The connectedness of Energy Transition Metals

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Abstract: We assess the degree of connectedness among 16 metals that are critical for the production of clean energy technologies. These commodities are the constituents of the Energy Transition Metals (ETMs) price index maintained by the International Monetary Fund and comprise base, precious, and minor metals. We rely on Vector Autoregressive models and generalised forecast error variance decomposition to quantify spillovers among ETMs returns and volatilities. By calculating both static and dynamic measures of connectedness, we gain insight into the patterns of shock transmission between ETMs. Our static analysis reveals that base and precious metals are net shock transmitters, while minor and most battery metals are net receivers. By splitting the analysis into three groups, we find that almost half of the connectedness originates within each group, whereas the other half is due to cross-group spillovers. Moreover, we find that the system-wide connectedness of returns is positively correlated with proxies of economic activity, whereas volatility connectedness seems to be more related to global economic policy uncertainty.

Key Words: Connectedness; Energy Transition; Metals; Raw materials.

JEL Codes: C32; Q02; Q41; Q43; Q48.

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1 Introduction

There is by now broad consensus on the need to drastically reduce emissions of greenhouse gases worldwide if we are to limit the temperature increase to 1.5-2°C relative to preindustrial levels and thus prevent the major damages from climate change. Awareness of these risks has stimulated a process of radical change of energy systems and of decarbonisation of economies more generally.

The global energy transition (ET) is now well under way and has recently focused on the goal of reaching net zero emissions (NZE) by mid-century. The alternative pathways to NZE that several institutions have analysed share a common trait: the complexity of the transition. Decarbonisation entails increasing penetration of renewable energy technologies especially in power generation, electrification of entire sectors of the economy such as transport, diffusion of more energy efficient devices, instruments, appliances, and consumer goods, increasing use of hydrogen.

Besides the clear environmental benefits, it has been claimed that the ET will also create jobs and stimulate economic growth. The downside is that a host of critical minerals and metals are required for green energy technologies. For example, solar photovoltaic panels use silicon, tellurium, gallium, and indium; fuel cells use elements from the platinum group; batteries for electric vehicles and energy storage use lithium and cobalt; wind turbines and electric vehicles use dysprosium, terbium, europium, neodymium, and yttrium. Lists of CRMs are compiled and regularly updated by many governmental agencies (European Commission, 2020b; Nakano, 2021; U.S. Department of the Interior, 2022). On 16 March 2023 the European Commission presented a Proposal for a *Regulation establishing a framework for ensuring a secure and sustainable supply of critical raw materials* known as "European Critical Raw Materials Act".[1]

Critical raw materials (CRMs) are increasingly relevant in several technological domains and having access to them might soon become as essential as having access to reliable energy supplies. While phasing out fossil fuels, countries engaged in the ET have to phase in critical materials. Broadly speaking, CRMs are economically and strategically important inputs

[1] See `https://ec.europa.eu/commission/presscorner/detail/en/ip_23_1661`.

characterised by a low degree of substitutability and a high-supply risk. As an advanced country that is ahead in the race toward NZE, the EU is largely "materials-dependent". This follows from the fact that the ET is materials-intensive and the supply of CRMs is largely controlled by a limited number of countries. Scarcity of these CRMs might hamper the large-scale deployment of technologies in strategic sectors such as renewable energy, e-mobility, defence, and aerospace (European Commission, 2020a) and lead to price shocks that propagate to macroeconomic aggregates (Boer et al., 2023; Considine et al., 2023).

The oil and gas dependence that characterises several countries presents many analogies with the potential materials dependence those countries might soon experience. There are also important differences, one of which is the fact that while there is only "one" oil – and only "one" gas – there are many CRMs and they are largely intertwined as subsets of them are mined together, they are jointly processed and are often complementary, or low substitutable, inputs. As a consequence, CRMs have to be considered in a "connected" way.

In this paper we focus on a subset of raw materials, which are known as Energy Transition Metals (ETMs) and are input in the production of clean energy technologies such as solar, wind, batteries and fuel cells. Specifically, we assess the degree of spillovers or connectedness among 16 ETMs that represent the constituents of the ETMs price index maintained by the International Monetary Fund (IMF). By calculating both static and dynamic measures of connectedness for commodity returns and volatilities, we can gain insight into the patterns of shock transmission within the ETMs. We rely on the methodology put forth by Diebold and Yilmaz (2009, 2012, 2014) and implement a Generalised Forecast Error Variance Decomposition (GFEVD) from Vector Autoregressive (VAR) models to construct measures of directional spillovers among ETMs.

GFEVD-based connectedness is probably the most widely used approach and has the advantage of measuring spillover from each commodity to others without identification assumptions or imposing a particular ordering of the endogenous variables in the VAR (Koop et al., 1996; Pesaran and Shin, 1998). Moreover, Diebold and Yilmaz (2014) highlight the close relationship between connectedness measures based on GFEVD and key statistics used in the field of network analysis. Estimating network effects is crucial because it is well recognised that sectoral microeconomic shocks can propagate and eventually result in aggregate fluctuations (Acemoglu et al., 2012) and contagion from a large number of entities or markets may result in systemic crises (Bandt et al., 2012). Additionally, ETM price shocks, like any other commodity price shock, are important in that they can affect commodity supply, may weaken the financial sector and price stability and eventually result in a deterioration of the terms of trade for commodity exporter economies (Garcia and González, 2013; Kilian, 2009; Kinda et al., 2018; Sekine and Tsuruga, 2018).

An application of the GFEVD-based methodology to commodity connectedness, focusing on volatility spillovers, is provided by Diebold et al. (2018). Recent surveys of the literature dealing with this methodology are provided by Balcilar et al. (2022); Diebold and Yilmaz (2023). Alternatives ways to measure connectedness have been proposed in the literature. These include principal components analysis and Granger-causality (Billio et al., 2012) and the approach based on network analysis techniques for time-series (Barigozzi and Brownlees, 2019; Barigozzi et al., 2022). Moreover, other works focus on the asymmetry of connectedness at different frequencies, quantiles of the distribution, or rely on time-varying parameter models (Baruník et al., 2016, 2015; Baruník and Kley, 2019; Baruník and Křehlík, 2018; Chen et al., 2022; Wang et al., 2023; Zhu et al., 2019).

As far as we know this paper is the first to focus on the connectedness of a large set of ETMs. Measuring ETMs connectedness is central for risk measurement and management both from the perspective of private sector investment (e.g. for producers of clean energy technologies) and for the formulation of public policies (e.g. connectedness tends to increase during commodity-market crises).

The rest of the paper is organized as follows. Section 2 describes data and econometrics methods underlying our analysis; Section 3 presents our main results while Section 4 concludes. An Appendix with further details and results completes the paper.

2 Data and methods

2.1 Data

We analyse 16 ETMs, comprised of 7 base metals (aluminum, cobalt, copper, lead, molybdenum, nickel, zinc), 3 precious metals (palladium, platinum, silver) and 6 minor metals (chromium, lithium, manganese, rare earth elements, silicon, vanadium) that we will define generically as "other ETMs". These metals are the constituents of the IMF's ETMs price index.[2] This index and the prices of its constituents are available at monthly sampling frequency and therefore are not suitable for our analysis that requires returns and realised volatility (RV) measures. To build such measures, we recover daily prices of the constituents of the IMF's ETMs price index from Refinitiv Eikon.

Table 1 shows the list of commodities and the clean energy technologies for which they are used. This table also reports the weight of each commodity in IMF's ETMs price index that is based on the share of imports of each metal in total world commodity imports. As we can see, traditional base metals – such as aluminium and copper – with a wide range of industrial uses get most of the weight in the IMF index. On the contrary, cobalt, rare earth elements (REE), lithium and other minor metals – chiefly used in clean energy technologies – represent a small share of global imports.[3] Table 1 also reveals that the production of most minor metals is highly geographically concentrated. For instance, over 60% of the world production of REE, silicon and vanadium is concentrated in China, while the Democratic Republic of Congo is the leader producer of cobalt.

Some base and precious metals in our sample have been traded in future exchanges for many years, while other minerals – notably those labelled "other ETMs" in the second column of Table 1 – have a much shorter price history. The low liquidity of markets for these ETMs implies that their prices change infrequently and hence working with daily or weekly

[2]The ETM price index is described in the "Technical Documentation" that accompanies the data avaiable on the IMF Primary Commodity Prices portal. See: `https://www.imf.org/en/Research/commodity-prices` and Table A1 in Appendix A.

[3]Some of these metals – such as cobalt, copper, nickel, lithium and manganese – are often referred to as battery metals.

Table 1: Energy Transition Metals: classification, sources and uses

Metal	Group	IMF weight %	Top Producer (% world)	Main Uses
Aluminum	Base	15.9	Australia (28)	All sectors
Cobalt	Base	0.6	Congo (DRC) (71)	Li-ion batteries. Fuel Cells
Copper	Base	34.3	Chile (26)	All sectors
Lead	Base	3.8	China (47)	Wind. PV
Molybdenum	Base	5.3	China (43)	Wind. PV
Nickel	Base	6.7	Indonesia (37)	Li-ion batteries. Fuel Cells. PV. Wind
Zinc	Base	6.1	China (32)	PV
Palladium	Precious	3.1	South Africa (40)	Fuel Cells
Platinum	Precious	4.4	South Africa (72)	Fuel Cells
Silver	Precious	7.0	Mexico (23)	Fuel Cells. PV
Chromium	Other	3.2	South Africa (44)	Fuel cells. Wind
Lithium	Other	0.3	Australia (55)	Li-ion batteries
Manganese	Other	3.7	South Africa (37)	Wind. Li-ion batteries
REE	Other	0.5	China (60)	Wind. EV
Silicon	Other	5.1	China (71)	Li-ion batteries
Vanadium	Other	0.2	China (66)	Fuel Cells

Notes: data on the leading producing countries and the relative production as a share of world total are provided by the USGS in the Mineral Commodity Summaries 2022 report. The main uses for each mineral are taken from the Critical Raw Materials for Strategic Technologies and Sectors in the EU report by the European Commission and refer to the use within the European Union. IMF weights represent the share of imports of metal m in total global commodity import and are available at `https://www.imf.org/en/Research/commodity-prices`. PV stands for photovoltaic, EV for electric vehicles.

data is unfeasible.[4]

Daily data are then aggregated to construct monthly returns and realised volatilities that span a sample running from June 2012 to December 2022, for a total of 127 observations. Denoting daily real prices for metal m as P_{m,t_d} and daily log-returns as $r_{m,t_d} = 100 \times \log(P_{m,t_d}/P_{m,t_d-1})$, we compute monthly RV as follows:[5]

$$RV_{m,t} = \frac{1}{D_t}\sum_{t_d=1}^{D_t} r^2_{m,t_d},$$

where D_t is the number of days in month t. In subsequent analyses we rely on monthly real returns $r_{m,t} = (1/D_t)\sum_{t_d=1}^{D_t} r_{m,t_d}$ and $\log\sqrt{RV_{m,t}}$. We consider log of realised standard deviations in that RV_t is extremely skewed, while $\log\sqrt{RV_{m,t}}$ is approximately Gaussian

