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**Az árutőzsde piacok volatilitásának dinamikus összekötöttsége: globális
válságok hatása és a kapcsolatot meghatározó tényezők elemzése**

**Dynamic volatility connectedness of commodity markets: unravelling
global crisis impacts and key drivers of connections**

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I Introduction

Similar to other financial assets, commodity prices traditionally have been determined by the force of supply and demand. However, after the structural break caused by the Global Financial Crisis in 2008, the commodity markets have witnessed a significant transformation, where supply and demand dynamics alone are no longer sufficient to explain price movements ([Basak and Pavlova \[2016\]](#)). The substantial increase in commodity trading volume has notably boosted the liquidity of commodity futures markets. The popularity of hedging against risk has soared, leading to increased price volatility and speculative activities. Globalization, technological advancements, trade integration, and financial liberalization have further reshaped commodity markets. Finally, the financialization of commodity markets resulted in greater connectedness across energy, metal, and agricultural commodity markets ([Tang and Xiong \[2012\]](#), [Nazlioglu et al. \[2013\]](#), [Cheng and Xiong \[2014\]](#), [Henderson et al. \[2015\]](#), [Da et al. \[2023\]](#)). As a result, the literature on commodity markets has witnessed a notable increase in interest.

The existence of the spillover effect between financial assets, such as commodities, has been well-established in previous research ([Dahl et al. \[2020\]](#)). Spillover between assets implies that shock arising from one asset not only affects that particular asset but also spills over to others. It has been firmly established that return correlations are heterogenous over time, particularly during bull and bear market conditions, leading to intensified spillover effects during financial crises ([Longin and Solnik \[1995\]](#), [Longin and Solnik \[2001\]](#), [Ang and Bekaert \[2002\]](#), [Campbell et al. \[2002\]](#), [Goetzmann et al. \[2001\]](#), [Bekaert et al. \[2009\]](#)). Over the last decade, the connectedness approach introduced by [Diebold and Yilmaz \[2014\]](#) has emerged as the standard for measuring the shock spillover effect between financial assets and related econometrics frameworks have been increasingly evolving ever since ([Baruník and Křehlík \[2018\]](#), [Demirer et al. \[2018\]](#)).

This subject holds significance for both policymakers and portfolio managers alike ([Vivian and Wohar \[2012\]](#), [Sensoy \[2013\]](#)). Understanding the assets that serve as key transmitters of shocks is crucial for policymakers in crisis prevention and management. In addition, considering the connectedness of commodity markets is vital for investors as well. Commodities serve as valuable hedging options and safe-haven assets, with precious metals as a notable example ([Büyükhahin and Robe \[2014\]](#)). Such assets enable portfolio diversification and allocation strategies and downside risk reduction ([Belousova and Dorfleitner \[2012\]](#), [Skiadopoulos \[2012\]](#),

Silvennoinen and Thorp [2013], Andreasson et al. [2016], Karyotis and Alijani [2016]). Understanding the network of commodities is also a crucial aspect of asset and derivative pricing (Gardebroek et al. [2016]). Therefore, analyzing the dynamics of interconnectedness in commodity markets is essential for both effective risk management and investment decision-making.

The connectedness of energy and agricultural commodities has been analyzed in many articles (Yip et al. [2020], Balcilar et al. [2021]). Some studies have broadened their scope to analyze the network of various groups of commodities such as energy, metals and agricultural commodities (Farid et al. [2022]). However, previous research has only focused on a limited number of commodities, typically examining either the total connectedness index or the net pairwise connectedness, neglecting use the aggregation to analyse the network more deeply. This paper seeks to fill this gap by measuring the connectedness among all liquid assets across all 6 groups of commodities: energy, industrial metals, precious metals, grains, softs, and livestock employing group aggregation and regularization (Diebold et al. [2017]). Daily future data is used for 33 commodities to compute daily volatilities from 25th August 1998 to 1st April 2024. The analysis is twofold. Firstly, the full-sample static analysis examines inter-group connectedness. Secondly, the dynamics of the total connectedness and the net inter-group connectedness are explored.

It has been well established that global events and crises have played a significant role in shaping the dynamics of commodity markets, demonstrating that the market is no longer solely sensitive to supply and demand shocks (Demirer et al. [2018]). However, previous research primarily focused on a limited number of relevant events, such as the COVID-19 pandemic (Farid et al. [2022]).¹ This study enriches the literature by considering all the significant global events and crises identified in previous research. The impact of the Global Financial Crisis (GFC), the European Sovereign Debt Crisis (ESDC), the Crude Oil Collapse (OIL), the COVID-19 Pandemic (COVID), and the Russo-Ukrainian War (WAR) on the dynamics of the network is examined. In addition the significance of the change in the network of commodities due to the previously mentioned crises is tested using the moving-block bootstrap method.

Uncertainty shocks have also emerged as an important driver of commodity market fluctuations and turbulence (Badshah et al. [2019]). These determining factors can be categorized into

¹In this study, analyzing the effects of a crisis entails the construction of either a connectedness table or a graph before and after the crisis, followed by an examination of the observed changes.

three groups: economic, financial and geopolitical. Macroeconomic uncertainty, such as monetary policies, macroeconomic information, and the business cycle, including the U.S. Economic Policy Uncertainty (EPU), the Baltic Exchange Dry Index (BDIY), and the Spread (difference between the 10-year U.S. bonds and the 3-month U.S. bills) also play a significant role in shaping the dynamics of the connectedness ([Al-Yahyaee et al. \[2020\]](#)). Similarly, financial uncertainty, exemplified by the Volatility Index (VIX) or the S&P500, has proven to be an important driver of commodity market dynamics ([Hu et al. \[2020\]](#)). Moreover, although geopolitical uncertainty has been present only on the spectrum for the last few decades, the outbreak of the Russo-Ukrainian war has notably intensified its relevance ([Cui and Maghyreh \[2024\]](#), [Lu et al. \[2023\]](#)). Despite the established importance of uncertainty in shaping commodity futures dynamics, previous research has only focused on a few relevant drivers. This study contributes to the existing literature by analyzing all significant factors mentioned in existing literature.

To sum up, this paper makes three primary contributions. Firstly, it evaluates all liquid commodities across all six groups and employs aggregation methods and regularization to compute inter-group volatility connectedness. Secondly, it investigates the influence of all previously identified significant global events and crises (GFC, ESDC, OIL, COVID, WAR). Thirdly, this study incorporates all macroeconomic, financial and geopolitical factors identified in previous literature to assess their significance in explaining the dynamic network of commodities.

The rest of the paper is structured as follows. [Section II](#) provides a brief review of the connectedness of commodity markets. In [Section III](#) the description of the data is presented. [Section IV](#) introduces the methodology. [Section V](#) reports the empirical results. [Section VI](#) presents the robustness test. [Section VII](#) is the conclusion of this study.

II Literature review

In this section, relevant literature is reviewed on the topic of commodity connectedness. Various studies have analyzed spillover among the network of commodities focusing on different numbers and groups of assets employing a wide range of econometric frameworks.

[Kang et al. \[2019\]](#) and [Uddin et al. \[2019\]](#) extend the [Diebold and Yilmaz \[2012\]](#) connectedness framework, employing the frequency-domain spillover approach introduced by [Baruník and Křehlík \[2018\]](#). They find that negative and positive shocks result in asymmetric spillovers, which are more apparent during financial uncertainty. Specifically, [Kang et al. \[2019\]](#) find that vegetable oil plays the biggest role in volatility transmission in the network of crude oil and 5 agricultural assets (cereals, vegetable oils, sugar, meat, and dairy), while [Uddin et al. \[2019\]](#) highlight gold and silver as the main transmitters of shocks to platinum and palladium.

