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Extreme Connectedness among Energy Transition Metals and Commodity Markets

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Summary

The global energy transition is reshaping commodity demand, yet its implications for commodity risk transmission remain unclear. We analyze connectedness among Energy Transition Metals (ETMs) – a subset of metals that are key inputs in clean energy technologies – energy commodities, and industrial metals using a Quantile Factor VAR framework. We document strong state dependence: spillovers are substantially larger in the tails of the return distribution than at the median. While crude oil remains influential, its dominance weakens post-Covid as ETMs, particularly base ETMs, gain centrality. A complementary event-study shows ETM-related policy announcements amplify spillovers in extreme regimes, indicating structural reconfiguration and systemic implications.

Keywords: Raw materials; Energy transition; Quantile Connectedness; Spillover effects; Commodity Markets

JEL Classification: C32; C58; Q02; Q41; Q43; Q48

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Abstract: The global energy transition is reshaping commodity demand, yet its implications for commodity risk transmission remain unclear. We analyze connectedness among Energy Transition Metals (ETMs) – a subset of metals that are key inputs in clean energy technologies – energy commodities, and industrial metals using a Quantile Factor VAR framework. We document strong state dependence: spillovers are substantially larger in the tails of the return distribution than at the median. While crude oil remains influential, its dominance weakens post-Covid as ETMs, particularly base ETMs, gain centrality. A complementary event-study shows ETM-related policy announcements amplify spillovers in extreme regimes, indicating structural reconfiguration and systemic implications.

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1 Introduction

The global transition toward a low-carbon economy is not only an environmental imperative but also a profound structural transformation of commodity markets. Achieving the 1.5°C target set by the Paris Agreement requires a rapid shift away from fossil fuels toward renewable energy systems and clean technologies. Clean energy investments have increased by 40% since 2020, and renewables are projected to account for 80% of new power capacity additions by 2030 (see e.g., Bouckaert et al., 2021; Gielen et al., 2019; IEA, 2023b). Supporting the deployment of clean energy technologies at the scale implied by this ambitious target entails a sharp increase in demand for a subset of metals that we refer to as Energy Transition Metals (ETMs), with projected growth potentially exceeding current production capacity.

While much attention has focused on the technological dimension of this transition, far less is known about how it reshapes the structure, direction, and state-dependence of risk transmission across global commodity markets. From a network perspective, structural shifts in demand and supply may alter the centrality of specific commodities, thereby changing how shocks are amplified and propagated throughout the system. As emphasized in network models of shock propagation, changes in node centrality can significantly modify the aggregate impact of idiosyncratic disturbances (Acemoglu et al., 2012, 2015). In this paper, we provide econometric evidence that the energy transition is not only changing commodity demand patterns but is also reconfiguring the network of spillovers that links traditional energy commodities, industrial metals, and transition-related resources.

The rapid deployment of clean energy technologies has prompted many countries to adopt official lists of Critical Raw Materials (CRMs) in order to monitor the supply of metals and materials that are strategically important for their economies and key policy objectives (Nakano, 2021).[1] Within this broader category, we focus on ETMs, a subset of metals that are essential inputs for wind turbines, electric vehicle batteries, electricity grids, and storage technologies.[2] In the Net Zero Emissions by 2050 (NZE) Scenario, demand for these minerals is projected to increase by between 1.5 and 7 times by 2030. Demand for minerals used in electric vehicles and battery storage alone is expected to grow at least 30-fold by 2040 (Bibra et al., 2022; Kim et al., 2021). Metals that were once considered peripheral industrial inputs are therefore becoming macroeconomically relevant assets with increasing financial and geopolitical importance.

Much like fossil fuels, the supply of ETMs is highly rigid. Developing new mining capac-

[1]See e.g. the "European Critical Raw Materials Act of 2022". `https://ec.europa.eu/commission/presscorner/detail/en/ip_23_1661`.

[2]The IMF regualarly compiles a price index with 16 ETMs. These are the same we analyse and include seven base metals (aluminum, cobalt, copper, lead, molybdenum, nickel, zinc), three precious metals (palladium, platinum, silver), and six minor metals (chromium, lithium, manganese, rare earth elements, silicon, vanadium). See `https://ec.europa.eu/commission/presscorner/detail/en/ip_23_1661`.

ity is a lengthy process, often exceeding a decade from exploration to production. At the same time, production and refining are geographically concentrated in a limited number of countries, creating significant exposure to supply disruptions and geopolitical tensions.[3] These structural characteristics imply that shocks originating in ETMs markets may propagate across broader commodity systems, particularly during periods of stress. When commodities become more central within a production and financial network, disturbances affecting them may generate disproportionate aggregate effects through amplification mechanisms. As the energy transition accelerates, quantifying these evolving interdependencies becomes essential for assessing systemic risk, energy security, and the stability of the clean energy supply chain.

In our analysis, we examine how the topology of global commodity markets evolves in the context of the energy transition. In particular, we ask whether energy transition metals are merely passive recipients of shocks from traditional energy markets, or whether they are increasingly emerging as independent sources of systemic spillovers. If ETMs are gaining network centrality, shocks to these markets may no longer remain localized but instead cascade across energy and industrial commodity systems. To address this question, we construct eight commodity price indices (base ETMs, precious ETMs, minor ETMs, gold, industrial metals, coal, natural gas, and crude oil) and estimate a quantile factor vector autoregressive model that captures connectedness across the entire conditional return distribution. The quantile-based framework (see Ando et al., 2022) allows spillover parameters to vary across market states, thereby identifying heterogeneous transmission mechanisms that remain hidden in mean-based specifications. By explicitly modeling tail dynamics, we assess whether amplification effects become stronger under extreme market conditions, when diversification benefits may weaken and contagion risks become more pronounced.

We complement the static analysis with a time-varying connectedness framework that compares pre- and post-Covid-19 spillover structures, thereby capturing potential structural shifts in commodity market interconnectedness. In addition, using the bootstrap-after-bootstrap methodology proposed by Greenwood-Nimmo et al. (2024), we identify policy-related events that trigger statistically significant changes in connectedness. This event-based perspective enables us to distinguish between spillovers driven by broad macroeconomic forces and those associated with CRMs policies and regulatory interventions, while formally assessing their statistical relevance.

Our findings reveal three main results. First, connectedness is strongly state-dependent. Spillovers are substantially larger in the tails of the return distribution than at the median, indicating that commodity markets become significantly more interconnected during

[3] According to IEA (2023a), the Democratic Republic of the Congo supplies 70% of the world's cobalt, China provides 60% of rare earth elements (REEs), and Indonesia supplies 40% of the world's nickel. Australia accounts for 55% of lithium mining, 25%. Moreover, China is expected to account for 80% of the announced additional copper production capacity by 2030 and to dominate refining capacity for key metals used in batteries, with 95% for cobalt and around 60% for lithium and nickel.

episodes of stress or exuberance. While crude oil remains an important shock transmitter under extreme conditions, energy transition metals—particularly base ETMs—have gained prominence as spillover sources, especially in the post-Covid-19 period.

Second, we document a structural shift in the configuration of commodity market linkages. Compared to the pre-Covid-19 period, the post-pandemic era is characterized by higher overall connectedness and a greater role for ETMs and gold in transmitting shocks to energy commodities and industrial metals. This evidence suggests a reordering of commodity market centrality consistent with the increasing macro-financial relevance of transition-related resources.

Third, the event study uncovers a pronounced asymmetry across market states. Policy announcements related to CRMs significantly affect connectedness primarily in the tails of the distribution, while their impact is limited under normal conditions. This evidence indicates that policy interventions and regulatory changes activate transmission mechanisms predominantly during extreme market episodes, reinforcing the importance of state-dependent econometric analysis.

Taken together, our results suggest that the energy transition is not only transforming patterns of commodity demand but is also altering the econometric structure and amplification dynamics of risk transmission across global commodity markets.

The rest of this paper is organized as follows: Section 2 presents the literature review on connectedness detection, Section 3 describes the data and methodology, Section 4 presents and discusses the empirical results, and Section 5 concludes. Finally, three Appendices report additional details, which can be found as Online Supplement.

2 Literature review

The study of financial and production networks shows that disruptions to specific nodes can propagate across the entire economy. This effect is particularly pronounced when certain nodes or sectors occupy disproportionately central positions within the network (Acemoglu et al., 2012; Carvalho, 2014). Moreover, as highlighted by Acemoglu et al. (2015), the magnitude of shocks plays a critical role in determining their propagation: once shocks exceed certain thresholds, network interactions amplify these disturbances, leading to heightened systemic fragility. In the context of commodity markets, structural shifts in demand and supply—such as those induced by the energy transition—may alter the centrality of specific commodities and thereby modify the transmission of shocks across the system.