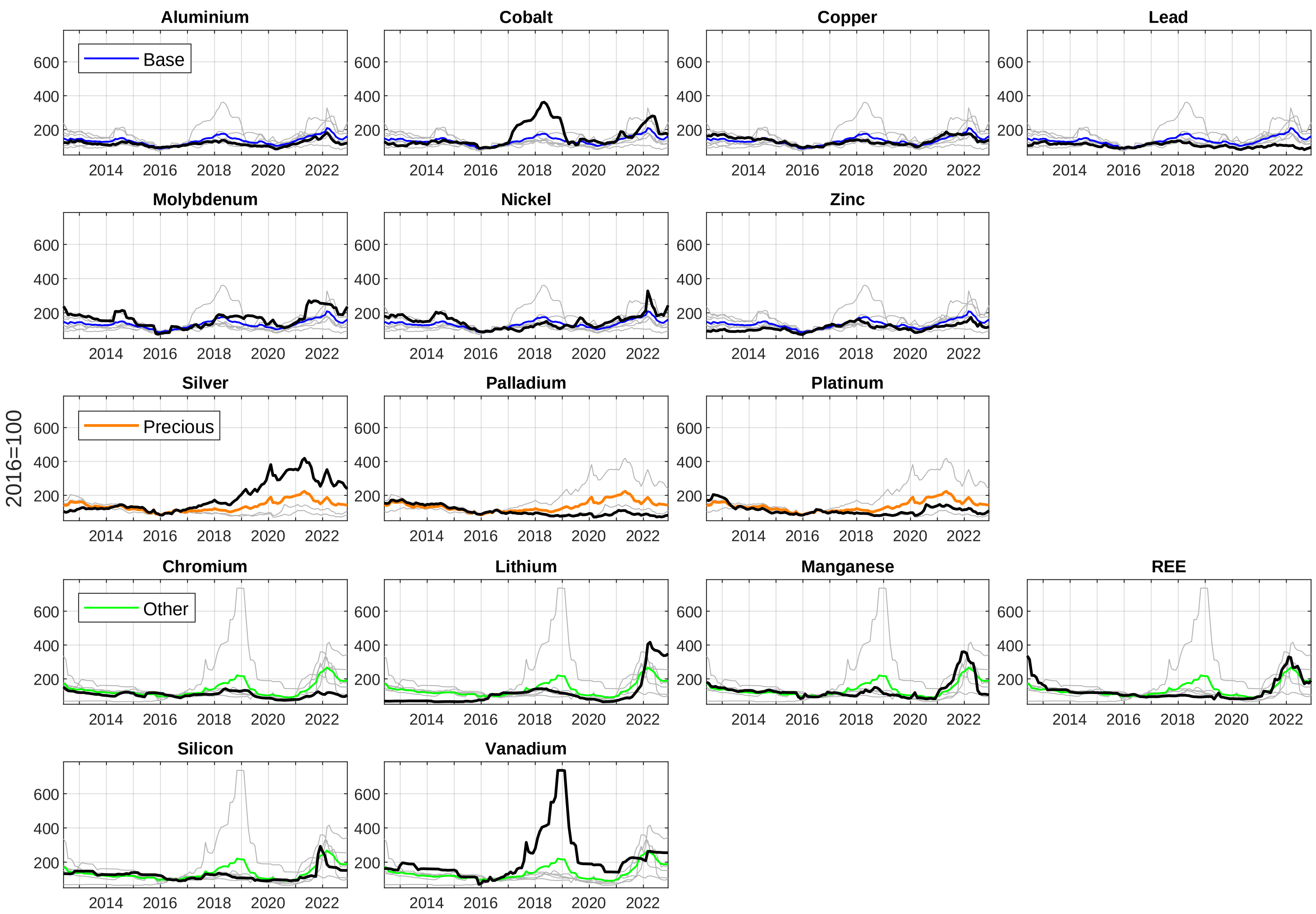
[4] We report the percentage of zero monthly returns as a measure of illiquidity of different markets: cobalt (3.97%), molybdenum (7.95%), manganese (7.14%), silicon (38.10%), vanadium (37.30%).

[5] Daily prices are deflated using the interpolated Consumer Price Index for the US.

for most commodities (see Andersen et al., 2001; French et al., 1987, for a discussion in the context of stock market volatilities). For simplicity, from now on we keep on using the shorthand notation RV, even though we rely on log $\sqrt{RV_{m,t}}$ in the analyses.

Figure 1 shows the real prices of ETMs in our sample. The prices of base metals, reported in first two rows of the figure, exhibit some cycles and tend to be higher at the end of the sample. Among precious metals – shown in the third row of Figure 1 – silver displays the largest surge during the second part of the sample. Finally, other ETMs prices are in general characterised by less variability, and for the majority of them there is evidence for a price increase after the COVID-19 pandemic. The only exception is vanadium price, exhibiting a remarkable spike between 2017 and 2020. Such a spectacular rise is due to a set of events affecting both the supply and demand-side of the Chinese market. First, in 2017 China enforced stricter environmental rules; as a consequence, inspections led to temporary or even permanent closing of some vanadium producers. Moreover, in 2018, China released a new standard for high-strength reinforcing bars. These were required to have a higher percentage of vanadium and hence increased overall domestic consumption of this metal. Further graphs, descriptive statistics and details about the data are reported in Appendix A.

Figure 1: Price of Energy Transition Metals: June 2012 - December 2022



Notes: for each commodity, the figure shows its price (black line) and the price index for the category of metals (coloured line) to which it belongs. Prices have been normalised as follows: $100 \times P_{mt}/\bar{P}_m^{2016}$ where $\bar{P}_m^{2016}$ is the average price of m for 2016. Metal groups are defined in Table 1.

2.2 VAR estimation

To obtain connectedness measures based on the GFEVD, the first step is to estimate VAR models for monthly returns and RVs. While we do include a constant in our specification, for ease of notation we now consider a zero-mean VAR process:

$$\mathbf{y}_t = \sum_{\ell=1}^{p} \mathbf{A}_\ell \mathbf{y}_{t-\ell} + \mathbf{u}_t, \tag{1}$$

where $\mathbf{y}_t$ is an $M \times 1$ vector with $M = 16$ and the m-th element corresponding either to r_t^m or $\log \sqrt{RV_{m,t}}$, $\mathbf{u}_t \sim (\mathbf{0}, \mathbf{\Sigma})$ and $\mathbf{A}_\ell$ is an $M \times M$ matrix of coefficients. The choice of the lag order, p, is critical in that the number of coefficients to be estimated is $M + M^2 p$ and hence grows quadratically with p.[6]

We handle dimensionality issues by estimating VAR models with an adaptive elastic-net penalty (Zou and Zhang, 2009) which involves both shrinkage and selection. The penalised estimation approach induces sparsity in the coefficient matrices $\mathbf{A}_\ell$. As noted in Nicholson et al. (2017), taking into account the sparsity patterns allows to address over-parametrisation in VAR models without having to select a low lag order p. In low-dimensional settings, the VAR model in Equation (1) is estimated via Ordinary Least Squares. However, as M and p increase, reducing the parameter space of the VAR becomes essential. The adaptive elastic-net consists of adding an appropriate penalty term to Equation (1). Specifically, fitting a sparse VAR involves solving the following penalised estimation problem:

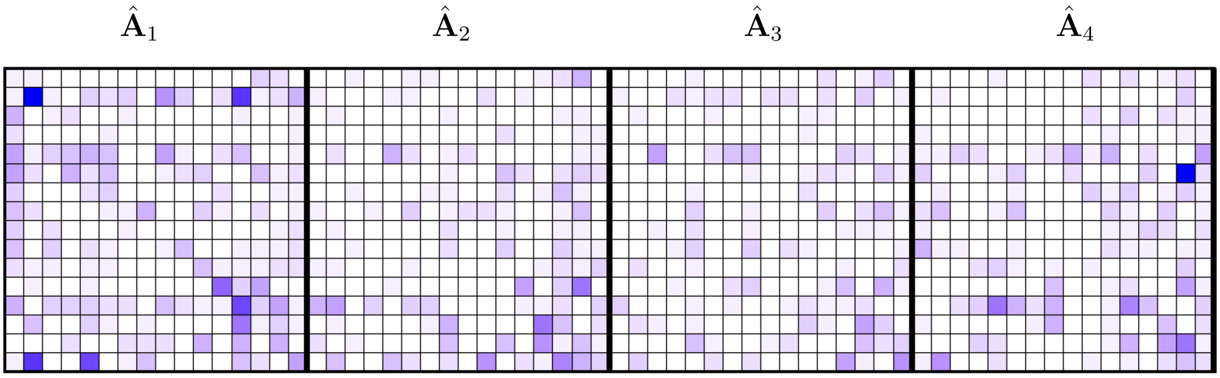
$$\min_{\mathbf{A}} \sum_{t=1}^{T} \left|\left| \mathbf{y}_t - \sum_{\ell=1}^{p} \mathbf{A}_\ell \mathbf{y}_{t-\ell} \right|\right|_F^2 + \lambda \mathcal{P}_y(\mathbf{A}) \quad \text{for } \lambda \geq 0, \tag{2}$$

where $||\cdot||_F$ denotes the Frobenius norm and $\mathcal{P}_y(\mathbf{A})$ represents the penalty structure applied to the coefficient matrices $\mathbf{A} = [\mathbf{A}_1, \ldots, \mathbf{A}_p]$.[7] The adaptive elastic-net VAR estimator

[6] For instance, with $M = 16$, VAR(3) and VAR(4) models respectively involve estimating 784 and 1040 coefficients.

[7] The Frobenius norm of an $(Z \times K)$ matrix $\mathbf{B}$ is defined as $||\mathbf{B}||_F = \sqrt{\sum_{z=1}^{Z} \sum_{k=1}^{K} |b_{zk}|^2}$. The 1-norm is $||\mathbf{B}||_1 = \max_{1 \leq k \leq K} \sum_{z=1}^{Z} |b_{zk}|$ and the 2-norm can be written as $||\mathbf{B}||_2 = \sqrt{\lambda_{max} \mathbf{B}^* \mathbf{B}}$, where λ_{max} is the maximum eigenvalue of $\mathbf{B}^*\mathbf{B}$ and $\mathbf{B}^*$ is the conjugate transpose of $\mathbf{B}$.

Figure 2: VAR model for returns: sparsity



Notes: colored shades indicate active coefficients, with darker shades referring to parameters that are larger in magnitude. White areas denotes coefficients that have been set to zero.

imposes the following penalty to Equation (2):

$$\mathcal{P}_y(\mathbf{A}) = \alpha||\mathbf{A}||_1 + (1-\alpha)||\mathbf{A}||_2^2, \quad \text{for } 0 \leq \alpha \leq 1. \tag{3}$$

The parameter α measures the trade-off between LASSO and ridge penalties in Equation (3). When $\alpha = 1$, the penalty function yields the LASSO estimator (Tibshirani, 1996). On the other hand, as $\alpha \to 0$, the LASSO penalty shrinks toward 0, the elastic-net becomes closer to ridge regression (Hoerl and Kennard, 1988). The optimal penalty parameters λ and α can be determined using cross-validation, allowing for a completely data-driven approach.[8]

Figure 2 shows the sparsity pattern for the estimated matrices of coefficients in the case of a VAR(4) for returns. As we can see, elements along the main diagonal of $\hat{A}_1$ have darker shades, while off-diagonal elements are often shrunk toward zero. It is worth noting that within this framework, VAR(p) denotes a VAR with a lag order at most equal to p, and the effective lag order is determined equation by equation by the penalty function (see Nicholson et al., 2017, for further details).

[8]We set α equal to $(1+M)^{-1} \approx 0.059$. Then, the optimal $\hat{\lambda}$ is selected from a grid of values $\lambda_1, \ldots \lambda_n$ via a rolling procedure, between times $T_1 = T/3$ and $T_2 = 2T/3$. The final $\hat{\lambda}$ is the value that minimises the Mean Squared Forecast Error. The grid of values for the choice of $\hat{\lambda}$ is specified by selecting the grid depth and the number of grid values. We set for the returns analysis the grid depth at 50 and the number of values to 10, whereas for RV we opt for an increased grid depth of 500.