Several studies have identified different regimes to understand commodity market dynamics better. [Barbaglia et al. \[2020\]](#) use the [Diebold and Yilmaz \(\[2009\],\[2012\]\)](#) approach to explore the network of ten commodity future volatilities from energy and agriculture groups, observing less apparent spillover at times of low energy prices. [Yip et al. \[2020\]](#) extract the high and low volatility regimes of crude oil using the Markov Switching Autoregressive model of [Hamilton \[1990\]](#), noting a decline in the net spillover from crude oil to agricultural commodities (corn, wheat, soybean) during high volatility regimes and vice versa. Examining the impact of crises and structural breaks on commodity market connectedness, [Zhang and Broadstock \[2020\]](#) utilize the framework of [Diebold and Yilmaz \[2014\]](#) and the pairwise Granger causality approach by [Billio et al. \[2012\]](#) to assess the robustness of the results and found that the Global Financial Crisis (GFC) served as a structural break in the connectedness of 6 commodity indices from the groups of metals and agriculture causing average total connectedness levels to rise permanently from 14.82% to 47.87%. [Dahl et al. \[2020\]](#) determine two subsamples to assess the structural variation of crude oil and employ the univariate marginal distribution model ([Engle \[2001\]](#)) to estimate conditional volatility, which serves as the input in the spillover [Diebold and Yilmaz \(\[2009\],\[2012\],\[2014\],\[2015\]\)](#) estimation, and find that the effect of information spillover is minimal in the pre-2006 subsample, however in the post-2006 subsample crude oil emerges as the main information receiver. [Guhathakurta et al. \[2020\]](#) utilize the connectedness measure and based on the methodology developed by [Bai and Perron \[2003\]](#), define five structural breaks in the sample period to identify different oil price shifts, and find that crude oil price shocks play

an important role in the network of 17 commodities from the groups of energy, precious metal, industrial metal, and softs. Several studies analyze the significance of various factors in explaining the connectedness. [Hu et al. \[2020\]](#) measure the impact of the US Economic Policy Uncertainty Index (EPU), Citi Economic Surprise Index (ESI), Default Spread (DEF), Investor Sentiment Index (SI), Volatility Index (VIX), and the Global Geopolitical Risk Index (GPR) indicators within the connectedness network of crude oil, gold and soybean. The results show that crude oil and gold are mostly affected by market sentiment, while soybeans are more reactive to the DEF, GPR and macroeconomic factors are found to be the most relevant for crude oil. [Al-Yahyaee et al. \[2020\]](#) apply quantile regression to test the impact of EPU and VIX on the total connectedness (TCI) and find that they have predictive power on the spillover among precious (gold, silver) and industrial metals (copper, aluminium, zinc, lead). Results also show that silver, copper, zinc, and lead are net information receivers, while gold and aluminium are net contributors.

[Gong et al. \[2021\]](#) investigate the spillover between crude oil, natural gas, heating oil, and gasoline, while [Balcilar et al. \[2021\]](#) focus on the relationship between crude oil and 11 agricultural commodities. Both studies utilize an extended version of the connectedness framework and find that spillover indices peak during crises such as the oil price crash of 2014, the GFC, the European Sovereign Debt Crisis (ESDC), or the COVID-19 pandemic. Notably, crude oil emerges as a crucial net information transmitter. [Umar et al. \[2021\]](#) further confirm that crude oil demand and risk shocks are key participants among the most dominant industrial commodities, including copper, aluminium, zinc, lead, nickel, and tin. [Maitra et al. \[2021\]](#) investigate the asymmetric volatility spillover among 23 commodity futures from all 6 six groups of commodities (energy, industrial metals, precious metals, grains, soft, and livestock) employing the [Diebold and Yilmaz \(\[2012\]\[2014\]\)](#) method and find that negative volatility dominates positive volatility. [Caporin et al. \[2021\]](#) explore the asymmetric short- and long-run volatility spillover among 12 commodities, uncovering distinct group clustering, weak inter-group connectedness, and strong intra-group connectedness among energy, metal, and grains. Their findings underscore the long-run nature of spillover effects. [Hung \[2021\]](#) examine the evolution of the return spillover pre- and post-COVID-19, affirming that the level of connectedness is stronger during the crisis. [Ma et al. \[2021\]](#) analyze 21 commodities from all six groups, employing group aggregation to assess connectedness within each group. Their research extends to the impact of various indices, including the Default Spread (DEF), Citi Economic Surprise Index (ESI), Volatility

Index (VIX), and Financialization Index, revealing the significance of non-fundamental factors in driving co-movements. Furthermore, they explore the structural variations in the network induced by the GFC, confirming its lasting impact on market dynamics.

[Just and Echaust \[2022\]](#) scrutinize the network dynamics of wheat, soybean, rice, oats, maize, and barley using the spillover approach by [Baruník and Křehlík \[2018\]](#), underlining how uncertainties like the COVID-19 pandemic or geopolitical tensions, such as the Russo-Ukrainian war, amplify spillover effects. In a different vein, [Zhou et al. \[2022\]](#) analyze the return, the volatility, the skewness and the kurtosis spillover among carbon, energy and nonferrous metals using a quantile VAR framework and a GARCHSK model. Their findings reveal inconsistent spillovers in the different dimensions and heterogeneous patterns over time. [Gong et al. \[2022\]](#) extended the framework by employing the TVP-VAR-SV model and found that the six major industrial metals realized skewness and kurtosis connectedness is similar to the volatility connectedness, however, the spillover effect is not as notable. [Tiwari et al. \[2022\]](#) examine the volatility spillover among 10 energy and agricultural commodities employing the rolling window-based Quantile VAR (QVAR) model. Their study sheds light on the impact of the COVID-19 crisis. It showcases that volatility spillover in the right tail is higher than in the left tail of the conditional volatility distribution. Examining return and frequency spillovers among 20 agricultural commodities, [Naeem et al. \[2022\]](#) employ group aggregation to investigate static inter- and intra-group connectedness. They also analyze the impact of the GFC and the Shale Oil Revolution, alongside the COVID-19 pandemic further highlighting the significance of the crisis on the network of connectedness. Similarly, [Farid et al. \[2022\]](#) explore the quantile connectedness among 37 commodity futures from all 6 groups, utilizing group aggregation in order to scrutinize inter- and intra-group connectedness, and the dynamics of the net connectedness between groups, emphasizing the significant shift in connectedness induced by the COVID-19 crisis. Furthermore, their results show higher spillover in the left tail of the conditional return distribution. [Jiang and Chen \[2022\]](#) employ the [Diebold and Yilmaz \[2012\]](#) and the [Baruník and Křehlík \[2018\]](#) methodology on the network of metals (gold, silver, copper, and aluminium), energy (oil, natural gas and coal) and carbon markets and find that the time-frequency connectedness is significantly higher after the outbreak of the COVID-19 and the total connectedness is contributed mainly by short-term spillover effects. Moreover, [Gong and Xu \[2022\]](#) examine the volatility spillover between energy, precious metals, industrial metals, agriculture and livestock and reveal the significant influence of the Geopolitical Act Index

(GPA), with a positive effect on energy, agriculture and livestock and a negative effect on the others. [Wang et al. \[2022\]](#) study a wide range of 16 commodities and the impact of GPR on the TCI with Granger causality, OLS and quantile regression and show that a high level of geopolitical risk causes a high level of return and volatility connectedness.