A growing body of research further supports the use of network-based approaches for analyzing systemic risk and spillovers. For instance, Battiston et al. (2012); Battiston and Caldarelli (2013) emphasize how network structure can amplify financial shocks, while Bardoscia et al. (2017) investigate the mechanisms that lead to systemic instability. These insights suggest that changes in network topology, rather than solely the size of shocks, can materially influence aggregate outcomes.

Unlike trade networks, financial and commodity market networks are not directly observable, and the strength of connections across units must be estimated. Diebold and Yilmaz (2009) propose an h-step-ahead forecast error variance decomposition (FEVD) from a vector autoregression (VAR) model to quantify connectedness and spillover effects, capturing how much of the variability of one variable is explained by shocks to other variables. Later, Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) extend this approach by proposing the usage of the *generalized* FEVD (GFEVD), which is invariant to the variables ordering and highlights both the strength and direction of spillovers (see also Koop et al., 1996; Pesaran and Shin, 1998, for more information on the generalized FEVD).[4]

Spillover effects based on GFEVD from VAR models have been widely studied in applications concerning financial markets (Casoli and Pedini, 2026; Diebold and Yilmaz, 2009; Greenwood-Nimmo et al., 2024) and commodity prices (Bastianin et al., 2023; Diebold et al., 2017). Other works include studies on petroleum markets (Baruník et al., 2015), non-ferrous metals and clean energy stocks (Wang et al., 2023; Chen et al., 2022a,b), as well as the interconnections between oil, non-energy commodities, and financial markets (Marobhe and Kansheba, 2023; Baruník and Kocenda, 2019). While these studies document substantial spillovers within and across commodity groups, they typically focus on mean-based transmission mechanisms and do not explicitly account for state-dependent amplification or structural changes in commodity centrality.

The standard VAR-based GFEVD method captures connectedness at the mean level but may overlook the heterogeneous propagation of large shocks relative to smaller ones, as well as tail-specific transmission mechanisms that emerge under extreme market conditions. Quantile VAR (QVAR) models address this limitation by allowing connectedness to vary across the conditional distribution of returns, thereby capturing spillover effects that are particularly relevant in the tails (Koenker, 2005; Cecchetti and Li, 2008). From a network perspective, tail-dependent connectedness is especially important, as amplification mechanisms are more likely to materialize when shocks are sufficiently large.

Examples using dynamic quantile connectedness include Chatziantoniou and Gabauer (2021), examining interest rate swaps, and Chatziantoniou et al. (2022), extending the approach to include green equity markets. However, applications to broad commodity systems remain limited, particularly in settings where structural shifts may alter the relative importance of individual assets within the network.

In a QVAR, a relevant assumption is that residuals are cross-sectionally uncorrelated. However, in practice, residuals are often correlated, and standard equation-by-equation quantile regression methods fail to account for cross-sectional interdependence, leading to inefficient or biased parameter estimates and unreliable predictions. To resolve this issue, Ando

[4] Alternative approaches for evaluating connectedness are based on Granger-causality and Network VAR models (see e.g. Barigozzi and Brownlees, 2019; Barigozzi et al., 2022; Billio et al., 2012).

and Bai (2020); Ando et al. (2022) introduce the quantile factor VAR (QFVAR) model, which attributes residual correlation to common factors, isolates idiosyncratic shocks, and reduces potential estimation bias.

Against this background, our article contributes to the empirical literature on connectedness by applying the quantile factor vector autoregressive (QFVAR) framework proposed by Ando et al. (2022) to a broad system of metals and energy-related commodity markets. We jointly analyze energy transition metals, traditional energy resources, and other key commodities to assess whether the ongoing energy transition is associated with changes in spillover intensity and direction, particularly in the tails of the return distribution. By examining tail-specific connectedness while accounting for latent common factors, our analysis provides evidence on how structural shifts in commodity demand may reconfigure risk transmission across global commodity markets.

3 Data and methods

3.1 Data

According to the IMF Primary Commodity Price Index Technical Documentation, 16 minerals are classified as ETMs. Our dataset consists of the prices of seven commodities categorized as base ETMs (copper, aluminum, nickel, zinc, molybdenum, lead, and cobalt), three commodities categorized as precious ETMs (silver, platinum, and palladium), and six commodities categorized as other ETMs (silicon, manganese, chromium, rare earth elements, lithium, and vanadium). It also includes the prices of gold, industrial metals (iron and tin), and energy resources such as Newcastle coal, natural gas (Dutch TTF for the EU and Henry Hub for the US), and crude oil (WTI, Brent, and Dubai). The dataset includes commodity prices from June 2012 to November 2023, totaling 2,994 daily observations per commodity. Daily prices are converted to U.S. dollars and averaged weekly, resulting in 599 weekly observations per series. To account for inflation, the weekly averages are deflated using the interpolated U.S. Consumer Price Index (CPI), reflecting real prices. Subsequently, the real prices are normalized to their average prices in 2016, following the guidelines provided in the IMF Primary Commodity Price Index Technical Documentation.

Using these normalized weekly real prices, we construct eight indices (see Table 1 and Appendix A): ETM-B (base ETMs), ETM-P (precious ETMs), ETM-M (minor and other ETMs), Gold, INDMET (iron and tin), Coal, Nat Gas (natural gas for the EU and US), and Crude Oil (WTI, Brent, and Dubai).[5]

Figure 1 shows the weekly prices for eight indices. While most indices show slight increases, there is a notable surge in the prices of INDMET, Coal, and Nat Gas beginning

[5]Each index is weighted by the share of individual commodities in global imports, ensuring that the combined weights for each index sum to 100%. The weighting scheme is sourced from the IMF Primary Commodity Price Index Technical Documentation. See `4https://www.imf.org/en/Research/commodity-prices`.

in 2020, driven by the effects of Covid-19.

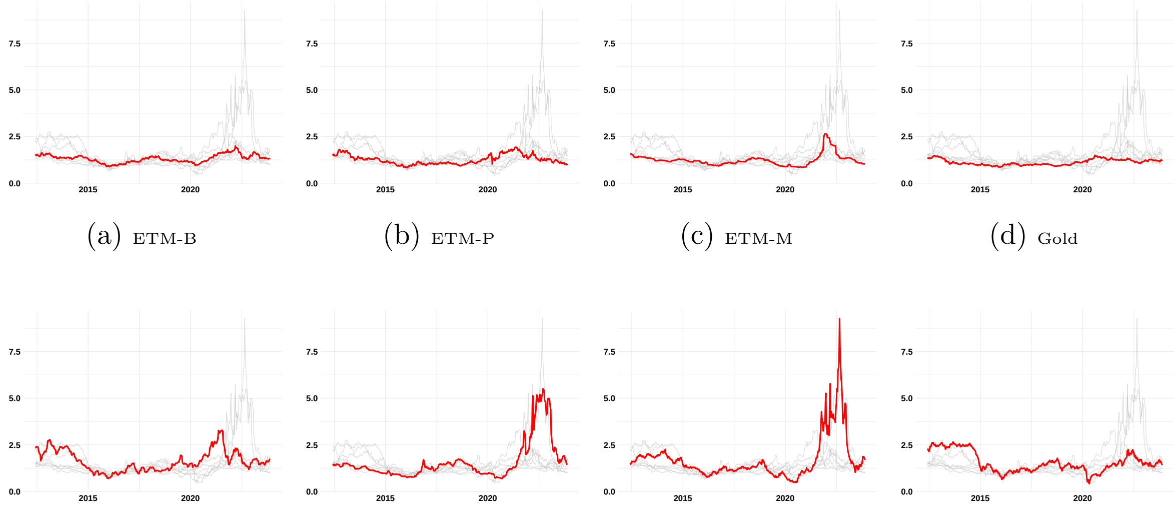
Table 1: Commodity Weights by Index Type

Index	**Commodity**	**Weight (%)**	**Currency**
ETM-B	Copper	47.17	USD
	Aluminum	21.87	USD
	Nickel	9.22	USD
	Zinc	8.39	USD
	Molybdenum	7.29	USD
	Lead	5.23	USD
	Cobalt	0.83	USD
ETM-P	Silver	48.28	USD
	Platinum	30.34	USD
	Palladium	21.38	USD
ETM-M	Silicon	39.22	USD
	Manganese	28.46	USD
	Chromium	24.62	CNY
	Rare Earth (REE)	3.85	CNY
	Lithium	2.31	CNY
	Vanadium	1.54	USD
Gold	Gold	100.00	USD
INDMET	Iron Ore	94.00	USD
	Tin	6.00	USD
Coal	Newcastle Coal	100.00	USD
Nat Gas	Dutch TTF	50.00	EUR
	Henry Hub	50.00	USD
Crude Oil	Dubai Fateh	33.00	USD
	WTI	34.00	USD
	Brent Forties	33.00	EUR

The spillover index in this paper is constructed using the GFEVD matrix obtained from a quantile factor VAR estimated on weekly percentage log-returns. In quantile factor models, factor estimation can be distorted when extreme observations cause factors to capture idiosyncratic variation rather than common movements across variables, potentially biasing the identification of systemic spillovers. To mitigate this issue, we adjust for outliers and standardize weekly returns to ensure comparability across series.[6] Descriptive statistics are reported in Appendix A.