2.3 Measuring connectedness

Our connectedness analysis relies on the GFEVD of the VAR as proposed in a series of papers by Diebold and Yilmaz (2009, 2012, 2014). The GFEVD does not require orthogonalising shocks and is invariant to the ordering of the variables in the VAR:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\mathbf{e}_i' \mathbf{\Phi}_h \mathbf{\Sigma} \mathbf{e}_j\right)^2}{\sum_{h=0}^{H-1} \left(\mathbf{e}_i' \mathbf{\Phi}_h \mathbf{\Sigma} \mathbf{\Phi}_h' \mathbf{e}_i\right)} \quad H = 1, 2, \dots \text{ and } i, j = 1, ..., M$$

where $\mathbf{\Sigma}$ is the covariance matrix of the σ_{jj} the standard deviation of the disturbance of the j-th equation, $\mathbf{e}_j$ is a selection vector with one as j-th element and zero otherwise and the matrices $\mathbf{\Phi}_k$ are derived from the moving average representation of the VAR model in Equation (1).[9] Since the variance shares do not sum to one (i.e. $\sum_{j=1}^{M} \theta_{ij}(H) \neq 1$), we consider the following normalization:

$$C_{i \leftarrow j}^{H} \equiv \tilde{\theta}_{ij}(H) = 100 \times \frac{\theta_{ij}(H)}{\sum_{j=1}^{M} \theta_{ij}(H)}. \tag{4}$$

The generic element $C_{i \leftarrow j}^{H} \equiv \tilde{\theta}_{ij}(H)$ is a measure of *Gross-Pairwise* directional connectedness from j to i; it measures the percentage contribution of mineral j to mineral's i generalised forecast error variance at horizon H. Note that in general $C_{i \leftarrow j}^{H} \neq C_{j \leftarrow i}^{H}$. Armed with pairwise directional connectedness measures, we can compute the following statistics (from now on we drop the H superscript for ease of notation):

$$\textit{Net-Pairwise:} \qquad C_{ij} = C_{j \leftarrow i} - C_{i \leftarrow j} \tag{5}$$

$$\textit{From:} \qquad C_{i \leftarrow \bullet} = \frac{1}{M} \sum_{\substack{j=1 \\ i \neq j}}^{M} \tilde{\theta}_{ij}(H) \tag{6}$$

$$\textit{To:} \qquad C_{\bullet \leftarrow j} = \frac{1}{M} \sum_{\substack{i=1 \\ i \neq j}}^{M} \tilde{\theta}_{ij}(H) \tag{7}$$

$$\textit{Net:} \qquad C_i = C_{\bullet \leftarrow i} - C_{i \leftarrow \bullet} \tag{8}$$

[9] A stable VAR process can be rewritten in moving average form as follows: $\mathbf{y}_t = \sum_{k=0}^{\infty} \mathbf{\Phi}_k \mathbf{u}_{t-k}$, where $\mathbf{\Phi}_0 = I_M$ and $\mathbf{\Phi}_k = \sum_{\ell=1}^{k} \mathbf{\Phi}_{k-\ell} \mathbf{A}_\ell$ for $k = 1, 2, \dots$ and $\mathbf{A}_\ell = \mathbf{0}$ for $k > p$.

$$Total: \qquad C = \frac{1}{M} \sum_{i=1}^{M} \sum_{\substack{j=1 \\ i \neq j}}^{M} \tilde{\theta}_{ij}(H) \tag{9}$$

Notice that *Net-Pairwise* connectedness in Equation (5) differs from *Gross-Pairwise* directional connectedness in Equation (4). First, while there are $(M^2 - M)/2$ net-pairwise connectedness measures, there are M^2 gross-pairwise connectedness measures. In our framework, gross-pairwise directional connectedness represents a measure of bilateral spillovers, whereas its "net" counterpart allows to divide minerals into net-receivers and net-transmitters of shocks. Measures in Equation (6) and (7) are often labelled respectively as *From* and *To* connectedness, since they define the transmitted and the received spillover for the i-th mineral, and correspond to the off-diagonal row and column sums of the connectedness table (CT). A sketch of the CT for our analysis is shown in Figure 3.

Total or system-wide connectedness. Connectedness simply corresponds to the sum of From – or To, equivalently – directional connectedness. Note that $\sum_{j=1}^{M} C_{\bullet \leftarrow j} = \sum_{i=1}^{M} C_{i \leftarrow \bullet} = C$. The connectedness table is a $(M + 1) \times (M + 1)$ matrix with $C_{i \leftarrow j}$ in the first M rows and columns. The $M + 1$-th column (row) reports From (To) connectedness, while system-wide connectedness appears in the lower right corner. Diebold and Yilmaz (2014) show that the GFEVD represents the adjacency matrix of a directed weighted network.[10] Specifically, the GFEVD delivers a matrix whose entries capture the strength and direction of spillovers between commodities. Moreover, it can be shown that From, To and system-wide connectedness are equivalent to key statistics used in the network literature (e.g. in-degrees, out-degrees and mean degree).

Connectedness within and across groups. In order to capture the differential impact of different groups of commodities, the CT is aggregated into blocks that correspond to base, precious, and other metals, respectively. See Figure 3. To this end, we define a group index vector $\mathbf{G}$ of size $(M \times 1)$ that assigns each of the M commodities to a group $g = 1, 2, 3$.[11]

[10]Note that, in general, a graph or adjacency matrix $\mathcal{A}$ has elements a_{ij} that indicate edges from i to j. On the contrary, in our approach each entries of the CT measures a spillover from j to i.

[11]In our setting, the commodities are ordered according to the group they belong to, with the first 7 entries of $\mathbf{G}$ identifying base metals and being equal to one, entries 8-10 identifying precious metals and being equal to two, and the remaining 6 entries identifying other metals and being equal to three.

To compute the *within-group connectedness* of each group, we sum all the elements in the CT that pertain to that group, net of the contribution of own shocks to GFEVD:

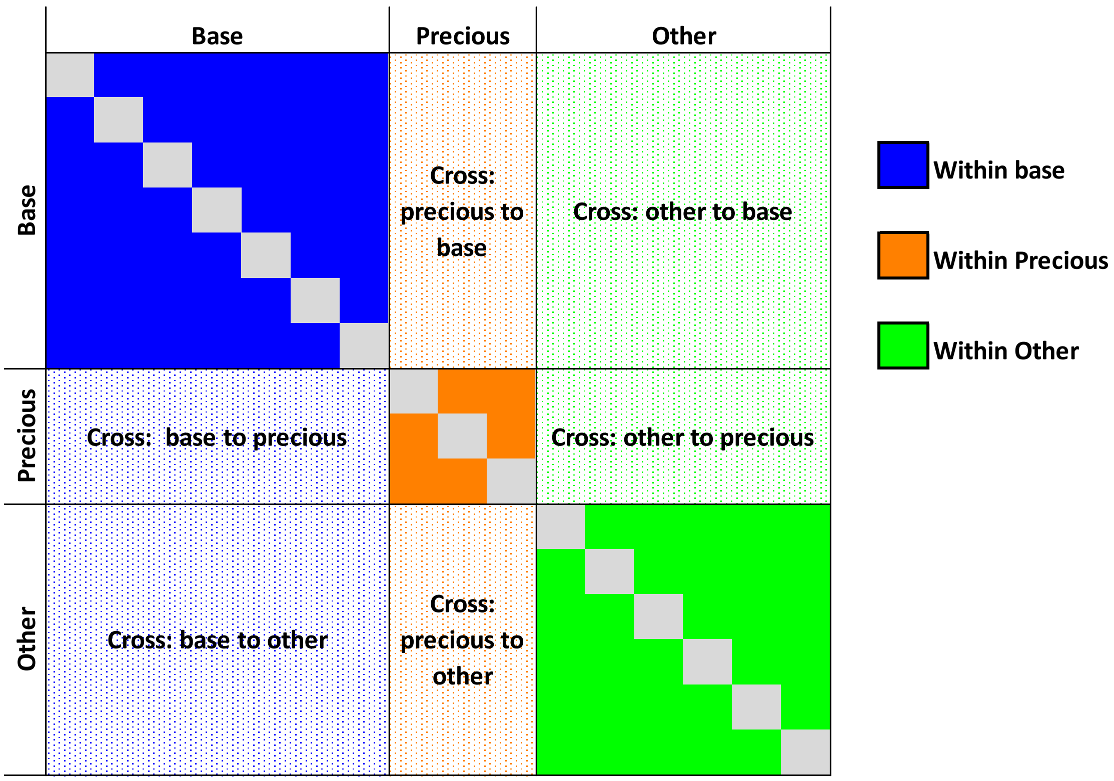
$$C_{g\leftarrow g} = \frac{1}{M}\sum_{i=1}^{M}\sum_{\substack{j=1\\ j\neq i}}^{M} C_{i\leftarrow j}\cdot I(G_i = g)\cdot I(G_j = g) \quad g = 1, 2, 3, \tag{10}$$

where $I(G_i = g)$ is an indicator function that is equal to 1 if $G_i = g$ and 0 otherwise. Summing over g we get the *system-wise within-group connectedness*: $C_{within} = \sum_{g=1}^{3} C_{g\leftarrow g}$. *Connectedness across groups* can be defined as follows:

$$C_{k\leftarrow z} = \frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{M} C_{i\leftarrow j}\cdot I(G_i = k)\cdot I(G_j = z) \quad k, z = 1, 2, 3 \text{ with } k \neq z. \tag{11}$$

Notice that with three groups there are 6 different cross-group connectedness measures. System-wide cross-group connectedness is equal to $C_{between} = \sum_{k=1}^{3}\sum_{\substack{z=1\\ k\neq z}}^{3} C_{k\leftarrow z}$. It follows that: $C = C_{within} + C_{between}$. The distinction between connectedness within and across groups is illustrated in Figure 3.

Figure 3: Connectedness within and between groups



To and From group-connectedness. To connectedness for group g is simply the sum of to connectedness for metals in group g:

$$C_{\bullet\leftarrow g} = \sum_{j=1}^{M} C_{\bullet\leftarrow j} \cdot I(G_j = g). \tag{12}$$

Similarly, From connectedness for groups is:

$$C_{g\leftarrow\bullet} = \sum_{i=1}^{M} C_{i\leftarrow\bullet} \cdot I(G_i = g) \tag{13}$$

It follows that $C = \sum_{g=1}^{3} C_{\bullet\leftarrow g} = \sum_{g=1}^{3} C_{g\leftarrow\bullet}$.

3 Results

The VAR lag order, p, is equal to 4 in the case of returns, whereas we set $p = 3$ for RV. We report results based on the GFEVD at $H = 3$ months horizon.[12] Since returns and volatilities measure different economic concepts, so does connectedness among them. Connectedness for returns relates to changes in expectations, whereas connectedness for volatilities captures the fear and uncertainty of investors.

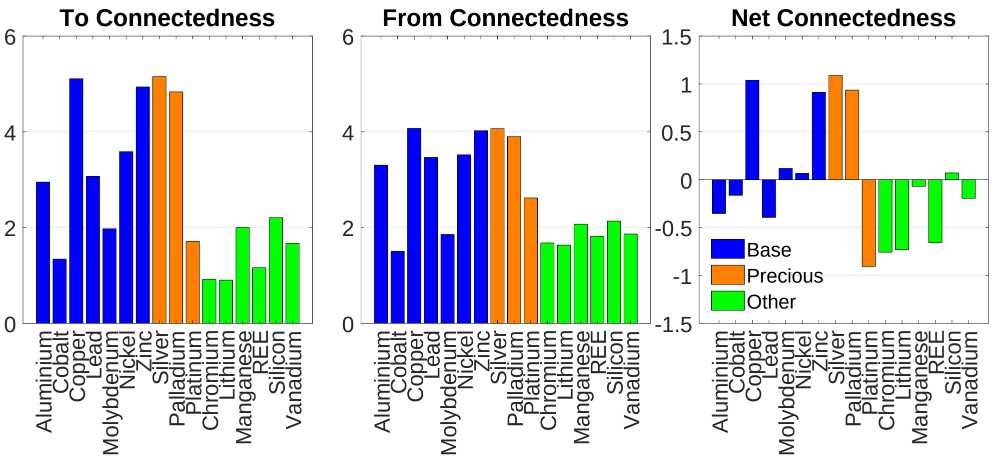
While we highlight the differences between results when appropriate, we mainly focus on connectedness for volatilities, for two reasons. Firstly, when examining groups as well as individual ETMs, the static analysis of connectedness for volatilities and returns produces comparable results. Secondly, understanding volatility connectedness is critical for real-time crisis monitoring. In fact, volatilities tend to move together only during times of crises and are often more responsive than returns which, on the contrary, move together in both downturns and upswings. The full set of results is available in Appendix B.