[Ghosh et al. \[2023\]](#) focus on the dynamics of clean and dirty energy commodities during COVID-19 employing quantile regression, documenting a significant increase in the TCI, especially in the upper quantiles. [Hu et al. \[2023\]](#) confirm that crude oil is the key shock transmitter in the network of various energy commodities. [Wu et al. \[2023\]](#) compare the effects of the COVID-19 and the Russo-Ukrainian war and reveal that the pandemic served as a greater shock, also emphasizing the difference in the impact on the dynamics. [Mandaci et al. \[2023\]](#) found that the GPR index drove the TCI during important events like the pandemic and the Russo-Ukrainian conflict. [Lu et al. \[2023\]](#) examine the relationship between GPR for the leader of precious metal production, China and the connectedness of 4 precious metals (gold, silver, platinum, palladium) and reveal that precious metals have received spillover from the GPR index, especially during times of high geopolitical tension.

Finally [Jiang and Chen \[2024\]](#) also confirm that the Russo-Ukrainian war significantly changed the dynamics of the connectedness, and drove the TCI up among various energy, metal and agricultural commodities in China. In addition [Furuoka et al. \[2023\]](#) further confirm the fact that TCI rises at times of high uncertainty.

These studies collectively contribute to understanding the complex dynamics of commodity market interconnectedness, especially under varying market conditions and crises. The summary of the Literature review is provided in Table 5 in the Appendix.

III Data

III.1 Data of commodity volatilities

We study the daily volatility connectedness between a large number of 33 commodities from all six categories (energy, industrial metals, precious metals, grains, softs and livestock), previously identified in related literature, similar to [Farid et al. \[2022\]](#). The energy group includes WTI crude oil (CL1), heating oil (HO1), gasoline, brent oil (CO1), gasoil (QS1) and natural gas (NG1). As for gasoline, HU1 is used until the 10th of May 2006 and after that, XB1 is utilized, because XB1 took the place of HU1. Industrial metals contain aluminium (LA1), copper (HG1), nickel (LN1), lead (LL1), zinc (LX1), and tin (LT1). Precious metals consist of gold (GC1), silver (SI), platinum (PL1), and palladium (PA1). Grains include Chicago wheat (W1), Kansas (red) wheat (KW1), corn (C1), soybeans (S1), soymeal (SM1), soyoil (BO1), oats (O1), and rough rice (RR1). Softs contain coffee (KC1), sugar (SB1), cocoa (CC1), cotton (CT1), lumber (LB1), and orange juice (JO1). Finally, livestock consists of lean hogs (LH1), live cattle (LC), and feeder cattle (FC1). More information on the assets is provided in Table 7 in the Appendix. The sample period ranges from 25th August 1998 to 1st of April 2024 including several global events and crises such as the GFC, ESDC, OIL, COVID, and WAR.

The daily 1st generic future prices are obtained from Bloomberg. We choose commodity futures² due to the empirical evidence demonstrating their effectiveness in offering essential price signals guiding the commodity demand and spot prices ([Yang et al. \[2005\]](#)). In addition, futures are much more liquid than spot markets. Price volatilities are computed using the squared of returns methodology, $(\ln(P_{it}) - \ln(P_{it-1}))^2$, consistent with [Triacca \[2007\]](#), [Giles \[2008\]](#), and [Guhathakurta et al. \[2020\]](#). The daily volatilities of each of the 33 commodity futures are plotted in Figure 9 in the Appendix.

The descriptive statistics are presented in Table 8 in the Appendix. Natural gas has the highest mean, followed by gasoline and lumber, while feeder cattle, followed by gold and live cattle, have the lowest mean. Tin has the highest standard deviation, followed by silver, conversely Chicago wheat, Kansas (read) wheat, corn, and oats report the lowest. The stationarity of the data is tested using the augmented Dickey and Fuller (ADF) test, and the results show that all 33 time series are stationary at the 1% level of significance.

²The use of future data is widely employed in related literature ([Wu et al. \[2023\]](#)), [Cui and Maghyereh \[2024\]](#).

III.2 Data of fundamental and non-fundamental determinants

In this study, three dimensions of determining factors' significance are assessed in explaining the net connectedness between the six aggregated groups of commodity futures and the total connectedness measures, as seen in Table 1. These dimensions encompass macroeconomic, financial, and geopolitical factors. The macroeconomic factors include the U.S. Economic Policy Factor (EPU), the Baltic Exchange Dry Index (BDIY), and the Spread. The financial factors are the Volatility Index (VIX), and the S&P500 index. Finally, the geopolitical factors include the Geopolitical Risk Index (GPR), the Geopolitical Act Index (GPA), and the Geopolitical Threats Index.

The economic factors consist of the U.S. economic Policy Uncertainty (EPU)³ Index proposed by Baker et al. [2016], which is based on the frequency of newspaper reports (Hu et al. [2020]). The Baltic Dry Index (BDI) is a shipping and trade index created by the London-based Baltic Exchange (Ma et al. [2021], Kilian [2009], Fan and Xu [2011]). The Spread (Mandaci et al. [2023]) is the difference between the 10-year U.S. bonds and 3-month U.S. bills. It provides information about future short-term interest rates and also inflation rates (Bakas and Triantafyllou [2018]). The data for BDI and the Spread is obtained from Bloomberg.

The Chicago Board Options Exchange (CBOE) Volatility Index, the VIX index, is a well-established measure of investors' expectations of implied volatility for S&P 500 options (Hu et al. [2020], Al-Yahyaee et al. [2020], Mandaci et al. [2023]). It is widely referred to as the investor fear index, therefore it can serve as a proxy for market sentiment. The S&P 500 stock index tracks the 500 large-cap US companies' stocks, and therefore represents overall stock market performance. It is used to represent risk in the financial market (Ma et al. [2019]). The data for the two financial factors are from Bloomberg.

Finally, we use the Geopolitical Risk Index⁴ of Caldara and Iacoviello [2022] to proxy geopolitical uncertainty (Cui and Maghyereh [2024], Lu et al. [2023], Wang et al. [2022]). Two other indices proposed to further separate geopolitical events from geopolitical risks: Geopolitical Threats (GPT) and Geopolitical Act (GPA) (Gong and Xu [2022]).

³The data is obtained from: <https://www.policyuncertainty.com/>.

⁴The data is sourced from: <https://www.matteoiacoviello.com/gpr.htm>.

Table 1 Fundamental and non-fundamental determinants

Dimension	Acronym	Factor
Economic	EPU	U.S. Economic Policy Uncertainty
	BDIY	Baltic Exchange Dry Index
	SPREAD	difference between the 10-year U.S. bonds and 3-month U.S. bills
Financial	VIX	Volatility Index
	SP500	Standard and Poor's 500 stock market index
Geopolitical	GPR	Geopolitical Risk Index
	GPT	Geopolitical Threats
	GPA	Geopolitical Act

Notes: The three dimensions of fundamental and non-fundamental determinants (economic, financial, geopolitical) and their acronyms are presented. Their impact on the net aggregated group and the TCI with and without aggregation is tested.

IV Methodology

IV.1 The Diebold and Yilmaz framework

Diebold and Yilmaz ([2009],[2012], [2014]) introduce the connectedness measure derived from vector-autoregressive models (VAR; Sims [1980]) and the forecast error variance decompositions (FEVD). This method provides a relatively simple and intuitive way of measuring the contribution of own and other variable's shocks to the total forecasted variance. Compared to other approaches, it provides both the direction and the intensity of the spillover and enables static and dynamic analysis. In the final stage of the process, the breakdown of forecast error variances can be condensed into a spillover table, known as the DY spillover table. In the following, the approach is presented in detail.