[6]We remove some extreme observations following the approach of McCracken and Ng (2016). Outliers are defined as values beyond median $\pm 10 \times IQR$, where the IQR is the range between the 25th and 75th percentiles. These outliers are replaced with zero: ETM-B (0), ETM-P (1), ETM-M (7), Gold (0), INDMET (0), Coal (4), Nat Gas (0), and Crude Oil (0). After this adjustment, each series is standardized by subtracting its mean and dividing by its standard deviation.

Figure 1: Weekly Prices



(a) ETM-B (b) ETM-P (c) ETM-M (d) Gold

(e) INDMET (f) Coal (g) Nat Gas (h) Crude Oil

Note: The y-axis represents the price normalized by the average price in 2016.

3.2 The Quantile Factor VAR

We follow Ando et al. (2022) and rely on a QFVAR model to incorporate common factors that capture latent macroeconomic comovements in commodities. The factor structure of the model helps to mitigate the impact of cross-sectional correlation in the error terms, allowing for equation-by-equation quantile estimation. Consider a standard VAR model with p lags, denoted as VAR(p), where the vector of intercepts is omitted for simplicity of notation:

$$\mathbf{x_t} = \sum_{\mathbf{j=1}}^{\mathbf{p}} \mathbf{A_j x_{t-j}} + \mathbf{u_t}, \quad t = 1, \ldots, T, \tag{1}$$

In this model, $\mathbf{x_t}$ is an $m \times 1$ vector of variables and $\mathbf{A_j}$ represents the j-th $m \times m$ autoregressive coefficients matrix. The residuals $\mathbf{u_t}$ form an $m \times 1$ zero-mean, serially uncorrelated vector with a positive-definite $m \times m$ covariance matrix $\mathbf{\Sigma}$, that is, $\mathbf{u_t} \sim (0, \mathbf{\Sigma})$. The residuals have a factor representation such that:

$$\mathbf{u_t} = \mathbf{\Lambda f_t} + \upsilon_\mathbf{t} \tag{2}$$

where $\mathbf{\Lambda}$ is a $m \times f$ matrix of factor loadings with $f < m$, $\mathbf{f_t}$ is a $f \times 1$ vector of common factors, and $\upsilon_\mathbf{t}$ is a $m \times 1$ vector idiosyncratic components. The idiosyncratic shocks, $\upsilon_\mathbf{t}$ are assumed to be cross-sectional uncorrelated and normal distrubuted as $\upsilon_\mathbf{t} \sim N(0, \Omega)$, where Ω is a diagonal $m \times m$ covariance matrix, defined as $\mathbf{\Omega} = diag(\omega_{11}, \omega_{22}, ...\omega_{mm})$.

By combining Equations (1) and (2), we derive the factor VAR model with f factors, denoted as FVAR(p, f), as follows:

$$\mathbf{x_t} = \sum_{\mathbf{j=1}}^{\mathbf{p}} \mathbf{A_j x_{t-j}} + \mathbf{\Lambda f_t} + \upsilon_{\mathbf{t}}, \quad t = 1, \ldots, T. \tag{3}$$

To account for tail dependence, the QFVAR model evaluates the system at the τ-th conditional quantile, represented as QFVAR(p, τ, f), which modifies Equation (3) as follows:[7]

$$\mathbf{x_t} = \sum_{\mathbf{j=1}}^{\mathbf{p}} \mathbf{A_{j(\tau)} x_{t-j}} + \mathbf{\Lambda_{(\tau)} f_t} + \upsilon_{\mathbf{t}(\tau)}, \quad t = 1, \ldots, T, \tag{4}$$

where $\tau \in (0, 1)$ denotes the quantile level.

In the QFVAR analysis, the number of factors can vary across quantiles. We select the optimal number of factors by minimizing the information criterion proposed by Ando and Bai (2020). For further details on the QFVAR estimation and the optimal number of factors, see Appendix B.

3.3 Generalized Forecast Error Variance Decomposition

For a given quantile, the GFEVD measures the proportion of the h-step-ahead forecast error variance of the j-th variable, x_{jt}, attributed to the i-th idiosyncratic shock, $\upsilon_{it(\tau)}$, for $i, j = 1, 2, \ldots, m$. Assuming that $Q_\tau(\upsilon_{\mathbf{t}(\tau)} | \mathcal{F}_{t-1}) = 0$, where $\mathcal{F}_{t-1}$ denotes the information set available at time $t-1$, and Q_τ represents the conditional quantile operator at quantile τ, the Wold representation is:

$$\mathcal{Q}_\tau(\mathbf{x_t} | \mathcal{F}_{\mathbf{t-1}}) = \sum_{\mathbf{j=0}}^{\infty} \mathbf{B_{j(\tau)}} \upsilon_{\mathbf{t-j}(\tau)} + \sum_{\mathbf{j=0}}^{\infty} \mathbf{C_{j(\tau)} f_{t-j}},$$

where $\mathbf{B_{j(\tau)}} = \mathbf{A_{1(\tau)} B_{j-1(\tau)}} + \mathbf{A_{2(\tau)} B_{j-2(\tau)}} \cdots$ for $j = 1, 2 \cdots$, with $\mathbf{B_{0(\tau)}} = \mathbf{I_m}$, and $\mathbf{C_{j(\tau)}} = \mathbf{B_{j(\tau)} \Lambda_{(\tau)}}$. The vector of forecast errors associated with the prediction $\mathbf{x_{t+h}}$ conditional on the information at time $t-1$ and on the common factors is given by:

$$\mathbf{V_{t+h(\tau)}} = \sum_{\iota=\mathbf{0}}^{\mathbf{h}} \mathbf{B}_{\iota(\tau)} \upsilon_{\mathbf{t+h}-\iota(\tau)}.$$

Given that the GFEVD is invariant to the ordering of the innovations, the contribution of the i-th idiosyncratic shock $\upsilon_{it(\tau)}$ to the h-step ahead GFEVD of the j-th variable in $\mathbf{x_t}$ at quantile τ is given by:

$$GFEVD(x_{jt}; V_{it(\tau),h}) = \frac{\omega_{ii}^{-1} \sum_{\iota=0}^{h} (\mathbf{e_j' B_{\iota(\tau)} \Omega e_i})^2}{\sum_{\iota=0}^{h} \mathbf{e_j' B_{\iota(\tau)} \Omega B'_{\iota(\tau)} e_j}}$$

[7]When exposing the empirical results, the QVAR model with p lags at the τ-th conditional quantile is denoted as QVAR(p, τ).

where $\upsilon_{\mathbf{t}(\tau)} \sim i.i.d(\mathbf{0}, \mathbf{\Omega})$ with $\mathbf{\Omega} = diag(\omega_{11}, \omega_{22}, \cdots \omega_{mm})$, $\iota = 0, 1, \cdots h$ and $i, j = 1, \cdots m$, $\mathbf{e_i}$ is an $m \times 1$ selection vector with a 1 in the i-th position and zeros elsewhere.

3.4 Connectedness measurement

Building on the GFEVD framework, we now introduce measures to quantify connectedness within the system, focusing on how idiosyncratic shocks propagate at different quantiles. For the baseline approach, we refer the reader to Diebold and Yilmaz (2012); Diebold and Yılmaz (2014).