[12]We have increased p up to 12, but this leads to a very low fraction of active coefficients, resulting in a highly sparse VAR. We conclude that 4 lags capture an adequate amount of autocorrelation in the case of returns, while for RV, exhibiting larger sparsity, 3 lags are sufficient. As a robustness check, we have also computed system-wide connectedness considering different horizons. Specifically, we set $H = 4, 6, 12$, and conclude that connectedness of both returns and RV is not particularly sensitive to the choice of H. These results are available from the authors upon request.

3.1 Full sample connectedness

Starting from the CT, we compute the From, To and Net connectedness for RV as defined in Equations (6), (7) and (8) respectively and display them in Figure 4 where base, precious and other ETMs are clustered and represented with different colors.

Figure 4: To, From and Net connectedness – volatilities



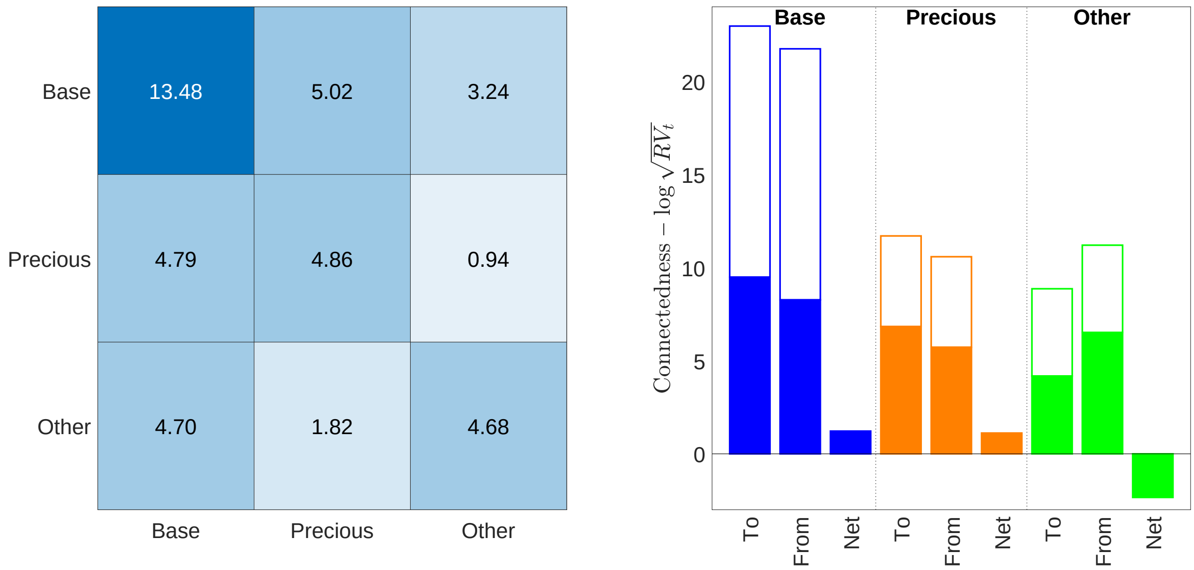
Base and precious metals exhibit greater From and To connectedness, whereas the other ETMs transmit and receive less volatility spillovers. Connectedness is thus stronger for the first two groups, while other ETMs are to some extent less sensitive to base and precious metal market dynamics. Moreover, other ETMs also exhibit a degree of From connectedness that is generally higher than the degree of To connectedness, suggesting that they are net receivers of shocks.

As a matter of fact, metals in the "other ETMs" group – with the exception of silicon – have a negative Net directional connectedness, and hence they are net receivers of volatility spillovers. On the contrary, two precious metals out of three - namely, silver and palladium - are net transmitters of shocks. Results for base minerals are mixed, with four out of seven metals being classified as net transmitters of shocks. It is worth noting that copper and zinc have the highest degree of From and To connectedness among base metals. When analysing spillovers for returns, copper is confirmed to be the most connected metal, thus it seems to be the principal driver of markets dynamics for ETMs.

We summarise the full-sample connectedness analysis for volatilities in Figure 5. The heatmap in Figure 5a represents the volatility CT for groups of ETMs. Within-group con-

Figure 5: Full sample group connectedness measures for volatility

(a) Within and cross group connectedness (b) To, From and Net connectedness



Notes: panel (a) shows within group connectedness along the main diagonal, while off-diagonal elements are cross group connectedness measures. Panel (b) shows the To, From and Net connectedness statistics for groups of metals. Colored areas refer to the off-diagonal statistics, whereas the white areas denote the statistics comprehending the diagonal elements.

nectedness (net of own connectedness for each metal) can be read along the main diagonal, while off-diagonal elements of the heatmap capture volatility spillovers across groups. Within-group spillovers are largest for base metals, while those for precious and other ETMs are much smaller and comparable in magnitude; this suggests that these two markets receive a large share of volatility spillovers from the base metal group. Figure 5b reports the To, From and Net group-connectedness, confirming the results obtained with individual commodities. Base and precious metals are overall net transmitters, while other ETMs are net receivers of shocks.

Some interesting facts also emerge from the CT for returns and RV, reported in Appendix B. Diagonal elements are in general lower for base and precious metals, and higher for minerals classified as "other ETMs". This means that other ETMs variability is more self-explained with respect to the other two metal categories. The only exception is molybdenum that, notwithstanding being classified as base metal, has a degree of self-explained volatility as high as other ETMs. Off-diagonal elements range from the very high levels of pairwise directional connectedness measured from zinc to lead and from palladium to platinum (more than 20%) to the marginal and often negligible connectedness arising from other ETM to base and precious metals (e.g. silicon and vanadium transmit around 1% of the RV to zinc and silver). Crucially, the opposite is not true, as the connectedness from any of the base and precious metals to other ETM is on average larger, denoting a remarkable asymmetry. Since the visualization of the pairwise connectedness measures is easier when represented via network graphs, the remainder of this discussion is delayed to Section 3.2.

Lastly, we focus on full-sample total or system-wide connectedness, as defined in Equation (9), which is equal to 44.93% for returns, and to 43.53% for RV. These results are in line with those of Diebold et al. (2018), estimating a total connectedness among commodity prices at 40%. This implies that almost half of metals variability uncertainty originates by "non-own" shocks. We can further disentangle total RV connectedness measuring within and between connectedness: 23.02% of the connectedness arises within the same group of ETMs, whereas the 20.51% of system-wide connectedness originates across groups.

3.2 Network visualisation

To better display the results, we consider the network representation of the CT in Figure 6.[13]

More precisely, we rely on Net-Pairwise statistics C_{ij} to determine the arrow direction that points towards net receivers of shocks. We use the ForceAtlas2 algorithm (Jacomy et al., 2014) that finds an equilibrium in which repelling and attractive forces among nodes are balanced. The nodes naturally repulse each other, whereas links attract nodes with different forces. Given the complexity of the graphs, visual cluttering is reduced by dropping arrows associated to metals with positive Net-Pairwise connectedness below the median. This means that only the strongest links are shown. The size of arrows and edges is also proportional to Net-Pairwise connectedness, while node size is determined by To connectedness $C_{\bullet \leftarrow j}$.

It is interesting to note that, even though we provide three *ex-ante* defined clusters, the completely data-driven algorithm groups together the base, precious and other ETM metals, both in the case of returns and RV analyses. The only exceptions are molybdenum and

[13]To produce network graphs, we use the Gephi open-access software available at `https://gephi.org/`.

cobalt, considered as base metals by the IMF but clustering together with the other ETMs according to the connectedness features both in the case of RV and returns.

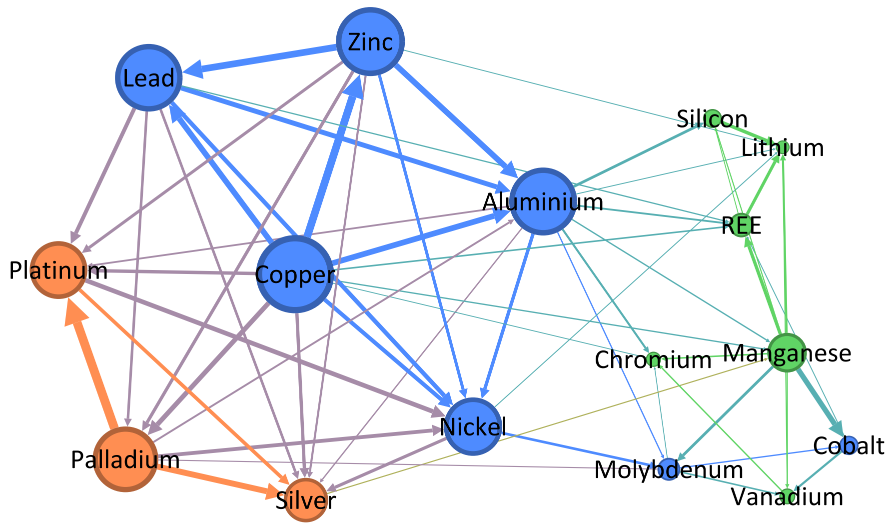
As for RV connectedness, shown in Figure 6b, chromium, REE and lithium are closer to base and precious metals, whereas when analysing connectedness in returns, they are grouped among the other ETMs. Base and precious metals have more weight in the network and are more connected than other ETMs. This can be appreciated by focusing on the size of the nodes and the number of arrows originating from each node, respectively.

Overall, the network visualisation strenghten the results obtained with the standard connectedness analysis and deliver an alternative, data-driven, grouping of ETMs. As a matter of fact, both molybdenum and cobalt tend to appear in the cluster of other ETMs. This can be rationalised at least in a couple of ways. First, both have a relatively small market size if compared to base and precious metals. Second, molybdenum and cobalt are mostly used in energy transition technologies, whereas the other base metals – such as aluminium, copper, zinc and nickel – have a wider range of applications for industrial production and construction.[14]

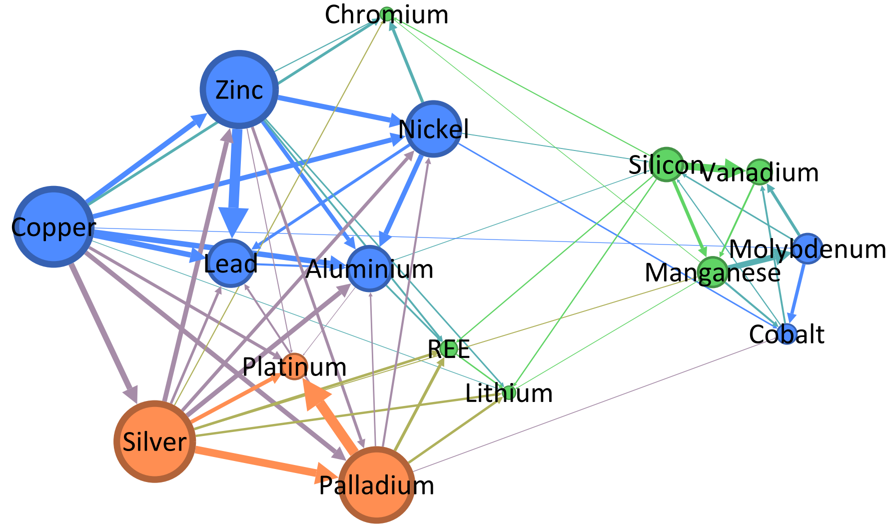
[14] See https://www.weforum.org/agenda/2022/10/all-the-metals-we-mined-in-2021-visualized/.

Figure 6: Network visualisation for ETMs returns and RV connectedness – June 2012 - December 2022

(a) Returns



(b) Volatilities



Notes: size of the nodes is determined by To connectedness. Arrows and edges refer to the Net-Pairwise connectedness above the median. Node colour reflects the grouping of metals into base (blue), precious (orange), and others (green).