First, the estimation process requires to specify an approximation VAR(p) model:

$$y_t = \mu + \sum_{j=1}^p A_j y_{t-j} + \varepsilon_t, \quad (1)$$

Where y_t is the $K \times 1$ vector containing assets volatility series that are assumed to be endogenously related to each other. The $k \times 1$ vector of constants is μ , A_j denotes the $K \times K$ autoregressive coefficient matrix to be estimated and $\varepsilon_t \sim (0, \Sigma)$ is the vector of independently and identically distributed disturbances. The time series of VAR(p) model are then transformed into their moving average (MA) representation, which can be written as $y_t = \phi + \sum_{j=0}^{\infty} B_j \varepsilon_{t-j}$.

After estimating the VAR(p) model the next step in the Diebold and Yilmaz [2012] framework is identification. Considering the Cholesky-factor ordering problem, this study employs the generalized forecast error variance (GVFED) proposed by Pesaran and Shin [1998] and Koop et al. [1996], which effectively overcomes the influence of the order of variables. Eq. (2) calculates variable j 's contribution to variable i 's H -step ahead generalized forecast error variance, $\theta_{ij}^g(H)$ as:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' B_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' B_h \sum B_h e_j)}, \quad H = 1, 2, \dots, \quad (2)$$

where the error term's covariance matrix is Σ , the H -step moving average coefficient matrix is B_h , the standard deviation of the error term for the j th equation is σ_{jj} , and e_i is a selection vector, with unity at the i th position, zeros otherwise.

Since the sum of the contributions of own variables and the cross-variable variance is not unity under the generalized decomposition in general, each entry of the variance decomposition matrix is normalized by the sum of its rows, as seen in eq. (3). This step allows for various spillover indices to be interpreted as a percentage.

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{i=1}^K \theta_{ij}^g(H)}, \quad (3)$$

making $\sum_{i=1}^K \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^K \tilde{\theta}_{ij}^g(H) = K$.

Diebold and Yilmaz (2012, 2014) introduce pairwise directional connectedness measures. First, the shocks received by variable i from all other variables is defined as:

$$S_{i \leftarrow \bullet}^g(H) = \frac{\sum_{j \neq i}^K \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^K \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{j \neq i}^K \tilde{\theta}_{ij}^g(H)}{K} \cdot 100 \quad (4)$$

Second, the directional connectedness transmitted by variable i to all other variables is measured as:

$$S_{\bullet \leftarrow i}^g(H) = \frac{\sum_{j \neq i}^K \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^K \tilde{\theta}_{ji}^g(H)} \cdot 100 = \frac{\sum_{j \neq i}^K \tilde{\theta}_{ji}^g(H)}{K} \cdot 100 \quad (5)$$

Third, net spillover is defined as the difference between eq. (4) and eq. (5), and measures each asset's net contribution to the volatility in other assets:

$$S^g(H) = S_{\bullet \leftarrow i}^g(H) - S_{i \leftarrow \bullet}^g(H) \quad (6)$$

Finally, the total connectedness of the system measures the average influence of one variable on others, regardless of the direction in the following way:

$$S^g(H) = \frac{\sum_{i,j=1}^K \tilde{\theta}_{ij}^g(H)}{\sum_{j=1}^K \tilde{\theta}_{ji}^g(H)} \cdot 100 = \frac{\sum_{i,j=1}^K \tilde{\theta}_{ij}^g(H)}{K} \cdot 100 \quad (7)$$

IV.2 Group Aggregation

This study aims to measure the connectedness between the six commodities groups: energy, precious metals, industrial metals, grains, soft, and livestock. In order to achieve that, a group aggregation method is employed, by [Greenwood-Nimmo et al. \[2016\]](#). This approach enables the measurement of connectedness not only in standard pairwise and total dimensions but also at the group level, providing a deeper understanding of the system-wide dynamics of a network. The connectedness matrix $S^g(H)$ consisting M markets may be expressed in M^2 blocks as follows:

$$S^g(H) = \begin{bmatrix} B_{1 \leftarrow 1}^{(h)} & B_{1 \leftarrow 2}^{(h)} & \cdots & B_{1 \leftarrow M}^{(h)} \\ B_{2 \leftarrow 1}^{(h)} & B_{2 \leftarrow 2}^{(h)} & \cdots & B_{2 \leftarrow M}^{(h)} \\ \vdots & \vdots & \ddots & \vdots \\ B_{M \leftarrow 1}^{(h)} & B_{M \leftarrow 2}^{(h)} & \cdots & B_{M \leftarrow M}^{(h)} \end{bmatrix} \quad (8)$$

Where block $B_{j \leftarrow i}^{(h)}$ represent the total within-market effects for market i , while $B_{i \leftarrow j}^{(h)}$ encapsulates the total between-market effects from market j to i . The total within-market contributions are computed as:

$$\mathcal{W}_{i \leftarrow i}^{(h)} = e_{m_i}' B_{i \leftarrow i}^{(h)} e_{m_i} \quad (9)$$

where e_{m_i} is an $m_i \times 1$ vector of ones and m_i is the number of variables in group i , indicating that the within-market effect for market i is simply the sum of its individual values. The total between-market effects are defined as:

$$\mathcal{F}_{j \leftarrow i}^{(h)} = e_{m_j}' B_{j \leftarrow i}^{(h)} e_{m_i}. \quad (10)$$

with the notations directly derived from eq. (9)

IV.3 LASSO regression

The traditional ordinary least squares (OLS) regression encounters challenges in statistical modelling with high-dimensional data. To overcome this problem when estimating eq. (1), regular-

ization or penalized methods are employed. One such method, introduced by Tibshirani [1996], is the LASSO regression. It incorporates an L1 penalty term to the least squares objective function. The LASSO estimator minimizes the value of:

$$\hat{\beta} = \arg \min_{\beta} \left[\sum_{t=1}^T (y_t - \sum_i \beta_i x_{it}) + \lambda \sum_{i=1}^K |\beta_i| \right], \quad (11)$$

where λ is the parameter of the penalty. As opposed to classical variable selections, the LASSO process is more stable and suitable for high-dimensional data. Next, we employ the Adaptive LASSO method, an extension of LASSO introduced by Zou [2006]. The adaptive LASSO estimator minimizes the value of:

$$L_n(\beta) = \|y - X\beta\|^2 + 2\lambda_n \sum_{j=1}^{pn} w_{nj} |\beta_j| \quad \text{where } w_{nj} = |\tilde{\beta}_{nj}|^{-1}, \quad j = 1, \dots, pn. \quad (12)$$

This approach allows a relatively high penalty for zero coefficient, thereby enhancing accuracy in variable selection and reducing estimation bias. One of the outstanding features of the adaptive LASSO method introduced by Fan and Li [2001] is called the 'oracles property'. It ensures the correct identification of zero coefficients with a high probability close to 1, and it also aligns the distribution of non-zero coefficients with that of the OLS estimator, as demonstrated by Zou [2006].

IV.4 Bootstrapping

To identify and distinguish significant changes in the spillover effects from non-significant changes, this study employs bootstrap confidence intervals for spillover measures on the total connectedness index and the net pairwise connectedness indices (Buse et al. [2022], Greenwood-Nimmo and Tarassow [2022]). The approach aims to analyze the uncertainty of the estimated spillover measures. Several bootstrapping methods have emerged in recent years, this study utilizes the residual-based moving-block bootstrap method by Brüggemann et al. [2016].

