications, these variables generally display economically plausible and recurring relationships with changes in volatility transmission. Moreover, the fixed-effects estimates are virtually identical to the baseline random-effects results: the significance patterns remain unchanged, and coefficient estimates differ only marginally, in several cases only beyond the fourth decimal place.

In summary, the robustness analyses confirm the validity and stability of our core findings. Across a range of methodological adjustments, including changes in model structure, volatility measurement, and explanatory variable selection, the main conclusions hold. Hereby, the additional findings reinforce the conclusion that energy-market conditions, broader commodity-market developments, and interest-rate conditions are relevant for particular components of the connectedness network, even though their associations are less uniform than those of the crisis indicators. These tests underscore the credibility of our results and reinforce their relevance for understanding systemic risk in commodity markets.

6. Conclusion

This study examines the evolving intensity and structure of volatility connectedness across industrial and precious metal markets under changing global economic and financial conditions. Metal markets are structurally interconnected through co-production, co-consumption, and co-trading, while their growing importance for the green transition and digital technologies further strengthens common demand and production linkages. At the same time, industrial and precious metals differ in their economic functions, as industrial metals are closely tied to real economic activity, whereas precious metals additionally serve as financial assets and respond to investment demand and safe-haven motives. These shared structural linkages and heterogeneous exposures create channels through which volatility shocks may remain concentrated within one metal segment or propagate across group boundaries.

Recognizing that connectedness is time varying and may change both in its overall intensity and in its underlying structure, this study contributes to the literature by examining which lagged macro-financial conditions are associated with its subsequent evolution. By applying existing connectedness measures at the system, group, and individual-market levels, we distinguish changes in overall connectedness from changes in transmission within and between industrial and precious metals and in the relative transmitter and receiver roles of individual markets.

In particular, this study applies the Diebold–Yilmaz connectedness framework, following Diebold and Yilmaz (2012), in a rolling-window setting to examine the evolution of volatility transmission across industrial and precious metal markets. Building on the resulting pairwise directional connectedness measures, we aggregate transmission into within-industrial, within-precious, and between-group components, following the approach of Gabauer and Gupta (2018). We then examine which lagged macroeconomic and financial conditions are associated with subsequent changes in total, group-specific, between-group, and directional connectedness using linear and panel regression models.

Our findings show that, on average, approximately 40% of future volatility in metal markets is attributable to cross-market spillovers, underscoring a significant level of interconnectedness. The group-level decomposition further reveals that 73% of total connectedness occurs within the industrial- and precious-metal segments, whereas the remaining 27% reflects transmission between the two groups. Cross-group transmission is largely bidirectional, although precious metals act as modest net transmitters toward industrial metals on average.

The dynamic analysis reveals a steady increase in market connectedness beginning in the early 2000s, likely driven by the financialization of commodity markets and the commodity boom, and peaking with the 2011 commodity supercycle. This period is followed by a gradual decline in spillovers, which is sharply reversed at the onset of the COVID-19 pandemic. This pattern aligns with existing literature, which emphasizes that volatility transmission tends to intensify during periods of systemic uncertainty. At the individual-market level, directional spillover analysis indicates that copper, zinc, gold, silver, and platinum are net transmitters on average, while aluminum, nickel, lead, tin, and palladium are net receivers on average. However, the dynamic analysis shows that these transmitter and receiver roles vary over time rather than remaining constant throughout the sample.

The regression results identify crisis conditions as the most consistent predictors of subsequent changes in volatility connectedness. The evidence is strongest for COVID-19, which is associated with increases in total, within-group, between-group, and metal-specific directional connectedness. By contrast, evidence for the global financial crisis is weaker and concentrated mainly in total and within-group transmission, although some positive associations also emerge for volatility transmitted and received by individual metals. At the group level, the negative net-connectedness coefficients observed during the crisis periods are consistent with a relative shift in the directional balance toward precious metals as net transmitters.