3.3 Dynamic rolling sample connectedness

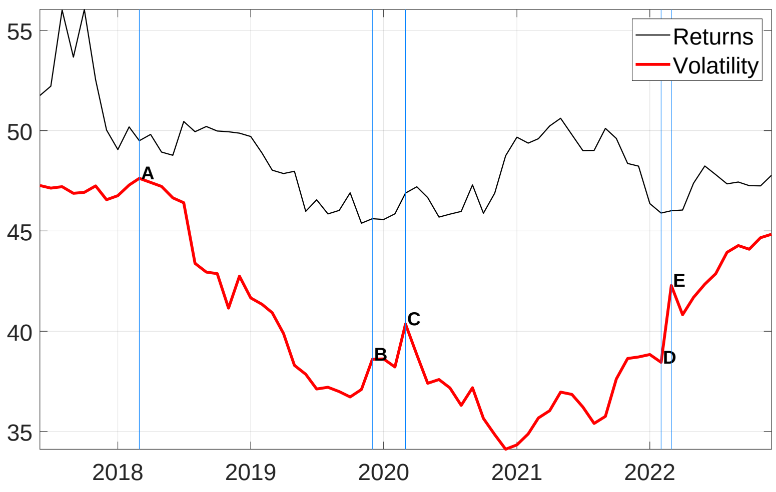
Static connectedness provides useful tools to measure the average degree of connectedness over the sample; however previous analyses show that such measures are usually time-varying. Figure 7 reports system-wide returns and volatility connectedness obtained by estimating VAR models over a rolling window.[15] The figure also reports vertical lines in correspondence of key events that are expected to affect connectedness.

Return connectedness from mid-2017 is always above the static full-sample average of 44.93%, suggesting that connectedness among the ETMs was lower in the beginning of the sample (i.e. 2012 – mid-2017) and has recently increased. Before the Covid-19 pandemic, return connectedness seems on a slightly decreasing path, while after reaching a minimum at the end of 2019, there is again a surge in total connectedness among ETMs. Volatility connectedness follows a similar patterns but displays more variability. It is downward sloped until the end of 2020. Thereafter, system-wide connectedness of ETMs RV is on an increasing trend. Surprisingly, we do not find evidence for an increase in RV connectedness during the only recession within our sample. This may be due to the particular features of the 2020/21 slowdown, characterised by high levels of uncertainty but also by an umprecedent economic freezing (i.e. production, trade and consumption dramatically dropped, affecting almost all markets around the world).

Nevertheless, RV connectedness does exhibit spikes in correspondence of key economic and geo-political events. On the contrary, connectedness for returns seems to be less responsive. The announcement of tarrifs on US aluminium imports by president Trump in March 2018 and the nickel short squeeze in the London Metal Exchange March 2022 are both associated with a decrease in RV connectedness. RV connectedness also decreases in correspondence of Britain's General Election in December (i.e. that with the victory of the conservatory party meant the confirmation Brexit) and the outbreak of the Covid-19 pandemic in March 2020. On the contrary, we see that in correspondence of the Russian invasion of ukraine in February 2022, RV connectedness rapidly rises. The effect is then confounded

[15]We set, as for the static full-sample analysis, a VAR(4) in the case of returns and a VAR(3) for RV, using a rolling window of 60 observations. Finally, we consider $H = 3, 4, 6, 12$, but report only results for $H = 3$ given the marginal and negligible differences in the estimated connectedness.

Figure 7: Retuns and volatility connectedness - rolling sample



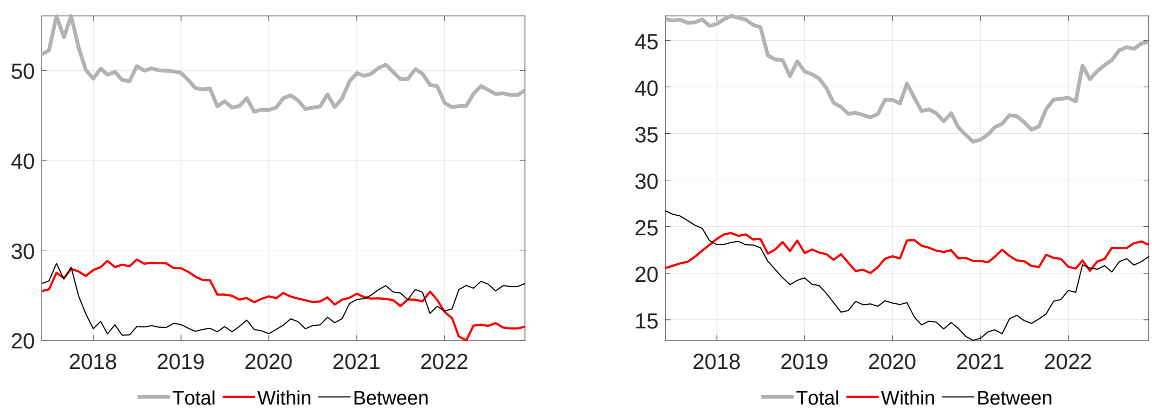
- A: 2018:03 - Tarrifs on Aluminium
- B: 2019:12 - Brexit
- C: 2020:03 - Covid
- D: 2022:02 - War in Ukraine
- E: 2022:03 - Nickel short squeeze

by the response to the nickel short squeeze in March 2022.[16]

We consider rolling-sample within- and between-group connectedness for both returns and RV in Figure 8. It is interesting to note that in both cases, the total connectedness mimic the evolution of the between-group connectedness, meaning that spillovers across- rather than within-groups are key in shaping the final time-varying system-wide connectedness.

Figure 8: Time-varying Connectedness: total, within and between groups

(a) Returns (b) $log\sqrt{RV_t}$

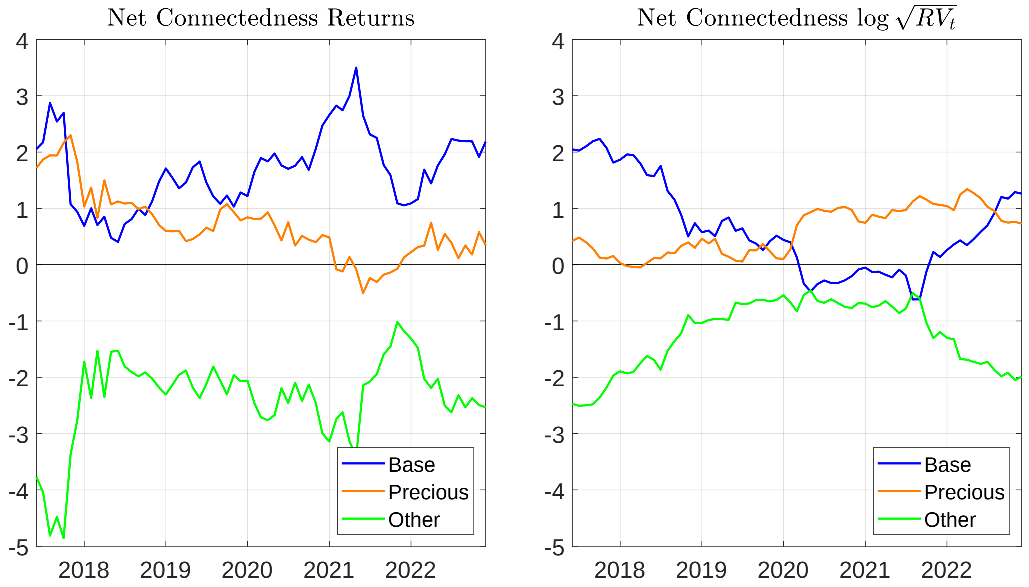


Lastly, Figure 9 shows the evolution of the Net connectedness for each group of metals. Overall, the dynamics of the total connectedness in returns or RV (Figure 7) are closer to the Net connectedness of base metals, which shows almost the same pattern. On the contrary,

[16]See e.g.: `https://internationalbanker.com/brokerage/the-nickel-short-squeeze-what-happened/`

the evolution of precious metals and other ETMs net connectedness is not in line with the fluctuations of total connectedness, neither considering returns nor volatilities. We believe this is a further confirmation of the relative importance of base metals within ETMs.

Figure 9: Time-varying net connectedness by groups



3.4 Connectedness and macroeconomic variables

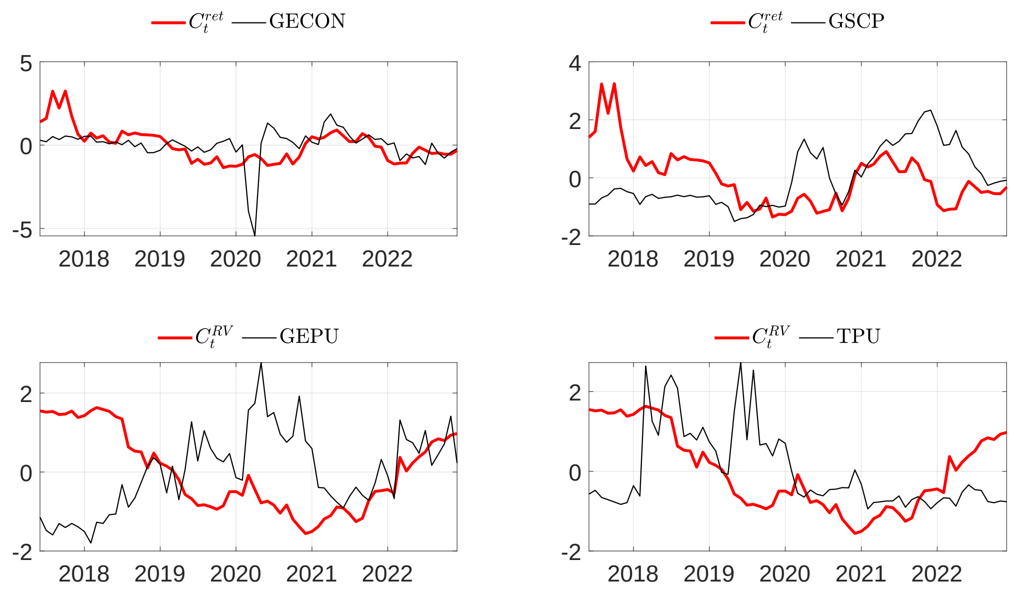
To better understand the drivers of total connectedness, we consider its correlation with different macoreconomic variables. Specifically, since connectedness in returns should be associated to fluctuations in the business cycle, we focus on the correlation between the estimated time-varying return connectedness (C_t^{ret}) and the Global Economic Conditions Indicator (GECON) of Baumeister et al. (2022). We further examine the correlation between C_t^{ret} and the Global Supply Chain Pressure Index (GSCPI) of Benigno et al. (2022), since this proxy should capture fluctuations strongly associated with commodities, including ETMs.

As for RV connectedness (C_t^{RV}), we focus on measures of economic uncertainty. In particular, we analyse the correlation of C_t^{RV} with the Global Economic Policy Uncertainty (GEPU) index (Davis, 2016) and the Trade Policy Uncertainty (TPU) indicator proposed by Caldara et al. (2020).[17] Figure 10 shows the selected indices together with returns and

[17]We also consider the VIX index, but since its dynamics are similar to the evolution of the GEPU, we

RV time varying connectedness measures.

Figure 10: Time-varying connectedness, economic activity, uncertainty and supply chain pressure



Interestingly, connectedness for returns increases during the Covid-induced recession of 2020, when the GECON index exhibits a severe drop. After the Covid-19 pandemic, however, the degree of connectedness for returns seems positively correlated with the economic activity (top-left panel). A simple leads-and-lags analysis between the GECON index and our measure for returns connectedness, C_t^r, reveals that the correlation coefficient is indeed positive and statistically significant at all lags and leads we consider (see Figure B3). On the contrary, we fail to detect statistically significant correlation between connectedness for ETMs returns and the global supply-chain pressure (Figure 10, top-right panel).

Focusing on the RV connectedness, it is clearly shown that, whereas at the beginning of the sample C_t^{RV} negatively correlates with economic uncertainty, starting from the mid-2021 the two indicators are both on a rising trend (bottom-left panel).[18] The correlation between C_t^{RV} and the GEPU indicator is negative sign and is only statistically significant when considering lags, that is, volatility connectedness is influenced by global economic

show results considering the GEPU only.