The residual-based moving-block bootstrap approach involves simulating $s = 1, 2, \dots, S$ bootstrap samples of the residuals from the estimated VAR model and then re-estimating the model on each bootstrap sample (MBB-VAR). Next, the DY spillover indices (SUM, FROM, TO, and NET) are calculated. More information is provided on the computation process in the thesis of Badics [2023].

V Empirical results

V.1 The static and dynamic analysis of the connectedness

This section explores the static full-sample average connectedness across the six aggregated groups of commodity volatilities. Next the dynamic evolution of the relationship between the commodities is examined both on macro (total connectedness) and micro (net spillover) levels.

Table 2 Connectedness table

	energy	industrial metals	precious metals	grains	softs	livestock	FROM
energy	88.79	2.98	2.05	2.94	2.04	1.20	11.21
industrial metals	3.70	86.43	3.07	3.33	2.38	1.09	13.57
precious metals	3.77	4.42	85.13	3.33	2.27	1.09	14.87
grains	2.64	2.33	1.60	90.14	2.22	1.07	9.86
softs	2.90	2.72	1.81	3.64	87.70	1.23	12.30
livestock	3.41	2.37	1.67	3.36	2.40	86.79	13.21
TO	16.42	14.82	10.20	16.59	11.32	5.68	12.51
NET	5.21	1.25	-4.67	6.73	-0.98	-7.53	

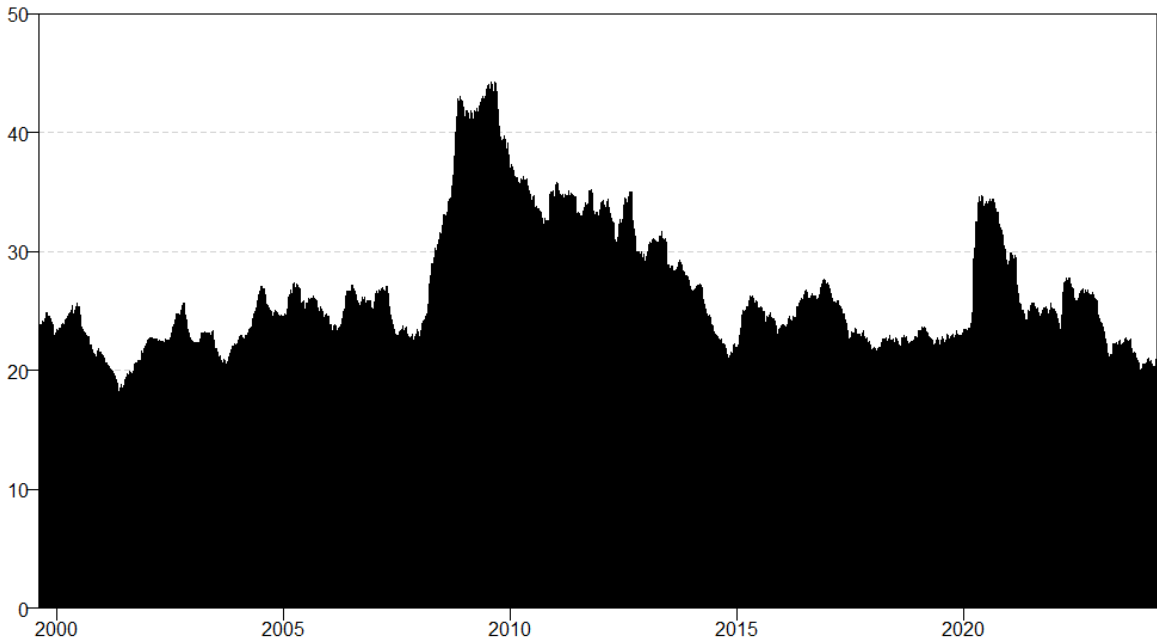
Notes: The connectedness table presents the static full-sample average connectedness of 33 commodity assets aggregated into the six categories of energy, industrial metals, precious metals, grains, softs, and livestock. The various measures were computed using LASSO regularization, a rolling window size of 250 days and a forecasting horizon of 10 days.

Table 2 presents the full-sample connectedness table gained by aggregating the original 33×33 connectedness table of the individual commodities from all six groups (energy, industrial metals, precious metals, grains, softs, livestock) after Diebold et al. [2017]. The off-diagonal elements of the upper-left 6×6 matrix are the pairwise directional connectedness measures, with the highest value 3.77% from precious metals to energy. The FROM column is the row sum of the pairwise connectedness measures, called the total directional connectedness from others to each of the six commodity categories, with precious metal emerging as the highest value of 14.78% again. Conversely, the TO row is the column sum of the pairwise connectedness measures, measuring each group's contribution to others' forecast error variances, with grains showing the highest value of 16.59%. The net connectedness is the difference between each group's TO and FROM value, with livestock emerging as the largest information receiver, and

grains as the largest contributor. Finally, the total connectedness is 12.51%, which indicates a somewhat lower level of overall connectedness than the findings of [Diebold et al. \[2017\]](#).

The static analysis approach provides information about the average relationship between the groups, but the connectedness measures show great variation across time, therefore examining the dynamics presents a more detailed picture. The dynamic TCI is calculated employing LASSO regression with a rolling window size of 250 days, and $H = 10$ days forecast horizon⁵. The evolution of total connectedness among 33 individual commodity assets, without aggregation is displayed in Figure 1, while the total connectedness among six aggregated groups of commodities is shown in Figure 2.

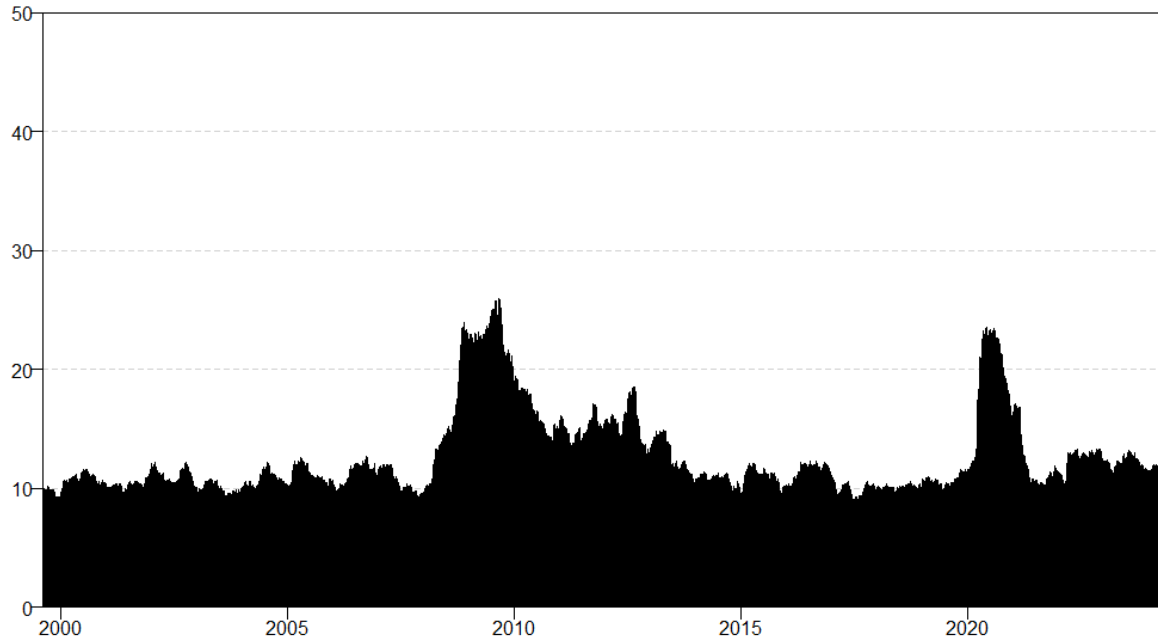
Figure 1: Dyanamic total connectedness without aggregation



Notes: The figure shows the evolution of the dynamic total connectedness among the 33 individual commodity assets without employing aggregation. The TCI was calculated using LASSO regularization, a rolling window size of 250 days, and 10-day forecast horizon.