The metric $\breve{\vartheta}^{(H)}_{j \leftarrow i,(\tau)} = GFEVD(x_{jt}; V_{it(\tau),h})$ captures the spillover of idiosyncratic shocks from variable i to variable j at the τ-th quantile over the h-step horizon. These spillovers are organized into the h-step $m \times m$ spillover matrix for $(\mathbf{x_t})$, evaluated at the τ-th conditional quantile:

$$\mathcal{A}^{(H)}_{(\tau)} = \begin{bmatrix} \breve{\vartheta}^{(H)}_{1 \leftarrow 1,(\tau)} & \breve{\vartheta}^{(H)}_{1 \leftarrow 2,(\tau)} & \cdots & \breve{\vartheta}^{(H)}_{1 \leftarrow m,(\tau)} \\ \breve{\vartheta}^{(H)}_{2 \leftarrow 1,(\tau)} & \breve{\vartheta}^{(H)}_{2 \leftarrow 2,(\tau)} & \cdots & \breve{\vartheta}^{(H)}_{2 \leftarrow m,(\tau)} \\ \vdots & \vdots & \ddots & \vdots \\ \breve{\vartheta}^{(H)}_{m \leftarrow 1,(\tau)} & \breve{\vartheta}^{(H)}_{m \leftarrow 2,(\tau)} & \cdots & \breve{\vartheta}^{(H)}_{m \leftarrow m,(\tau)} \end{bmatrix}$$

The standard VAR-based GFEVD contains on cross-sectionally correlated disturbances, which can lead to the row sums of the GFEVD table exceeding 100% and is generally solved by imposing a row-sum normalization. However, in the GFEVD derived from QFVAR framework, the assumption of a diagonal covariance matrix $\mathbf{\Omega}$ ensures that the row sums of the GFEVD table remains bounded between 0 and 1, satisfying:

$$\sum_{j=1}^{m} \breve{\vartheta}^{(H)}_{i \leftarrow j,(\tau)} = 1$$

and for the entire system:

$$\sum_{i=1,j=1}^{m} \breve{\vartheta}^{(H)}_{i \leftarrow j,(\tau)} = m.$$

The total spillover from the system to variable i, denoted as "FROM", measures how much variable i is affected by shocks from other variables:

$$FROM^{(H)}_{i \leftarrow \bullet,(\tau)} = \sum_{j=1, j \neq i}^{m} \breve{\vartheta}^{(H)}_{i \leftarrow j,(\tau)}.$$

Similarly, the total spillover from variable i to the system, denoted as "TO", quantifies the impact of shocks from i on other variables:

$$TO^{(H)}_{\bullet \leftarrow i,(\tau)} = \sum_{j=1, j \neq i}^{m} \breve{\vartheta}^{(H)}_{j \leftarrow i,(\tau)}.$$

Note that $TO^{(H)}_{\bullet\leftarrow i,(\tau)}$ can be greater than or less than one. The net directional connectedness for variable i, denoted as "NET", captures whether variable i is primarily a shock receiver or contributor:

$$NET^{(H)}_{i\leftarrow i,(\tau)} = TO^{(H)}_{\bullet\leftarrow i,(\tau)} - FROM^{(H)}_{i\leftarrow\bullet,(\tau)}.$$

Finally, the total connectedness index (TCI) at the τ-th conditional quantile provides an aggregate measure of spillovers across the system (see e.g. Chatziantoniou et al., 2021; Gabauer, 2021). It ranges between 0 and 1 and is defined as:

$$TCI^{(H)}_{(\tau)} = \frac{\sum_{i=1}^{m} FROM^{(h)}_{i\leftarrow\bullet,(\tau)}}{m-1}$$

The spillover index quantifies system interconnectedness as the percentage of off-diagonal elements in the GFEVD matrix, capturing cross-variable spillovers relative to self-driven shocks.

4 Empirical results

4.1 Model selection and factor analysis

We select the optimal lag order of the VAR by minimizing the Schwarz Information Criterion (SIC), resulting in a $p = 1$ order, which is uniformly applied to all our models.

Table 2 reports the results of the information criterion proposed by Ando and Bai (2020) for choosing the number of factors, for both QFVAR(p, τ, f) and FVAR(p, f) models across different τ levels and factor selections. In the QFVAR models, the optimal number of factors increases to 3 at the tail quantiles ($\tau = 0.1$ and $\tau = 0.9$), while a single factor is sufficient for intermediate quantiles.

The increase in the optimal number of factors at the tail quantiles suggests that extreme market conditions are characterized by a richer latent dependence structure. While a single common factor is sufficient to capture co-movements under normal conditions, stress episodes appear to activate additional common drivers. This pattern is consistent with the notion of state-dependent amplification in commodity networks, where extreme shocks trigger broader synchronization across asset classes. The higher-dimensional factor structure in the tails, therefore, indicates that common shocks become more pervasive when markets depart from their median regime.

Incorporating factors significantly reduces residual correlations, with the sum of absolute residual correlations decreasing from 4.06 in the QVAR model to 3.08 in the QFVAR model. These results highlight the effectiveness of factor inclusion in capturing common latent movements and mitigating cross-sectional residual correlations. For a visual screening of the absolute residual correlations between the QVAR and the QFVAR model, we refer

Table 2: Ando and Bai (2020) Information Criterion

f	QFVAR(1,τ,f) $\tau = 0.1$	$\tau = 0.2$	$\tau = 0.3$	$\tau = 0.4$	$\tau = 0.5$	$\tau = 0.6$	$\tau = 0.7$	$\tau = 0.8$	$\tau = 0.9$	FVAR(1,f)
1	-1.85	**−1.38**	**−1.22**	**−1.13**	**−1.11**	**−1.13**	**−1.22**	**−1.41**	-1.88	**−0.17**
2	-1.90	-1.36	-1.11	-1.02	-0.99	-1.02	-1.13	-1.39	-1.94	-0.16
3	**−1.98**	-1.29	-1.01	-0.89	-0.87	-0.89	-1.04	-1.32	**−1.98**	-0.15

Notes: Bold values indicate the optimal number of factors according to the Ando and Bai (2020) information criterion. A maximum of three factors is considered.

the reader to Appendix C.

From an economic perspective, the reduction in residual correlations is not merely a statistical refinement. By isolating common latent components, the QFVAR framework allows the spillover measures to reflect predominantly idiosyncratic transmission rather than mechanical co-movement driven by shared global shocks. This distinction is particularly important in commodity systems, where broad macroeconomic forces—such as global demand cycles or inflationary pressures—can induce spurious connectedness if not properly accounted for. The factor adjustment, therefore, enhances the interpretability of the estimated spillovers as genuine network effects.

Factor analysis. Table 3 displays the R^2 values from regressions of each of the eight individual commodity returns on the first three factors at the $\tau = 0.1$, $\tau = 0.5$ and $\tau = 0.9$ quantiles. The first factor primarily loads on ETM-B, ETM-P, and Gold, suggesting the presence of a transition-sensitive common component that links ETMs with traditional safe-haven assets. This factor appears to capture broad macro-financial forces affecting transition-related resources. The second factor is associated with ETM-P and Gold in the tails but shifts toward Coal and Natural Gas at the median, indicating that the composition of common shocks changes across market states. Under extreme conditions, precious metals co-move more strongly with transition metals, whereas in normal periods, fossil-related commodities regain relevance within the latent structure. The third factor predominantly loads on ETM-M, particularly at the median, pointing to a more segmented component related to minor transition metals that may reflect supply-specific dynamics.

Overall, the factor structure reveals that energy transition metals are not isolated assets but share common latent components with both traditional energy commodities and precious metals. Importantly, the configuration of these common components varies across quantiles, reinforcing the relevance of a state-dependent modeling framework for assessing commodity market connectedness during the energy transition.

Table 3: Pairwise Regression of Variables on Factors

R^2	Factor	ETM-B	ETM-P	ETM-M	Gold	INDMET	Coal	Nat Gas	Crude Oil
	Factor 1	0.312	0.318	0.011	0.221	0.138	0.127	0.065	0.173
$\tau = 0.1$	Factor 2	0.090	0.139	0.007	0.229	0.008	0.125	0.071	0.056
	Factor 3	0.004	0.029	0.218	0.005	0.216	0.043	0.064	0.061
	Factor 1	0.388	0.676	0.002	0.506	0.059	0.067	0.043	0.109
$\tau = 0.5$	Factor 2	0.000	0.061	0.025	0.128	0.000	0.205	0.320	0.126
	Factor 3	0.036	0.011	0.672	0.005	0.023	0.068	0.000	0.004
	Factor 1	0.270	0.333	0.023	0.249	0.167	0.082	0.060	0.146
$\tau = 0.9$	Factor 2	0.095	0.211	0.006	0.264	0.015	0.089	0.087	0.029
	Factor 3	0.034	0.021	0.126	0.001	0.098	0.000	0.100	0.146

Notes: The factors are extracted from QFVAR(1,τ,3) models at quantile levels $\tau \in \{0.1, 0.5, 0.9\}$. Each variable is regressed separately on each extracted factor using OLS, and the table reports the corresponding R^2 values.

4.2 Full sample static analysis

In the static analysis, the connectedness indices are estimated using the full sample, covering the period from June 2012 to November 2023. Table 4 presents the Connectedness Table for the QFVAR(1, 0.5, 1) model. The total connectedness among all indices remains relatively low at 13.38. Gold, as a safe-haven asset, acts as both a major transmitter (34.76) and a receiver of shocks (27.17). ETM-B, ETM-P, and Crude Oil exhibit high levels of both shock transmission and reception, indicating that they occupy relatively central positions within the commodity network. However, ETM-B and ETM-P emerge as the largest net shock receivers, with net measures of -2.75 and -4.97, respectively. This suggests that, in the median regime, transition metals are still predominantly influenced by broader commodity dynamics rather than acting as primary sources of systemic disturbances.

The relatively low level of total connectedness (TCI = 13.38) suggests that, on average, commodity markets retain a substantial degree of idiosyncratic behavior. In contrast to periods of systemic stress documented in the broader connectedness literature, the median regime is characterized by limited cross-market amplification. This finding implies that structural interdependencies among commodities are present but not dominant under normal conditions, consistent with a network configuration in which common shocks remain partially contained.