[18] A similar behaviour is observed also for the VIX index.

uncertainty, but the effect takes some months to manifest. The higher economic uncertainty is, the lower system-wide connectedness becomes after some periods, suggesting that markets interconnection decreases after periods of great uncertainty. On the contrary, it is hard to detect some kind of co-movement between the trade policy uncertainty indicator and ETMs volatility connectedness (Figure 10, bottom-right panel).

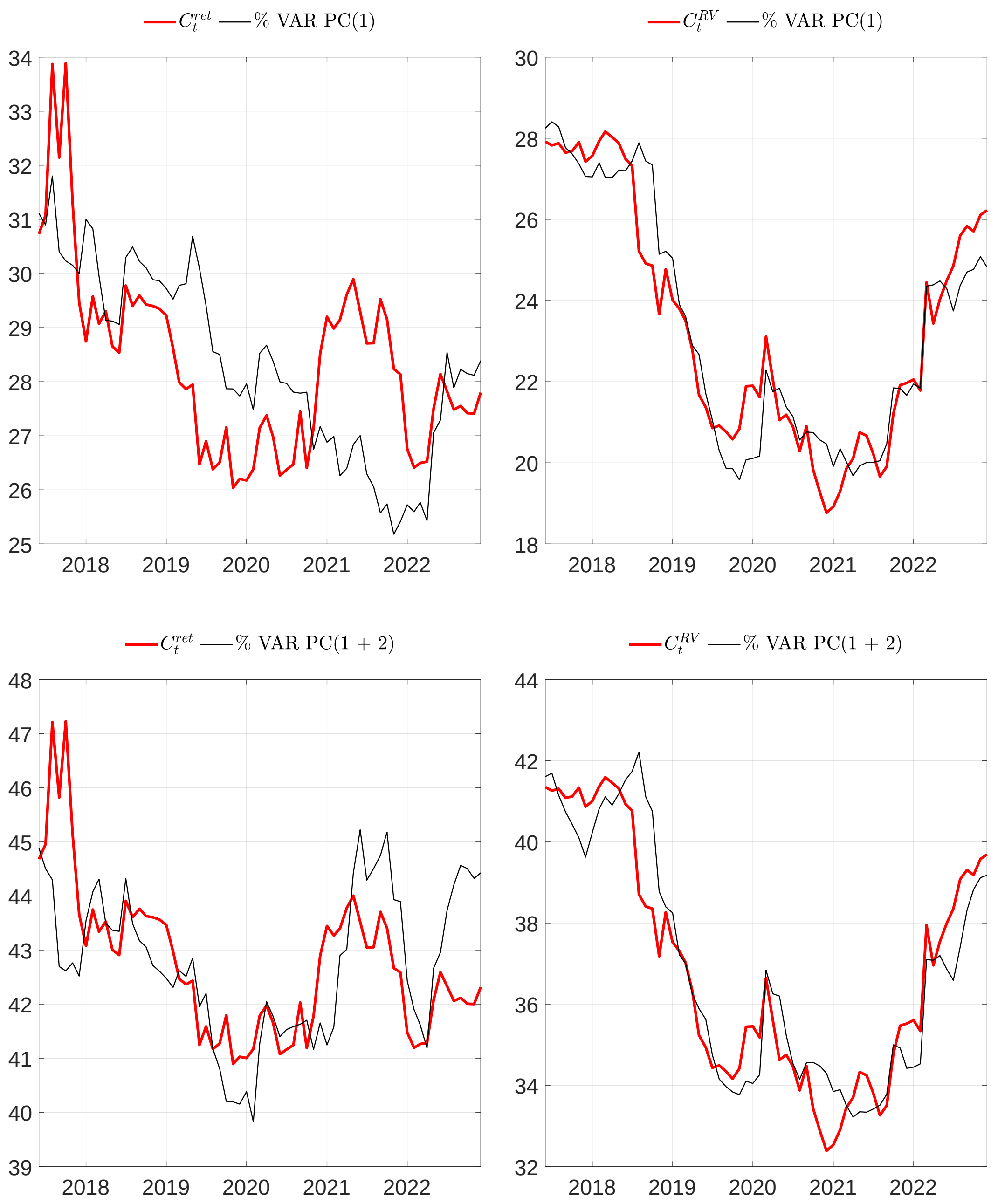
It is possible that the leads-and-lags analysis results are sensitive to different sub-sample definitions and that correlation between the time-varying connectedness and the selected measures in Figure 10 changes with time. However, since the set of observations is already limited, we find it hasty to analyse subsets of the five years span. Our conclusion is that the only significant drivers of the system-wide connectedness for the period of interest are business cycle fluctuations summarized by GECON in the case of returns and economic policy uncertainty as measures by GEPU for volatilities (see Figure B3).

3.5 Alternative measures of connectedness

As a robustness check, we compare our methodology with an alternative measure of connectedness suggested by Billio et al. (2012). Specifically we derive the time-varying system-wide connectedness for returns and volatilities relying on a principal component analysis (PCA). Billio et al. (2012) show that in a highly connected system, a small number of principal components is sufficient to explain most of the volatility of the entire system, thus constituting a valid alternative to the connectedness measure proposed by Diebold and Yilmaz (2009). To make a comparison, we extract the first two principal components as the major drivers of returns and volatilities over the rolling sample and plot the share of variance explained by the components.

Results in top panel of Figure 11 show the percent of variability explained by the first principal component and our baseline measure of connectedness, normalized to have the same mean and standard deviation of the PCA-based measure. We can see that for what concerns volatilities the two proxies are strikingly similar. As for returns, the similarity increases adding also the second principal component (bottom panel).

Figure 11: Alternative measures of time-varying connectedness



Notes: in top panel, C_t^{ret} and C_t^{RV} have been rescaled to ease the comparison. % VAR PC(1) represents the share of variance explained by the first principal component. % VAR PC(1+2) represents the share of variance explained by the first two principal components.

4 Conclusions

To combat climate change, countries have engaged in a historical effort to reduce greenhouse gas emissions. Among the necessary conditions for the success of these efforts are the substitution of fossil fuels with renewable energy sources in energy technologies for power generation, industry, mobility, buildings. This substitution entails at the same time a substantial increase in the demand for metals such as copper, nickel, cobalt, and lithium, which are key building blocks of the energy transition. For example, an electric car requires five times more of these metals than a conventional car. The problem governments, companies, experts, public opinions are becoming increasingly aware of is that a more mineral-intensive global economy raises concerns that supply might not catch up with soaring demand. Shocks that can occur along the supply chain of materials might have macroeconomic impacts on material-dependent economies and possibly on material-rich countries as well.

The deployment of low-carbon energy technologies is expected to make the energy-mineral nexus increasingly important. This is because these emerging technologies, characterized by a potential to mitigate global warming, require specific mineral resources in significant quantities which makes resource depletion a real concern. Because nearly all clean energy technologies employ several critical minerals, the degree of interconnection among them is relevant information and so is the pattern of transmission of potential shocks for both managers and policymakers.

In this paper we provide quantitative evidence on the spillovers that characterise a set of metals that are critical for the challenge represented by the radical change of energy sectors required by the goal of net zero emissions and the decarbonisation of economies. These are 16 metals that constitute the IMF's Energy Transition Metals index and are comprised of three groups: Base, Precious, and Other metals. We compute returns and realised volatilities and estimate spillovers among them by relying on the connectedness approach pioneered by Diebold and Yilmaz (2009, 2012, 2014). The static full-sample connectedness analysis shows that the Base and Precious metal groups transmit shocks to the Other ETMs that are net receivers. By splitting the 16 commodities in three groups we show that almost half of the connectedness originates within each group, whereas the other half is due to cross-group spillovers.

Our results also hightlight that system-wide volatility connectedness has increased after the COVID-19 outbreak. Moreover, the system-wide connectedness of ETM returns is positively correlated with the economic activity, whereas volatility connectedness seems to be more related to global economic policy uncertainty. Finally, alternative measures of connectedness may lead to slightly different results, but our results seem overall robust to the different definition of connectedness based on principal components.

These results deliver an important message for material-dependent countries and firms aiming to become more resilient to supply disruptions and unexpected price increases. Borrowing from the burgeoning literature on energy security, we can conceptualize ETMs security focusing on four dimensions: availability, affordability, efficiency, and environmental stewardship (Metcalf, 2014; Sovacool and Brown, 2010). While ETMs exhibit criticalities related to all of such dimensions, we mainly focus on the interplay between availability and affordability.[19]

In terms of availability, defined as the ability to procure a sufficient, safe and diversified supply of ETMs, the production of most of the metals considered in this study is highly concentrated geographically, often in poor or developing countries. This makes materials-dependent countries prone to supply shocks, just like oil-dependent economies. As a matter of fact, in the words of the European Commission President Ursula von der Leyen "*lithium and rare earths will soon be more important than oil and gas*".[20]

Affordability relates, among other things, to the provision of ETMs at stable prices (Yergin, 2006). Notice that, availability and affordability factors are intertwined and both help explain a large portion of the volatility observed in the prices of ETMs. In fact, the combination of low substitutability, low price elasticity of supply and demand and a high concentration of production in few countries implies that even small shocks arising on either side of the markets for ETMs can trigger large price responses (Boer et al., 2023; Fally and Sayre, 2018; Graedel et al., 2015a,b) and affect key macroeconomic aggregates (Considine et al., 2023; Su et al., 2023).

The existence of liquid futures markets – performing their functions of price discovery and risk mitigation – for ETMs could in principle contribute to ETM security by improving their affordability for different classes of stakeholders, including firms along the supply chain of technologies necessary for the ET. However, while for some of the ETMs in our sample derivative markets are liquid and have a long history (e.g. many base and precious metals),

[19] See Lèbre et al. (2020); Owen et al. (2022); Zhang et al. (2022) for a broader perspective.

[20] See: `https://ec.europa.eu/commission/presscorner/detail/en/STATEMENT_22_5523`.

most of the metals that are in high demand for clean energy technologies, such as cobalt or rare earth elements, do not have well developed futures markets. One of the main messages that this study conveys to policy makers is the urgency of developing well-functioning and liquid derivative markets that allow for risk diversification. This is particularly important because many of the technologies required for decarbonizing economies depend on critical materials, whose prices are closely interconnected.

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A Descriptive statistics

Here we report the log of the realised volatility in standard deviations for the 16 ETMs over the entire sample (Figure A1) and additional information considering aggregation of the 16 commodities in three groups. In particular, Figure A2 shows the price indices and the RV for each group (base metals, precious metals, other ETMs). Finally, Table A1 describes the IMF nominal commodity price indices used in the analysis and Table A2 reports the main descriptive statistics for the downloaded prices.