⁵The forecast horizon was selected based on [Diebold et al. \[2017\]](#), [Guhathakurta et al. \[2020\]](#), and [Farid et al. \[2022\]](#). The rolling window size is exactly one year (250 days) and was chosen based on the average size of the window used in related literature (e.g. [Barbaglia et al. \[2020\]](#), [Naeem et al. \[2022\]](#)). LASSO regression is implied based on [Diebold et al. \[2017\]](#).

Figure 2: Total connectedness among the six aggregated groups of commodities

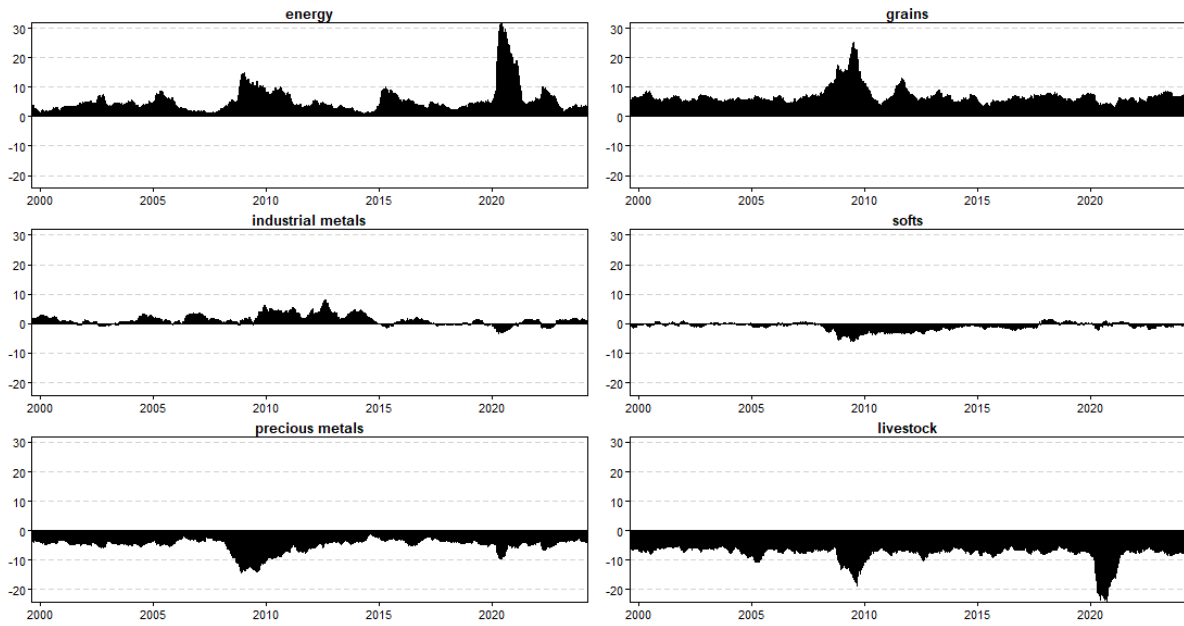


Notes: The figure presents the total dynamic spillover index among the six aggregated groups of commodities (energy, industrial metals, precious metals, grains, soft, and livestock) consisting of 33 individual assets. The index was computed by employing LASSO regularization, a rolling window size of 250 days, and a forecast horizon of 10 days.

The figures provide strong evidence that the evolution of the average value of the total connectedness is greater between the 33 individual assets with and without aggregation. The results imply that the spillover of shocks between each individual asset is strong, varying between approximately 20% to 45%. On the other hand, the information spillover between the six groups of aggregated commodities presents a much weaker average relationship, which varies between 10% and 30%. High intra-group connectedness and rather weak inter-group connectedness are in line with the findings of [Diebold et al. \[2017\]](#), [Caporin et al. \[2021\]](#), [Naeem et al. \[2022\]](#) and [Farid et al. \[2022\]](#). In addition, the TCI is heterogenous and shows great fluctuation over time, presenting a higher level of connectedness in crisis periods of The Global Financial Crises, The European Sovereign Debt Crisis, The Crude Oil Collapse, The COVID-19 Pandemic, and The Russo-Ukrainian war also found in previous literature ([Dahl et al. \[2020\]](#), [Jiang and Chen \[2022\]](#), [Furuoka et al. \[2023\]](#)).

Finally, to provide a deeper understanding of the evolution of the net connectedness among the six categories, the aggregated net dynamic connectedness results are displayed in Figure 3. The categories of grains and energy arise as the largest consecutive information spillover contributors to others, followed by industrial metals, which is mainly a contributor, but sometimes serve as a receiver of shocks. Conversely, livestock and precious metals are the most dominant consecutive receivers of information, followed by the group of softs, which sometimes is a contributor of shocks. Farid et al. [2022] and Caporin et al. [2021] also suggest that energy is a dominant information contributor. However Farid et al. [2022] find that from 2006 to 2020 livestock has to lowest time-varying net connectedness in the network of energy, metals, grains, livestock and soft underlining the significance of the asset and sample period choice. In addition, it can be noted that the net connectedness measures typically increase during crisis periods.

Figure 3: Net connectedness among the six aggregated categories



Notes: The figure consists of six sub-figures presenting each group's net connectedness measure with employing aggregation. Positive values mean that the given category acts as a net shock transmitter to other categories. Conversely, negative net connectedness measure implies the role of a net information receiver in the network of the six commodity groups.

V.2 The effects of global events and crisis on the network of commodities

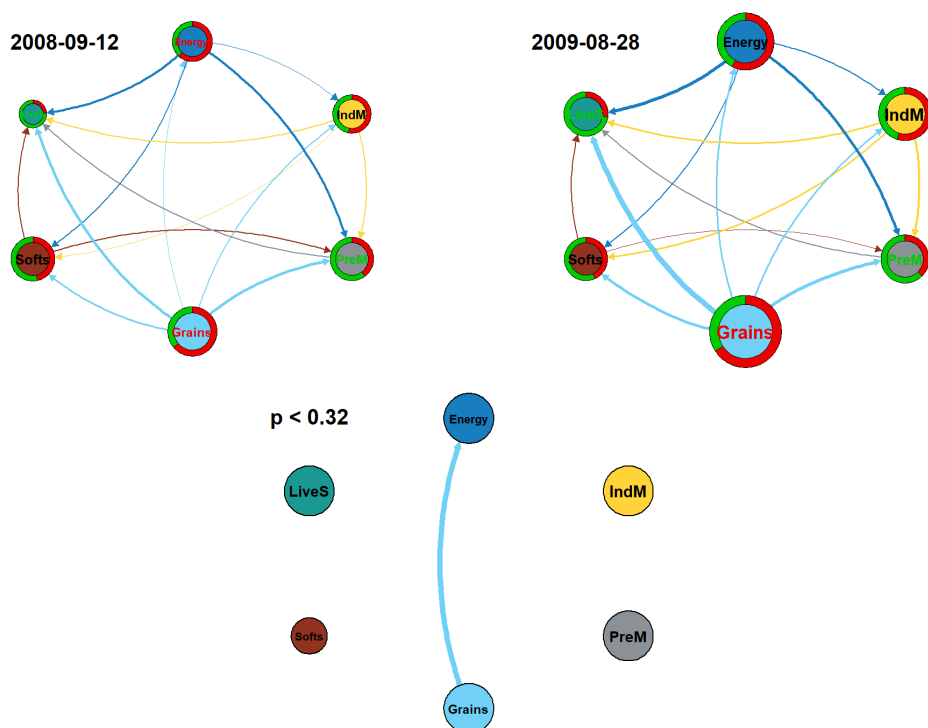
This section aims to examine the effects of the five main global crises in the sample period (GFC, ESDC, OIL, COVID, WAR) by computing the network graph of six aggregated groups of commodities before and after the shock and assessing the significance of the changes in them (Badics et al. [2023]) by employing the moving-block bootstrap approach by Brüggemann et al. [2016].