The rising demand for energy transition metals (ETMs) does not mechanically displace fossil fuels or traditional industrial metals. Instead, the energy transition generates a complex combination of substitution and complementarity effects. While transition metals gain prominence in renewable technologies, fossil fuels and industrial metals remain critical inputs in infrastructure, transportation, and manufacturing. Oil and industrial metals continue to play central roles in both real economic activity and financial portfolios, whereas gold maintains its distinct role as a safe-haven asset. As a result, commodity demand structures are

Table 4: Connectedness Table: QFVAR(1, 0.5, 1), $h = 4$

	ETM-B	**ETM-P**	**ETM-M**	**Gold**	**INDMET**	**Coal**	**Nat Gas**	**Crude Oil**	**FROM**
ETM-B	83.13	4.96	1.89	8.35	0.85	0.27	0.04	0.51	16.87
ETM-P	4.31	74.07	0.75	13.34	2.68	0.69	0.55	3.60	25.93
ETM-M	0.37	0.79	97.14	0.01	0.25	0.02	0.50	0.93	2.86
Gold	7.31	9.18	0.08	72.83	2.29	1.71	0.76	5.83	27.17
INDMET	0.65	3.12	0.15	3.05	92.53	0.26	0.15	0.10	7.47
Coal	0.35	0.52	0.03	2.12	0.18	92.47	4.07	0.26	7.53
Nat Gas	0.51	1.02	0.51	0.92	0.13	3.74	91.72	1.45	8.28
Crude Oil	0.61	1.38	0.79	6.97	0.10	0.04	1.01	89.10	10.90
TO	14.12	20.96	4.19	34.76	6.49	6.73	7.08	12.68	107.01
NET	-2.75	-4.97	1.33	7.59	-0.98	-0.80	-1.20	1.78	**TCI = 13.38**

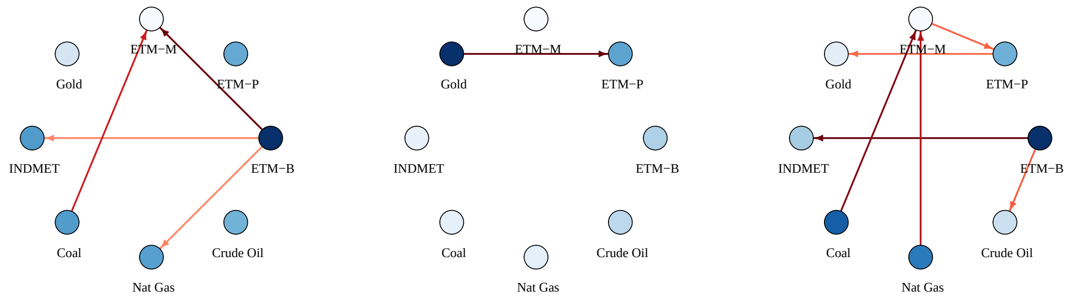
jointly shaped by technological change, industrial production, and financial portfolio allocation. These overlapping channels generate spillover patterns that can shift depending on whether complementarity or substitution effects dominate, thereby altering the direction and intensity of risk transmission across markets.

Our results at $\tau = 0.5$ align with the existing literature on commodity spillover effects. Specifically, natural gas is identified as a net recipient of connectedness from other commodities (Diebold et al., 2017), while non-ferrous metals (ETM-B and ETM-P) are net receivers compared to crude oil (Umar et al., 2022; Wang et al., 2023). Additionally, our findings are consistent with quantile-based studies indicating that crude oil serves as a larger driver of spillovers than gold, particularly in the tails rather than across all quantiles (see Chen et al., 2022a, and Appendix C). While our median-quantile findings are broadly consistent with prior evidence, the QFVAR framework allows us to disentangle common global factors from idiosyncratic spillovers. This distinction suggests that the observed net receiver status of ETMs at the median quantile reflects genuine network positioning rather than shared exposure to global demand or macroeconomic shocks.

Figure 2 presents the network visualization of spillover effects for the QFVAR(1, $\tau = 0.5$, f) model. Compared to the extreme quantiles ($\tau = 0.1$ and $\tau = 0.9$), spillovers are weaker at the median quantile ($\tau = 0.5$). At the tails, spillover effects occur both within the ETMs (ETM-P, ETM-B, and ETM-M) and between the ETMs and other commodities. Specifically, ETM-M receives shocks from energy commodities (Coal, Nat Gas), while ETM-B acts as a major transmitter to other commodities. Notably, the role of gold reverses across quantiles. While it acts as a net shock transmitter at the median quantile, it becomes a net receiver in the upper tail ($\tau = 0.9$). This reversal reflects the classical safe-haven behavior of gold: during extreme positive or negative commodity shocks, gold absorbs disturbances originating in other markets rather than initiating them. The quantile-specific reversal underscores the importance of state-dependent modeling in accurately capturing commodity network dynamics.

The emergence of stronger bidirectional spillovers at the tails indicates that extreme market conditions activate additional transmission channels within the commodity network. In these regimes, ETMs are no longer purely reactive assets but become more deeply embedded in cross-commodity feedback loops. This pattern is consistent with network amplification mechanisms, where large shocks increase synchronization across nodes and elevate the systemic relevance of assets that are otherwise peripheral in normal times.

Figure 2: Network Visualization of spillover

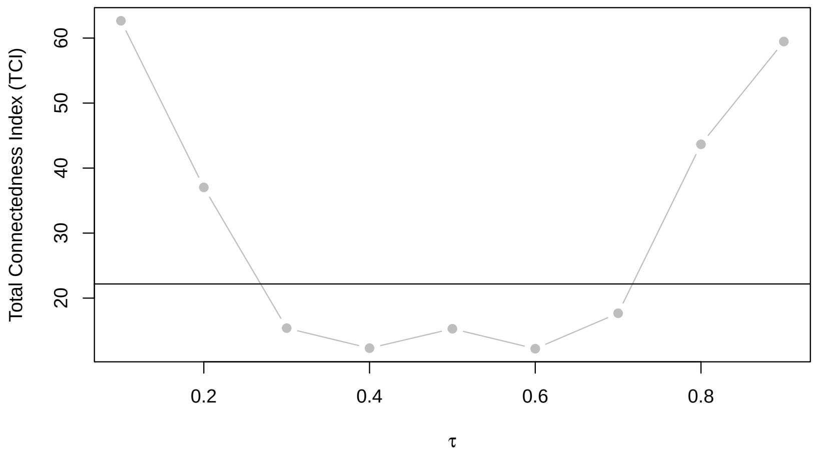


(a) $\tau = 0.1$ (b) $\tau = 0.5$ (c) $\tau = 0.9$

Notes: This figure highlights the main pairwise spillovers between commodities. The arrow direction represents the net spillover direction. Node color reflects the total magnitude of shocks transmitted by each commodity (darker nodes indicate larger shocks). Edge color indicates the strength of the spillover between nodes (darker edges indicate stronger spillovers, lighter edges weaker).

Figure 3 displays the evolution of the TCI across different quantiles, highlighting pronounced state dependence in commodity spillovers. At the extremes ($\tau = 0.1$ and $\tau = 0.9$), the TCI rises markedly, indicating that extreme returns are associated with substantially stronger cross-market transmission. In these regimes, shocks are less likely to remain localized and instead propagate across multiple commodity groups. By contrast, at the median quantile ($\tau = 0.5$), connectedness declines, suggesting that normal (or optimistic) market conditions are characterized by relatively segmented dynamics. This nonlinear pattern provides direct evidence of tail-specific amplification, consistent with network models in which systemic fragility increases once shocks exceed certain thresholds.

Figure 3: Total Connectedness Index across Quantiles



Note: The curve represents the total connectedness index (TCI) evaluated at the τ-th conditional quantile for the QFVAR(1,τ,f) model with a forecast horizon of 4. The number of factors for each quantile is optimally selected based on the information criterion in Ando and Bai (2020). For comparison, the solid line represents the VAR(1) model with a forecast horizon of 4.