Figure A1: Log realised volatility of energy transition metals: June 2012 - December 2022

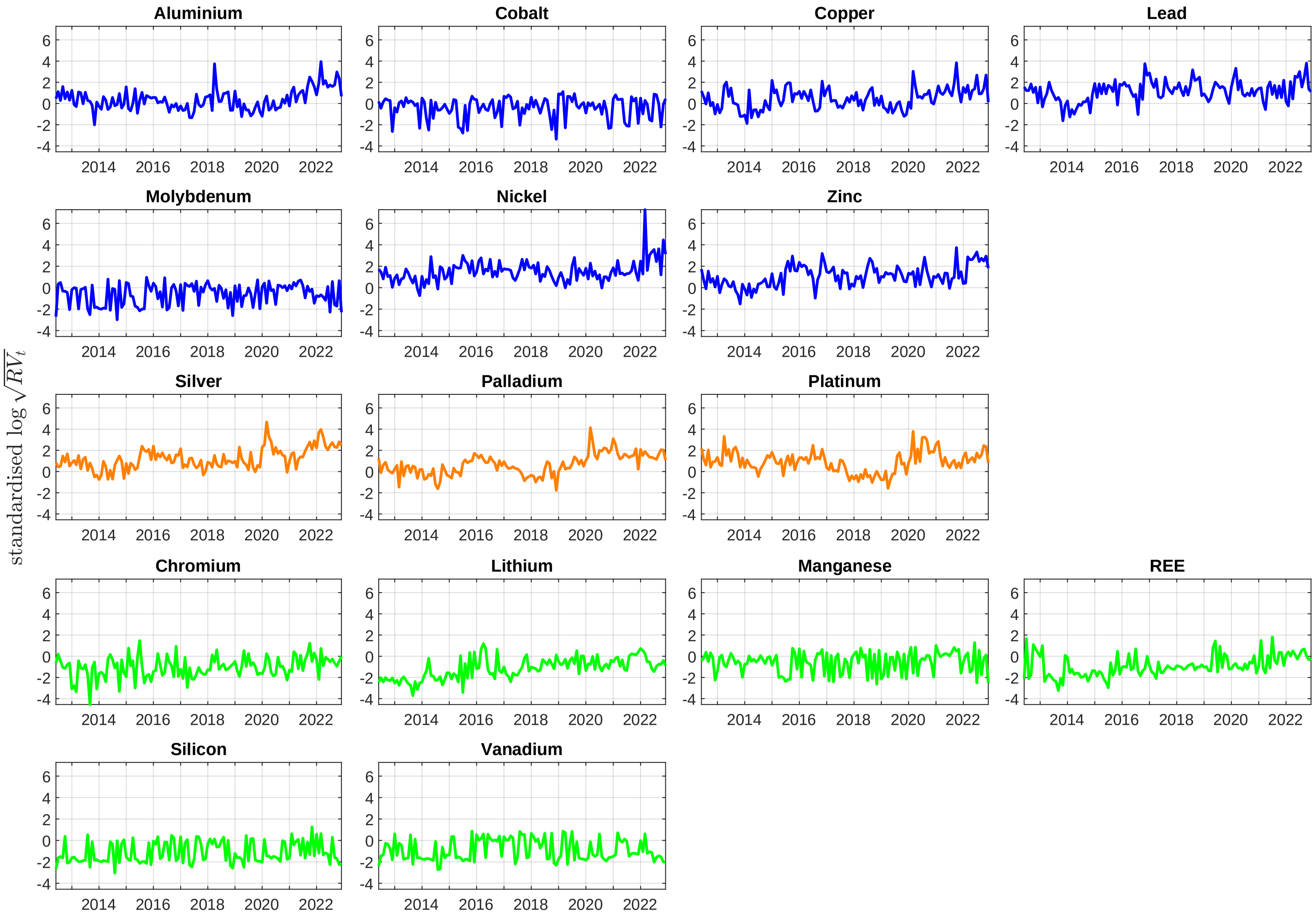
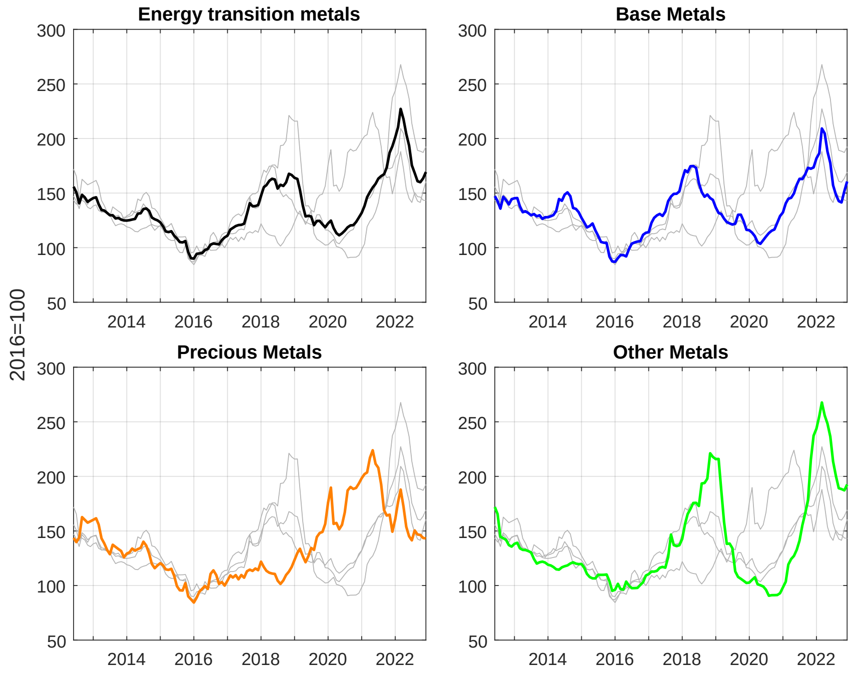
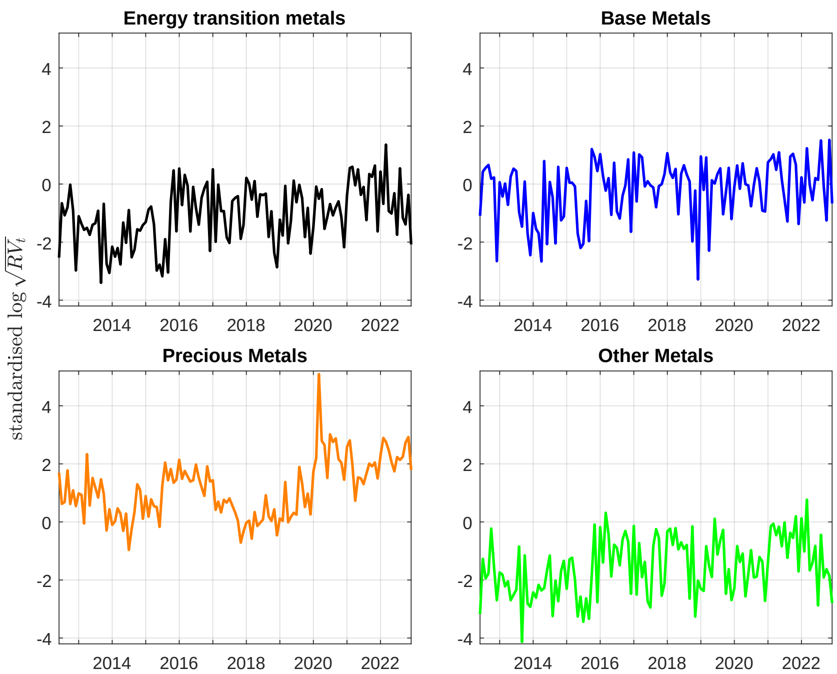


Figure A2: Energy Transition, Base, Precious and Other Metals: price indices and volatilities June 2012 - December 2022

(a) Price indices



(b) Log Realised Volatilities



Notes: price indices and log realised standard deviations for each category of metals. Price indices and volatilities shown in the graphs are computed as cross-sectional averages of the underlying series. Prices have been normalised as follows: $100 \times P_{mt}/\bar{P}_m^{2016}$ where $\bar{P}_m^{2016}$ is the average price of m for 2016. Metal groups are defined in Table 1.

Table A1: IMF Price indices and commodity price indices: metals

Commodity/Index	Group	Metal Group	Type	Unit	Details	Source
Base Metals Price Index	MET	BM	Index	2016 = 100		IMF
Energy Transition Metal Index	MET	ETM	Index	2016 = 100		IMF
Precious Metals Price Index	MET	PM	Index	2016 = 100		IMF
Aluminum	MET	ETM, BM	Price	USD/Metric Ton	99.5% min purity LME spot price CIF UK ports	LME
Chromium	ETM	ETM	Price	USD/Metric Ton	Chromium 99.2% Coarse Particle	Shanghai ME
Cobalt	MET	ETM, BM	Price	USD/Metric Ton	minimum 99.80% purity LME spot price	LME
Copper	MET	ETM, BM	Price	USD/Metric Ton	grade A cathode LME spot price, CIF European ports	LME
Lead	MET	ETM, BM	Price	USD/Metric Ton	99.97% pure LME spot price, CIF European Ports	LME
Lithium	ETM	ETM	Price	USD/Metric Ton	Lithium Metal 99% Battery Grade	Shanghai ME
Manganese	ETM	ETM	Price	USD/Metric Ton	Manganese Electro CIF NWE	Refinitiv
Molybdenum	MET	ETM, BM	Price	USD/Metric Ton	57 %-63% purity roasted molybdenum concentrate	Refinitiv
Nickel	MET	ETM, BM	Price	USD/Metric Ton	melting grade LME spot price, CIF European ports	LME
Palladium	MET	ETM, PM	Price	USD/troy ounce	Palladium LME spot price	LME
Platinum	MET	ETM, PM	Price	USD/troy ounce	Platinum LME spot price	LME
Rare Earth Elements	ETM	ETM	Price	USD/Metric Ton	Rare Earth Carbonate REO 42-45 Dom	Shanghai ME
Silicon	ETM	ETM	Price	USD/Metric Ton	Silicon Lumps, CIF NWE	Refinitiv
Silver	MET	ETM, PM	Price	USD/troy ounce	London Bullion Market Association	ICE
Vanadium	ETM	ETM	Price	USD/Metric Ton	Vanadium Pentoxide, CIF NWE	Refinitiv
Zinc	MET	ETM, BM	Price	USD/Metric Ton	high grade 98% pure	LME

Table A2: Main descriptive statistics for the downloaded ETM prices

	Unit	Mean	Min	Max	Std. Dev.	C.V.
Aluminium	USD/Metric Ton	2333.68	1695.34	3627.44	339.46	0.15
Cobalt	USD/Metric Ton	23.50	12.81	52.44	9.74	0.41
Copper	USD/Metric Ton	8075.05	5621.88	11261.10	1439.59	0.18
Lead	USD/Metric Ton	2457.27	1877.48	3090.72	288.55	0.12
Molybdenum	USD/Metric Ton	13.04	5.92	21.54	3.71	0.28
Nickel	USD/Metric Ton	17684.25	10413.82	39037.93	4809.93	0.27
Zinc	USD/Metric Ton	2933.32	1910.96	4508.40	536.88	0.18
Silver	USD/Troy ounce	1457.98	630.19	3185.95	705.83	0.48
Palladium	USD/Troy ounce	1299.42	874.25	2144.29	353.41	0.27
Platinum	USD/Troy ounce	23.67	16.84	43.42	5.98	0.25
Chromium	USD/Metric Ton	10915.45	7561.42	15562.99	1677.69	0.15
Lithium	USD/Metric Ton	139633.70	78334.29	505028.52	98720.14	0.71
Manganese	USD/Metric Ton	2931.55	1804.03	7933.20	1229.80	0.42
REE	USD/Metric Ton	5533.19	3370.55	14138.52	2467.15	0.45
Silicon	USD/Metric Ton	2612.07	1886.98	6114.71	674.76	0.26
Vanadium	USD/Metric Ton	9.58	3.07	32.45	5.97	0.62

Notes: the table reports, for each metal, the appropriate price unit of measure, the mean, minimum and maximum values, the standard deviation and the coefficient of variation.

B Additional tables and figures

This Section reports the connectedness tables for returns and RV of the 16 ETMs (Tables B1 and B2). Additionally, Figures B1 and B2 focus on From, To and Net connectedness statistics for returns, not reported in the paper. Figure B3 reports the leads and lags correlation analysis between the estimated connectedness and some selected indicators of economic activity, uncertainty and supply-chain pressure.