Before presenting the result, it is crucial to clarify the interpretation of the network graphs. Each snapshot graph consists of three networks: two plots on the top, and one on the bottom. The top two networks are obtained from the VAR estimation. The top left network presents the connectedness of the six aggregated groups before the given crisis (represented by a window size of 250 days spanning until the day before the outbreak), while the top right network presents the connectedness after the outbreak (represented by a window size of 250 days from the day of the outbreak). Each node represents a group of commodities, with the pie chart around them displaying the proportion of shocks transmitted (red) and received (green). The size of the node indicates the sum value. The top 10% of all possible net pairwise connections are represented by the edges, displaying both the direction (arrow) of net information flow and the magnitude (thickness). Nodes with red (green) letters represent time series where the to/sum (from/sum) ratio is greater than 60%.

The network on the bottom, obtained from the moving-block bootstrap method, displays only the significant changes between the upper graphs' connectedness measures (sum, from, to, and net) between the two periods at 32% levels⁶ The border color is red (green) if the net connectedness increased (decreased), the size of the node indicates if there was a significant change in the sum value. If the size of the node is below (above) the average size, it implies a significant decrease (increase) in the sum measure. Finally, the red (green) title of the node represents the groups where the to/sum (from/sum) ratio increased by more than 5%.

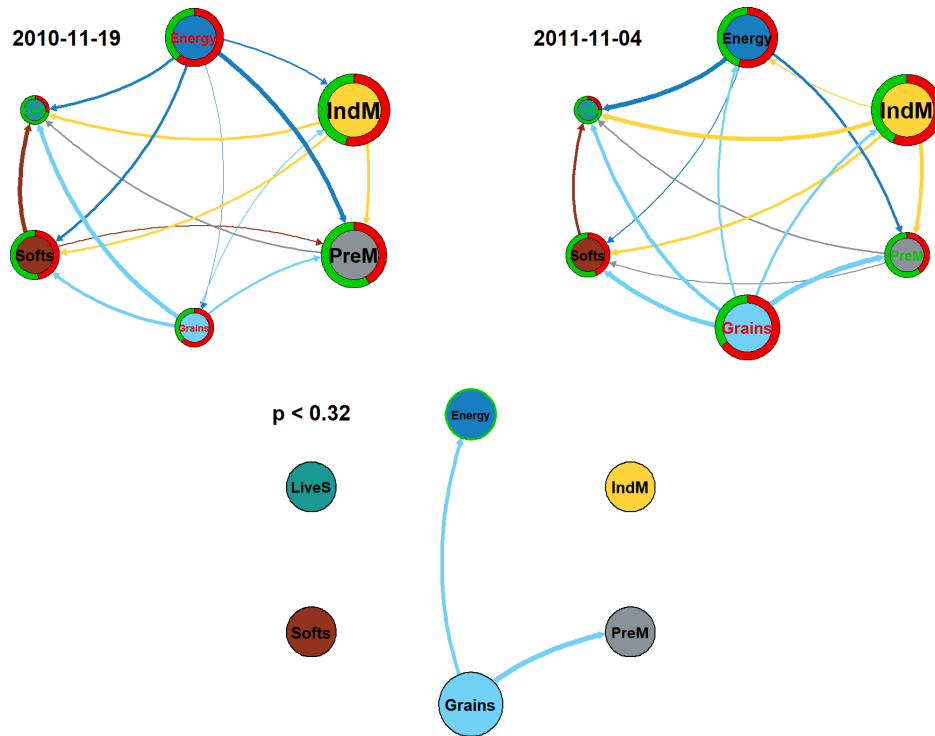
⁶The use of 32% significance level is the common choice in VAR bootstrap estimation.

Figure 4: The network graph of six commodities before and after the GFC



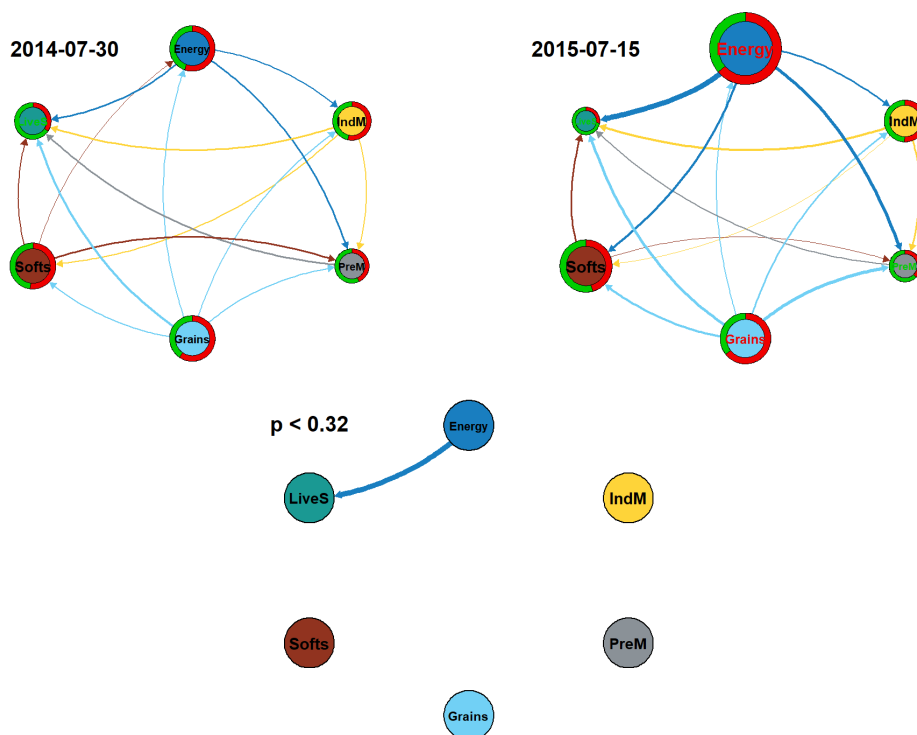
Notes: The three plots present the change in the network dynamics of the six aggregated groups of commodities (energy, industrial metals, precious metals, grains, softs, and livestock) due to the Global Financial Crisis. The top left graph shows the dynamics of the network before the crisis, while the top right graph presents the connectedness after the outbreak of the crisis. The bottom graph only reports the significant changes in the network caused by the crisis. Each node represents a commodity group and each edge shows the net spillover. Red (green) letters represent time series where the to/sum (from/sum) ratio is greater than 60% and the pie chart displays the proportion of shocks transmitted (red) and received (green).