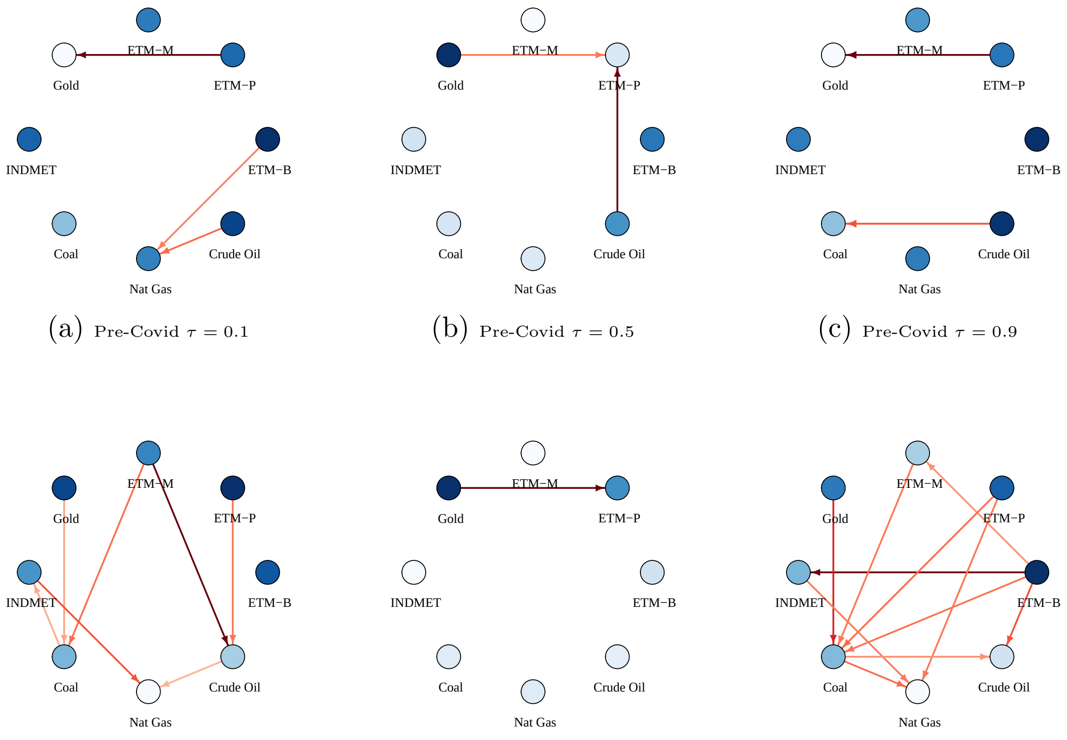
4.3 Pre- and post-Covid-19 analysis

We now examine spillover dynamics during the pre- and post-Covid-19 periods. The pre-Covid-19 period spans from June 8, 2012, to February 28, 2020, while the post-Covid-19 sample extends from March 6, 2020, to November 22, 2023.

The Covid-19 pandemic introduced a significant exogenous shock to the global economy and commodity markets. Government-imposed lockdowns, travel restrictions, and industrial shutdowns caused major disruptions on both the supply and demand sides. Firms experienced material shortages, while demand for many goods declined sharply. These effects were fundamentally different from those of typical economic downturns, as they originated from public health interventions rather than internal market dynamics. In comparison to the pre-Covid-19 period, the post-Covid-19 era can be seen as a broader phase of economic restructuring. This phase encompasses both the immediate response to the crisis and the gradual recovery, shaped by evolving supply chains, shifting industrial priorities, and a growing emphasis. on green investment. These structural changes are particularly relevant for ETMs, whose strategic importance in supporting low-carbon technologies has gained increased recognition.

Figure 4 depicts the network visualization of spillover effects for the QFVAR(1, $\tau = 0.5$, f) models. During the Pre-Covid period, Crude Oil functioned as a primary shock transmitter to other commodities, while ETM-P channeled shocks to Gold, particularly in the tails. In the Post-Covid period, the ETMs emerged as dominant spillover sources, amplifying their impact on other commodities at the tails, despite relatively weak intra-group

Figure 4: Network Visualization of spillover



(a) Pre-Covid $\tau = 0.1$ (b) Pre-Covid $\tau = 0.5$ (c) Pre-Covid $\tau = 0.9$

(d) Post-Covid $\tau = 0.1$ (e) Post-Covid $\tau = 0.5$ (f) Post-Covid $\tau = 0.9$

Notes: This figure highlights the main pairwise spillovers between commodities. The arrow direction represents the net spillover direction. Node color reflects the total magnitude of shocks transmitted by each commodity (darker nodes indicate larger shocks). Edge color indicates the strength of the spillover between nodes (darker edges indicate stronger spillovers, lighter edges weaker).

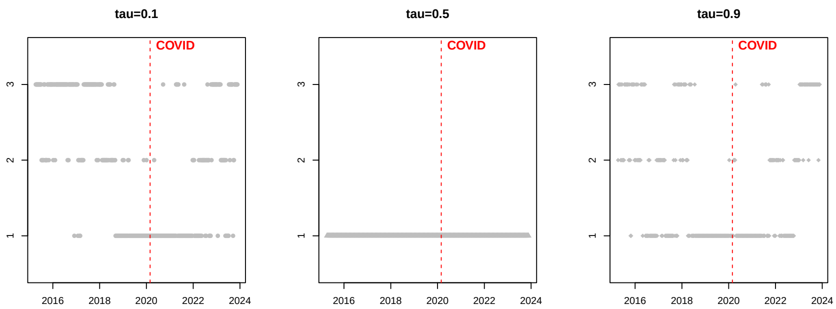
spillovers. Specifically, energy commodities (Coal, Nat Gas, and Crude Oil) and INDMET have increasingly become recipients of shocks from the ETMs and Gold. Note that the post-Covid period includes both the ongoing effects of the pandemic and phases of economic recovery. This makes it a transitional phase with changing market conditions. Because of this, and since it is difficult to clearly separate the shock-impact period from the recovery period, the results for this timeframe should be interpreted with caution. They mainly provide a general view of how the economy and connectedness patterns have changed before and after the onset of Covid-19.

4.4 Dynamic analysis

To analyze the temporal dynamics of the spillover effect, this section estimates connectedness using a 150-period rolling window approach. The number of factors is dynamically determined for each period based on the Information Criterion proposed by Ando and Bai (2020).

Figure 5 illustrates the optimal number of factors across time and quantiles. The grey horizontal dots indicate the optimal number of factors, while the red vertical line marks the onset of Covid-19. A single factor is consistently identified as optimal at the median quantile ($\tau = 0.5$), whereas the tails require additional factors to account for latent common movements.

Figure 5: Optimal Number of Factors

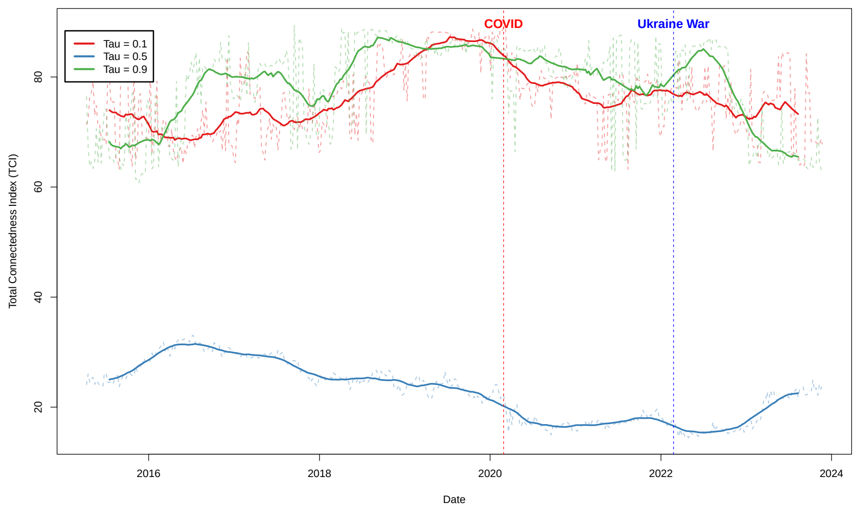


Notes: This figure shows the evolution of the optimal number of factors over time. The y-axis indicates the optimal number of factors (ranging from 1 to 3). The vertical red line marks the onset of Covid-19. As the number of factors increases, the model may capture idiosyncratic features rather than comovements across variables, potentially leading to a singularity problem. In such cases, we assume that a single factor is sufficient to capture the comovements. For the 451 rolling windows, these adjustments were applied to two rolling windows for $\tau = 0.1$ and 22 rolling windows for $\tau = 0.9$.

Notably, at the lower tail ($\tau = 0.1$), the post-Covid period exhibits a higher prevalence of a single optimal factor. This pattern suggests that extreme downside movements became increasingly driven by a dominant common component, consistent with heightened market synchronization during systemic stress. In such regimes, idiosyncratic commodity-specific shocks appear to be overshadowed by global risk factors, reflecting a compression of the network structure and stronger co-movement across markets.

Figure 6 presents the TCI over time for QFVAR$(1, \tau, f)$ models, with the period following the onset of Covid-19 marked by a vertical red line and the start of the Ukraine war indicated by a vertical blue line. Connectedness is notably higher at the tails of the return distribution. The time-varying evolution of the TCI reveals that commodity interconnectedness is not constant but evolves in response to major macroeconomic and geopolitical shocks. In particular, the widening gap between tail and median connectedness during crisis episodes indicates that systemic risk materializes primarily through extreme return realizations. This nonlinear behavior underscores the importance of modeling state-dependent spillovers in the context of the energy transition.