Table B1: Connectedness table for returns

	Base							Precious			Other						
	Aluminium	Cobalt	Copper	Lead	Molybdenum	Nickel	Zinc	Silver	Palladium	Platinum	Chromium	Lithium	Manganese	REE	Silicon	Vanadium	From
Aluminium	36.57	0.13	12.38	10.66	0.79	6.80	12.47	2.25	4.19	3.65	1.84	0.99	0.91	2.43	3.55	0.40	3.96
Cobalt	1.57	72.17	1.42	1.82	2.88	1.03	1.10	0.66	1.16	0.92	0.27	0.31	11.32	1.36	0.36	1.65	1.74
Copper	10.83	0.03	31.43	11.27	0.02	7.15	15.78	4.82	9.18	6.11	0.67	0.05	0.64	1.55	0.17	0.31	4.29
Lead	10.08	0.42	12.33	34.55	0.17	8.08	14.53	4.23	5.53	7.82	0.33	0.12	0.01	1.31	0.07	0.43	4.09
Molybdenum	2.82	1.44	1.59	1.61	71.70	5.70	1.35	0.79	2.37	1.40	1.28	0.23	6.09	0.82	0.06	0.75	1.77
Nickel	7.45	0.06	8.87	9.40	2.39	38.20	6.69	5.72	8.26	9.96	0.02	1.19	0.07	0.89	0.46	0.37	3.86
Zinc	11.49	0.02	16.73	14.06	0.13	5.80	33.37	3.28	6.65	5.74	0.67	0.97	0.10	0.52	0.23	0.24	4.16
Silver	2.99	0.44	7.13	5.70	0.15	6.87	4.58	46.34	12.84	7.87	1.05	0.08	1.64	0.51	0.99	0.82	3.35
Palladium	4.13	0.01	10.37	5.71	0.56	7.53	7.07	9.83	35.35	18.16	0.00	0.17	0.01	0.61	0.15	0.34	4.04
Platinum	3.92	0.08	7.38	8.57	0.36	9.67	6.51	6.46	19.22	37.19	0.06	0.02	0.10	0.30	0.10	0.07	3.93
Chromium	4.52	1.01	1.95	0.78	1.85	0.26	1.75	1.77	0.17	0.13	77.60	0.85	3.32	0.53	0.47	3.04	1.40
Lithium	2.05	0.60	0.36	0.34	0.61	2.09	2.02	0.68	0.38	0.03	1.24	69.02	4.55	6.71	7.51	1.83	1.94
Manganese	2.98	5.31	2.88	1.54	5.93	1.08	1.34	2.51	0.87	0.90	2.23	0.27	68.66	2.02	0.36	1.10	1.96
REE	3.99	2.08	3.46	2.75	1.64	1.03	0.75	1.74	1.25	0.48	0.56	3.05	7.19	67.22	1.70	1.08	2.05
Silicon	5.96	0.50	0.56	0.21	0.34	0.35	0.62	1.09	0.29	0.13	1.07	0.09	2.45	1.97	84.07	0.31	1.00
Vanadium	1.05	4.80	0.74	0.95	3.44	0.83	0.54	1.52	0.78	0.22	0.63	1.73	3.10	1.73	0.27	77.67	1.40
To	4.74	1.06	5.51	4.71	1.33	4.02	4.82	2.96	4.57	3.97	0.74	0.63	2.59	1.45	1.03	0.80	**44.93**
Net	0.77	-0.68	1.22	0.62	-0.44	0.15	0.65	-0.39	0.53	0.04	-0.66	-1.30	0.63	-0.59	0.03	-0.60	-

Notes: full sample connectedness. Entry in bold is total connectedness.

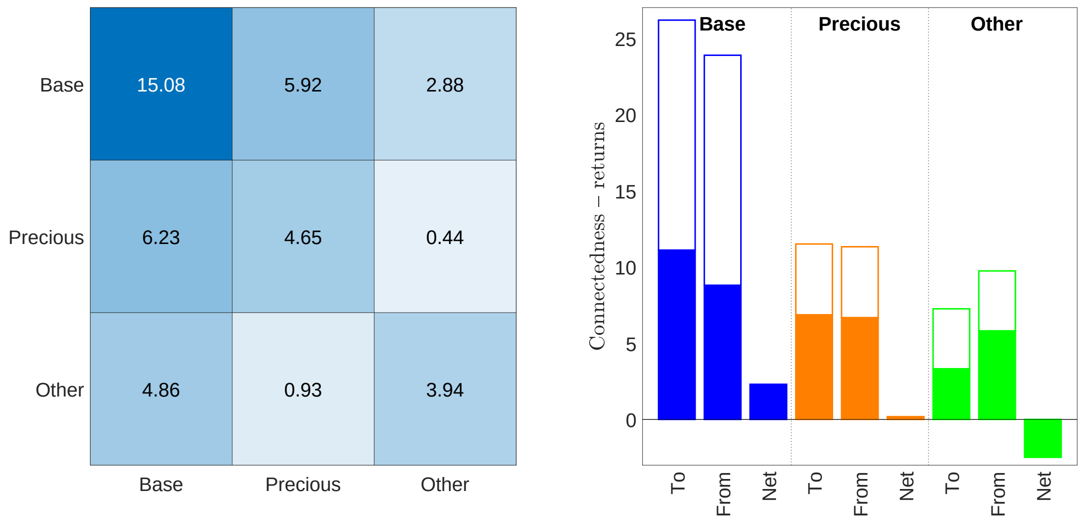
Table B2: Connectedness table for volatilities

	Base							Precious			Other						
	Aluminium	Cobalt	Copper	Lead	Molybdenum	Nickel	Zinc	Silver	Palladium	Platinum	Chromium	Lithium	Manganese	REE	Silicon	Vanadium	From
Aluminium	47.15	0.02	11.18	4.23	0.23	10.11	8.35	9.64	2.88	1.05	0.71	0.27	0.59	2.43	1.10	0.08	3.30
Cobalt	0.05	75.93	0.86	0.12	6.92	3.11	0.37	0.32	1.63	0.12	0.75	0.03	4.16	0.59	2.24	2.80	1.50
Copper	8.26	0.39	34.86	8.75	0.71	8.03	10.51	11.73	9.01	3.81	2.71	0.71	0.17	0.24	0.05	0.08	4.07
Lead	3.99	0.07	11.18	44.54	0.20	6.14	21.17	5.36	4.05	0.81	0.78	0.58	0.38	0.70	0.00	0.04	3.47
Molybdenum	0.37	6.72	1.45	0.31	70.30	0.31	0.69	0.17	1.26	0.02	0.19	0.31	12.16	0.12	1.40	4.22	1.86
Nickel	9.37	1.77	10.06	6.02	0.17	43.69	10.48	7.05	4.38	0.37	3.76	0.32	0.02	0.64	1.23	0.67	3.52
Zinc	6.30	0.17	10.74	16.92	0.34	8.54	35.61	9.79	5.67	1.23	1.11	1.49	0.08	1.90	0.01	0.08	4.02
Silver	7.15	0.14	11.76	4.21	0.07	5.64	9.61	34.95	14.58	4.93	1.10	2.25	1.05	2.55	0.02	0.01	4.07
Palladium	2.30	0.81	9.72	3.42	0.65	3.77	6.00	15.69	37.62	13.52	0.55	2.50	0.23	3.15	0.05	0.02	3.90
Platinum	1.29	0.09	6.36	1.06	0.03	0.50	2.00	8.19	20.88	58.10	0.06	0.43	0.31	0.33	0.12	0.25	2.62
Chromium	1.14	0.79	5.69	1.29	0.42	6.33	2.30	2.32	1.10	0.08	73.15	1.03	1.41	0.32	2.21	0.43	1.68
Lithium	0.64	0.09	1.50	1.02	0.30	0.69	3.23	4.73	5.08	0.54	0.92	73.86	1.52	2.98	2.65	0.26	1.63
Manganese	0.89	3.52	0.33	0.56	11.86	0.08	0.16	1.99	0.43	0.35	0.71	1.11	66.87	0.50	6.85	3.80	2.07
REE	3.73	0.64	0.54	1.15	0.41	1.09	3.89	5.29	6.09	0.39	0.32	2.19	0.76	70.89	2.49	0.12	1.82
Silicon	1.58	2.38	0.16	0.01	3.20	1.88	0.04	0.14	0.19	0.09	0.88	0.97	6.68	2.13	65.82	13.86	2.14
Vanadium	0.12	3.84	0.22	0.08	6.08	1.17	0.21	0.03	0.12	0.09	0.18	0.26	2.50	0.04	14.91	70.16	1.87
To	2.95	1.34	5.11	3.07	1.97	3.59	4.94	5.15	4.83	1.71	0.92	0.90	2.00	1.16	2.21	1.67	**43.53**
Net	-0.35	-0.16	1.04	-0.39	0.12	0.07	0.91	1.09	0.94	-0.91	-0.76	-0.73	-0.07	-0.66	0.07	-0.19	-

Notes: full sample connectedness. Entry in bold is total connectedness.

Figure B1: Full sample group connectedness measures for returns

(a) Within and cross group connectedness (b) To, From and Net connectedness



Notes: panel (a) shows within group connectedness along the main diagonal, while off-diagonal elements are cross group connectedness measures. Panel (b) shows the to, from and net connectedness statistics for groups of metals. Colored areas refer to the off-diagonal statistics, whereas the white areas denote statistics comprehending the diagonal elements.

Figure B2: To, From and Net connectedness – returns

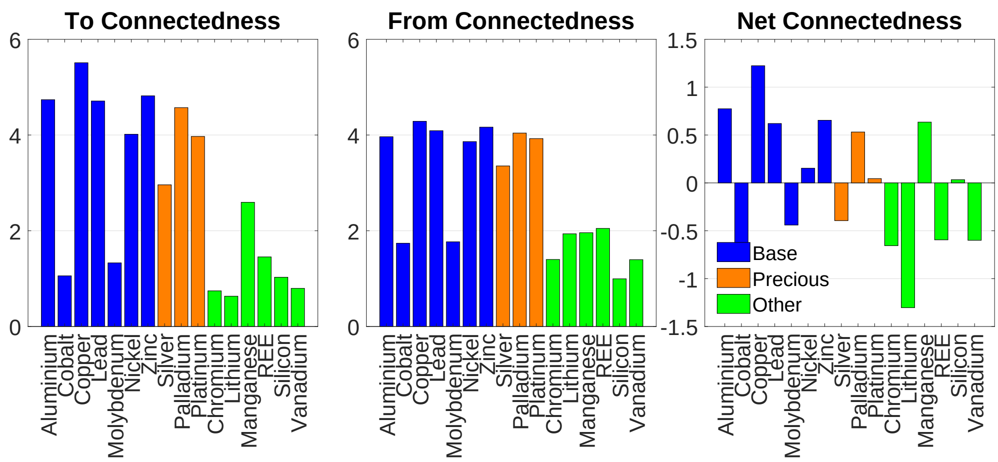
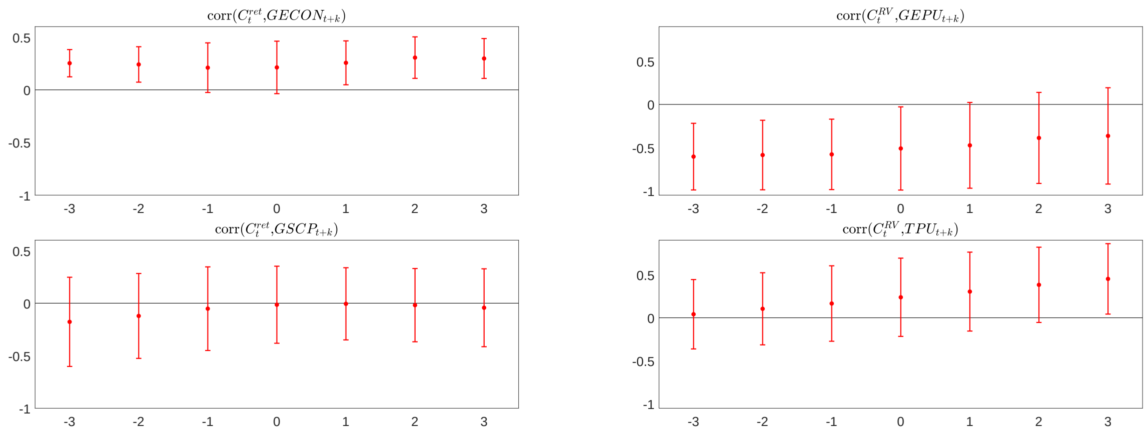


Figure B3: Leads and Lags correlation analysis

(a) Returns connectedness correlation (b) $log\sqrt{RV_t}$ connectedness correlation



Notes: red bars highlights the correlation coefficient and relative standard deviations for different leads (k up to 3) and lags (k up to -3).