The remaining macro-financial variables exhibit more heterogeneous associations across the different components of the connectedness network. At the individual-metal level, higher oil-price returns and an appreciation of the U.S. Dollar are associated with subsequent increases in received connectedness, whereas stronger emerging-market equity performance and higher long-term interest rates are associated with lower transmitted or received connectedness, although some of these relationships are only weakly significant. The robustness analyses provide additional evidence that oil prices, broader commodity-market conditions, and Chinese and U.S. interest rates contain predictive information for particular connectedness components. By contrast, the net transmitter and receiver positions of individual metals are primarily characterized by persistence and are not systematically associated with the remaining macro-financial variables. In sum, macro-financial conditions appear to be more closely associated with changes in the gross intensity of volatility transmission than with persistent changes in the relative network positions of individual metals.

Overall, the findings show that metal-market risk cannot be assessed solely from aggregate connectedness. For investors, producers, processors, and industrial hedgers with substantial metal exposure, the distinction between within-group and cross-group transmission is particularly relevant because shocks may propagate through shared production processes and value chains, while the metals acting as leading transmitters change over time. In particular, for investors, the strong predominance of within-group connectedness implies that diversification across metals belonging to the same segment may provide only limited protection against volatility shocks. Moreover, the increase in between-group transmission during the COVID-19 period shows that diversification between industrial and precious metals may also weaken precisely when protection is most valuable. Portfolio allocations and hedging strategies should therefore not rely on fixed classifications of metals as industrial, precious, safe-haven, or cyclical assets, but should account for time-varying connectedness and changing transmitter and receiver positions. In particular, the tendency of precious metals to become net transmitters toward industrial metals during periods of systemic stress cautions against assuming that they necessarily insulate a portfolio from shocks originating elsewhere in the metal-market network.

For risk managers, the results support the use of network-based monitoring systems that jointly track total, within-group, between-group, and directional connectedness. Because macro-financial conditions are more consistently associated with changes in gross transmitted and received volatility than with persistent changes in net positions, early-warning systems should focus primarily on increases in transmitted and received connectedness rather than on net measures alone. Crisis indicators provide the most stable warning signals, while oil prices, broad commodity-market conditions, exchange rates, and long-term interest rates may offer additional information about particular transmission channels. These measures could be incorporated into stress tests, dynamic hedge ratios, position limits, and collateral or margin assessments for portfolios with substantial exposure to metal markets.

The results are also relevant for policymakers and market regulators. The bidirectional nature of cross-group transmission indicates that shocks cannot be assessed separately within industrial- and precious-metal segments. Given the predominance of within-group connectedness, central banks and market regulators should monitor the industrial- and precious-metal segments separately rather than relying solely on an aggregate connectedness measure. Between-group connectedness should be monitored as a complementary indicator of whether segment-specific shocks are spreading across the wider metal-market network. Because individual transmitter and receiver roles vary over time, regulatory monitoring should be based on dynamic network positions rather than on a fixed list of systemically important metal markets. Such monitoring may help identify markets through which volatility is likely to propagate and support more targeted liquidity, margin, and risk-management measures during periods of market stress.

Several limitations also provide opportunities for future research. Extending the analysis to multiple commodity classes, including energy and agricultural commodities, could provide a more comprehensive understanding of their dependence structure by distinguishing volatility transmission within individual sectors from transmission across sectors. Future studies could examine investor

positioning, speculative activity, and hedging demand using more disaggregated trading data. In addition, nonlinear, threshold, or regime-switching models may reveal whether the relationships identified here change once connectedness or macro-financial stress exceeds particular levels.

Overall, this study shows that the practical relevance of metal-market connectedness lies not only in its average level but also in its changing composition and direction. Accounting for these network dynamics can improve portfolio construction, hedging, early-warning monitoring, and commodity-market risk assessment in an environment in which real and financial linkages across metal markets are increasingly important.

CRediT authorship contribution statement

Amelie Schischke: Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Andreas Rathgeber:** Writing – review & editing, Supervision, Conceptualization.

Declaration of generative AI in scientific writing

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.iref.2026.105971.

Data availability

Data will be made available on request.

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