Figure 6: TCI Over Time for QFVAR(1, τ, f) Models



Notes: The plot depicts the Total Connectedness Index (TCI) over time for QFVAR(1, τ,f) models with quantiles $\tau = 0.1$, $\tau = 0.5$, and $\tau = 0.9$. The forecast horizon is set to 4, and the number of factors is dynamically selected based on the optimal factor model shown in Figure 5. Dashed curves represent dynamic connectedness at quantiles 0.1, 0.5, and 0.9, while solid curves show the corresponding 30-period moving averages. The vertical red line marks the onset of Covid-19, while the vertical blue line indicates the start of the Russia–Ukraine war.

The sharp contraction of economic activity in early 2020, both in the United States and the European Union, coincided with an abrupt increase in cross-commodity spillovers. The sudden halt in industrial production, disruptions in global supply chains, and unprecedented fiscal and monetary interventions created a common macroeconomic shock that propagated across energy and metal markets. The prolonged recovery phase further sustained elevated interconnectedness, reflecting persistent uncertainty and synchronized adjustments across commodity sectors.

The TCI at the upper tail ($\tau = 0.9$) remained persistently elevated from 2020 through early 2022, indicating that extreme positive return episodes were accompanied by intensified cross-market transmission. This pattern suggests that recovery-driven price increases and supply-side constraints generated upward spillover cascades across commodities. Around 2022, the sharp surge in upper-tail connectedness coincides with the Russia–Ukraine war, which amplified energy price volatility and reinforced the systemic linkage between fossil fuels and energy transition metals. The dominance of upper-tail connectedness during this period indicates that the commodity network became particularly sensitive to positive price shocks, consistent with a regime characterized by greenflation pressures and geopolitical supply risk.

In contrast, the TCI at the lower tail ($\tau = 0.1$) remained comparatively subdued during the same period. This asymmetry suggests that the dominant transmission channel in the post-pandemic environment operated through price increases rather than collapses. While downside spillovers were present during the initial pandemic shock, subsequent dynamics were primarily characterized by upward pressure driven by supply bottlenecks, energy market disruptions, and heightened demand for transition-related inputs.

Finally, the confidence intervals of the TCI associated with Figure 6, derived with bootstrap techniques, are presented in Figure 7. At the median quantile ($\tau = 0.5$), spillovers of shocks leading to both positive and negative returns are estimated at an average level. In this case, spillovers remain low, and confidence intervals are wider, reflecting greater uncertainty. In contrast, at the extremes ($\tau = 0.1$ and $\tau = 0.9$), spillover effects associated with extreme negative or positive returns are estimated with greater sensitivity to tail dynamics, resulting in narrower confidence intervals. The comparatively narrower confidence intervals at the tails indicate that extreme-state connectedness is estimated with greater precision during periods of heightened spillovers. This reinforces the interpretation that tail dynamics are not statistical artifacts but reflect economically meaningful transmission regimes.

Overall, the dynamic analysis reveals a structural shift in the commodity network following Covid-19. Spillovers not only intensified but became increasingly concentrated in the upper tail of the return distribution, highlighting the growing systemic relevance of energy and transition-related commodities. These findings suggest that the energy transition unfolds within a highly state-dependent network, where extreme events activate stronger cross-market amplification mechanisms and alter the hierarchy of commodity centrality.

Figure 7: TCI Over Time for Different Quantiles

Notes: The plot depicts the confidence intervals derived using a bootstrap-based approach, as described in Greenwood-Nimmo et al. (2024). The mean TCI and 95% confidence intervals are computed from bootstrap-estimated TCI samples, while the original TCI is calculated directly from the observed dataset. The number of factors is consistently set to 1 across all rolling windows and quantiles.

4.5 Event study

We follow the approach developed by Greenwood-Nimmo et al. (2024) to identify events that drive increases in spillovers. An event is considered significant when the probability that spillovers rise shortly after the announcement exceeds 90%.[8] The event-based framework allows us to assess whether policy interventions act as catalysts that activate latent transmission channels within the commodity network. In the context of the energy transition, policy announcements may alter expectations regarding future supply conditions, demand prospects, or regulatory constraints, thereby affecting the perceived centrality of ETMs within the broader commodity system.

The QFVAR model estimated in the previous sections emphasizes spillovers driven by idiosyncratic shocks while filtering out common macroeconomic fluctuations. For this reason, we abstract from broad global macroeconomic events and instead focus on policy announcements directly related to critical raw materials and ETMs. This approach allows us to evaluate whether transition-related regulatory and strategic interventions generate measurable changes in spillover intensity beyond those driven by general business cycle fluctuations.

Policy announcements are obtained from the IEA Policies database, which reports the announcement dates of policy measures related to the energy transition, energy efficiency, and associated technologies and resources.[9] These policies include funding programs, regulatory measures, government strategies, and international cooperation agreements implemented between 2012 and 2023. Since policy processes often unfold over multiple stages (e.g., proposal, approval, implementation), we use the date of the initial announcement. The event study should therefore be interpreted as capturing the impact of policy news rather than the effects of policies once fully implemented.

Because connectedness is estimated using a rolling window of 150 weekly observations, the events included in the analysis begin in April 2015. The rolling-window structure implies that detected effects should be interpreted as changes in the local spillover regime rather than instantaneous responses. Consequently, the event study captures whether policy announcements modify the short-term trajectory of connectedness rather than inducing isolated one-period jumps.[10] We evaluate the probability that spillovers increase within three horizons after the announcement: one week, two weeks, and four weeks.

Table 5a summarizes statistically significant events across quantiles and time horizons, revealing strong asymmetry. A total of 77 spillover events are detected in the tails: 44 (57.1%) in the lower tail ($\tau = 0.1$) and 32 (41.6%) in the upper tail ($\tau = 0.9$), while only one occurs at the median ($\tau = 0.5$). This indicates that policy announcements rarely affect

[8]For a detailed discussion of the methodology, see Appendix A.3 and A.4.

[9]The complete list of policies can be accessed at `https://www.iea.org/policies`.

[10]For consistency, all event dates are aligned to the nearest Friday of the corresponding week. If an event occurs during a weekend, it is assigned to the following Friday. The full list of policy announcementsis provided in Appendix D.

connectedness under normal conditions but become relevant in extreme market regimes.

The timing suggests gradual spillover propagation. In the lower tail, 7 events (16%) occur within one week, while most materialize after two to four weeks (17 events, 39%; 20 events, 45%). A similar pattern emerges in the upper tail, with 9 events (28%) within one week, 14 (44%) within two weeks, and 9 (28%) within four weeks. Markets therefore appear to incorporate policy information with a delay as expectations adjust.

Table 5b classifies events by policy type. Resource governance and mining policies dominate. In the lower tail, they account for 18 events ($\approx$ 40%), followed by supply chain and circular economy measures (10; 23%), trade and investment coordination (9; 20%), and industrial or financial policies (7; 16%). The upper tail shows a similar structure: resource governance leads (15; 47%), followed by trade and investment (9; 28%), supply chain regulation (5; 16%), and industrial policies (3; 9%).

Overall, policies directly affecting mineral supply—such as mining regulation, strategic designations, and licensing—are the main drivers of increased connectedness. The concentration of effects in the tails further indicates that policy announcements activate transmission mechanisms primarily during periods of stress or rapid price increases.

Spillover dynamics also differ across regimes. In the lower tail, increases are mainly linked to regulatory tightening, permitting constraints, export restrictions, and strategic designations, which heighten supply risk and uncertainty, amplifying downside spillovers. In contrast, in the upper tail, spillovers are more often associated with clean energy initiatives, circular economy strategies, recovery plans, and international cooperation, which signal stronger future demand and induce synchronized price movements.

Overall, CRMs policies act as state-dependent transmission triggers: supply-side restrictions amplify downside spillovers, while demand-expanding policies strengthen upside comovements. This asymmetry implies that the systemic effects of the energy transition depend not only on structural demand shifts but also on the timing and nature of policy interventions.

5 Conclusions

This paper investigates spillover effects among eight commodity indices related to energy transition metals (ETMs) and traditional energy commodities using a Quantile Factor VAR framework. By estimating connectedness across the conditional return distribution and isolating idiosyncratic shocks from latent common factors, we provide evidence on how the structure of commodity risk transmission varies across market states. Our results indicate that the energy transition is associated not only with shifting demand for key inputs but also with a reconfiguration of spillover linkages between ETMs, fossil fuels, and industrial metals.

Spillovers are strongly state-dependent. Connectedness is substantially higher in the

Table 5: Summary of Significant Policy Events

Panel A: Events by Time Horizon			
Quantile (τ)	1 week	2 weeks	4 weeks
0.1	7	17	20
0.5	0	0	1
0.9	9	14	9
Total significant events: 77			

Panel B: Events by Policy Category			
Policy type	$\tau = 0.1$	$\tau = 0.9$	Total
Trade & Investment Coordination	9	9	18
Resource Governance & Mining Policy	18	15	33
Supply Chain & Circular Economy	10	5	15
Industrial Policy & Financial Support	7	3	10
Total	44	32	76

Notes: The table reports the number of statistically significant events detected using the bootstrap-based method of Greenwood-Nimmo et al. (2024). Only events with probability greater than 0.94 are included (** and *** levels in Appendix D). Panel A reports the number of events associated with increases in the spillover index at different horizons following the announcement. Each event–quantile–horizon combination is treated as a separate observation, so an event that is significant at multiple quantiles or horizons is counted more than once. Panel B classifies significant events according to the type of policy intervention. In both Panel A and Panel B, numbers represent the counts obtained after excluding events that belong to more than one policy category.

tails than at the median, indicating that commodity markets become more interconnected during extreme shocks, when network amplification mechanisms are most likely to operate. In the post-Covid-19 period, elevated upper-tail connectedness is consistent with supply bottlenecks, capacity constraints, and recovery-driven price pressures that propagated across energy and metal markets.

At the median, natural gas and ETMs primarily act as net shock receivers, while crude oil remains an important transmitter, in line with earlier evidence. However, the quantile perspective reveals important asymmetries: oil dominates transmission mainly in the tails and can itself become a net receiver in extreme scenarios, highlighting the bidirectional nature of stress-driven spillovers. We also document a post-Covid shift in centrality, with ETMs and gold gaining prominence as transmitters relative to crude oil, suggesting a gradual move away from a purely fossil-centric network configuration.

Substantial heterogeneity exists within ETMs. Minor ETMs predominantly receive shocks, whereas base ETMs increasingly act as net transmitters, reflecting their growing market depth and macro-financial relevance. Precious ETMs exhibit strong linkages with gold, consistent with their dual industrial and investment roles.

The event study provides complementary evidence that policy announcements related to CRMs significantly increase connectedness, primarily in the tails of the return distribution. This asymmetry suggests that regulatory interventions and strategic mineral policies activate transmission mechanisms mainly during stress or exuberance, amplifying systemic risk when markets are already in extreme regimes.

Overall, our findings suggest that the energy transition is reshaping commodity markets not only through changing demand patterns but through a structural transformation of risk transmission itself. As ETMs become more systemically relevant, transition-related shocks and policy actions can propagate across the broader commodity network in a state-dependent manner. This evolving configuration implies that supply security concerns, geopolitical fragmentation, and transition policies may carry wider macro-financial consequences, particularly when markets operate in extreme regimes.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608.

Ando, T. and Bai, J. (2020). Quantile co-movement in financial markets: A panel quantile model with unobserved heterogeneity. *Journal of the American Statistical Association*, 115(529):266–279.

Ando, T., Greenwood-Nimmo, M., and Shin, Y. (2022). Quantile connectedness: modeling tail behavior in the topology of financial networks. *Management Science*, 68(4):2401–2431.

Bardoscia, M., Battiston, S., Caccioli, F., and Caldarelli, G. (2017). Pathways towards instability in financial networks. *Nature communications*, 8(1):14416.

Barigozzi, M. and Brownlees, C. (2019). Nets: Network estimation for time series. *Journal of Applied Econometrics*, 34(3):347–364.

Barigozzi, M., Cavaliere, G., and Moramarco, G. (2022). Factor network autoregressions. *arXiv preprint arXiv:2208.02925*.

Baruník, J. and Kocenda, E. (2019). Total, asymmetric and frequency connectedness between oil and forex markets. *The Energy Journal*, 40(Special Issue).

Baruník, J., Kocenda, E., and Vácha, L. (2015). Volatility spillovers across petroleum markets. *The Energy Journal*, 36(3).

Bastianin, A., Casoli, C., and Galeotti, M. (2023). The connectedness of energy transition metals. *Energy Economics*, 128:107183.

Battiston, S. and Caldarelli, G. (2013). Systemic risk in financial networks. *Journal of Financial Management, Markets and Institutions*, 1(2):129–154.

Battiston, S., Puliga, M., Kaushik, R., Tasca, P., and Caldarelli, G. (2012). Debtrank: Too central to fail? financial networks, the fed and systemic risk. *Scientific reports*, 2(1):541.

Bibra, E. M., Connelly, E., Dhir, S., Drtil, M., Henriot, P., Hwang, I., Le Marois, J.-B., McBain, S., Paoli, L., and Teter, J. (2022). Global ev outlook 2022: Securing supplies for an electric future. Report, International Energy Agency (IEA), Paris.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics*, 104(3):535–559.

Bouckaert, S., Pales, A. F., McGlade, C., Remme, U., Wanner, B., Varro, L., D'Ambrosio, D., and Spencer, T. (2021). Net zero by 2050: A roadmap for the global energy sector. Report, International Energy Agency (IEA), Paris.

Carvalho, V. M. (2014). From micro to macro via production networks. *Journal of Economic Perspectives*, 28(4):23–48.

Casoli, C. and Pedini, L. (2026). Measuring spillovers and connectedness in gretl. *Computational Statistics*, 41(1):22.

Cecchetti, S. G. and Li, H. (2008). Measuring the impact of asset price booms using quantile vector autoregressions. *Brandeis University, Waltham, MA*.

Chatziantoniou, I., Abakah, E. J. A., Gabauer, D., and Tiwari, A. K. (2022). Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. *Journal of Cleaner Production*, 361:132088.

Chatziantoniou, I. and Gabauer, D. (2021). Emu risk-synchronisation and financial fragility through the prism of dynamic connectedness. *The Quarterly Review of Economics and Finance*, 79:1–14.

Chatziantoniou, I., Gabauer, D., and Stenfors, A. (2021). Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach. *Economics Letters*, 204:109891.

Chen, J., Liang, Z., Ding, Q., and Liu, Z. (2022a). Extreme spillovers among fossil energy, clean energy, and metals markets: Evidence from a quantile-based analysis. *Energy Economics*, 107:105880.

Chen, Y., Zhu, X., and Chen, J. (2022b). Spillovers and hedging effectiveness of non-ferrous metals and sub-sectoral clean energy stocks in time and frequency domain. *Energy Economics*, 111:106070.

Diebold, F. X., Liu, L., and Yilmaz, K. (2017). Commodity connectedness. Technical report, National Bureau of Economic Research.

Diebold, F. X. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534):158–171.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of forecasting*, 28(1):57–66.

Diebold, F. X. and Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of econometrics*, 182(1):119–134.

Gabauer, D. (2021). Dynamic measures of asymmetric & pairwise connectedness within an optimal currency area: Evidence from the erm i system. *Journal of Multinational Financial Management*, 60:100680.

Gielen, D., Gorini, R., Wagner, N., Leme, R., Gutierrez, L., Prakash, G., Asmelash, E., Janeiro, L., Gallina, G., Vale, G., et al. (2019). *Global energy transformation: a roadmap to 2050*. Hydrogen Knowledge Centre.

Greenwood-Nimmo, M., Kočenda, E., and Nguyen, V. H. (2024). Detecting statistically significant changes in connectedness: A bootstrap-based technique. *Economic Modelling*, 140:106843.

IEA, R. (2023a). *Energy technology perspectives 2023*. IEA, R.

IEA, R. (2023b). *World Energy Outlook*. IEA, R.

Kim, T.-Y., Gould, T., Bennet, S., Briens, F., Dasgupta, A., Gonzales, P., Gouy, A., Kamiya, G., Karpiniski, M., Lagelee, J., et al. (2021). The role of critical minerals in clean energy transitions. *International Energy Agency: Washington, DC, USA*, pages 70–71.

Koenker, R. (2005). *Quantile regression*, volume 38. Cambridge university press.

Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, 74(1):119–147.

Marobhe, M. I. and Kansheba, J. M. P. (2023). High frequency volatility spillover between oil and non-energy commodities during crisis and tranquil periods. *SN Business & Economics*, 3(4):91.

McCracken, M. W. and Ng, S. (2016). Fred-md: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, 34(4):574–589.

Nakano, J. (2021). *The geopolitics of critical minerals supply chains*. Center for Strategic and International Studies (CSIS) Washington, DC, USA.

Pesaran, H. H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, 58(1):17–29.

Umar, M., Farid, S., and Naeem, M. A. (2022). Time-frequency connectedness among clean-energy stocks and fossil fuel markets: Comparison between financial, oil and pandemic crisis. *Energy*, 240:122702.

Wang, L., Guan, L., Ding, Q., and Zhang, H. (2023). Asymmetric impact of covid-19 news on the connectedness of the green energy, dirty energy, and non-ferrous metal markets. *Energy Economics*, 126:106925.

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