Figure 5: The network graph of six commodities before and after the ESDC



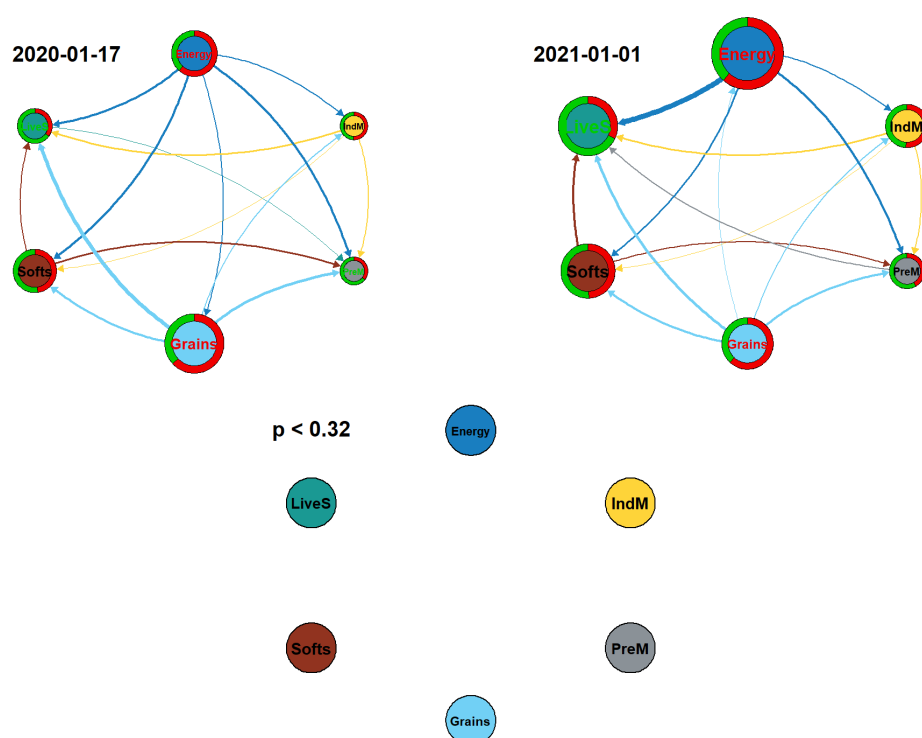
Notes: The three plots present the change in the network dynamics of the six aggregated groups of commodities (energy, industrial metals, precious metals, grains, softs, and livestock) due to the European Sovereign Debt Crisis. The top left graph shows the dynamics of the network before the crisis, while the top right graph presents the connectedness after the outbreak of the crisis. The bottom graph only reports the significant changes in the network caused by the crisis. Each node represents a commodity group and each edge shows the net spillover. Red (green) letters on the top two graphs represent time series where the to/sum (from/sum) ratio is greater than 60% and the pie chart displays the proportion of shocks transmitted (red) and received (green).

Figure 6: The network graph of six commodities before and after the Crude Oil Collapse



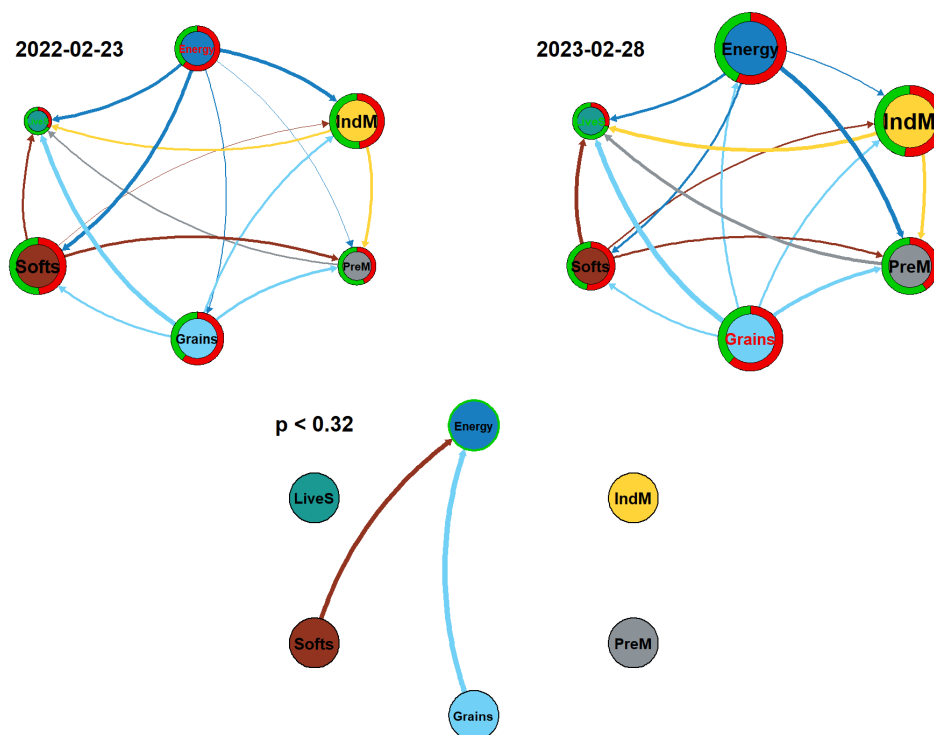
Notes: The three plots present the change in the network dynamics of the six aggregated groups of commodities (energy, industrial metals, precious metals, grains, softs, and livestock) due to the Crude Oil Collapse. The top left graph shows the dynamics of the network before the crisis, while the top right graph presents the connectedness after the outbreak of the crisis. The bottom graph only reports the significant changes in the network caused by the crisis. Each node represents a commodity group and each edge shows the net spillover. Red (green) letters on the top two graphs represent time series where the to/sum (from/sum) ratio is greater than 60% and the pie chart displays the proportion of shocks transmitted (red) and received (green).

Figure 7: The network graph of six commodities before and after the COVID-19



Notes: The three plots present the change in the network dynamics of the six aggregated groups of commodities (energy, industrial metals, precious metals, grains, softs, and livestock) due to the COVID-19 Pandemic. The top left graph shows the dynamics of the network before the crisis, while the top right graph presents the connectedness after the outbreak of the crisis. The bottom graph only reports the significant changes in the network caused by the crisis. Each node represents a commodity group and each edge shows the net spillover. Red (green) letters on the top two graphs represent time series where the to/sum (from/sum) ratio is greater than 60% and the pie chart displays the proportion of shocks transmitted (red) and received (green).

Figure 8: The network graph of six commodities before and after the Russo-Ukrainian war



Notes: The three plots present the change in the network dynamics of the six aggregated groups of commodities (energy, industrial metals, precious metals, grains, softs, and livestock) due to the Russo-Ukrainian War. The top left graph shows the dynamics of the network before the crisis, while the top right graph presents the connectedness after the outbreak of the crisis. The bottom graph only reports the significant changes in the network caused by the crisis. Each node represents a commodity group and each edge shows the net spillover. Red (green) letters on the top two graphs represent time series where the to/sum (from/sum) ratio is greater than 60% and the pie chart displays the proportion of shocks transmitted (red) and received (green).

As opposed to previous literature's findings the effects of the five crises have a relatively weaker impact on the network of commodity groups examined. This is because previous literature only focused on the before and after network graphs, and have not evaluated the significance of the changes induced by the crises ([Guhathakurta et al. \[2020\]](#)). In addition, previous studies have not employed aggregation methods. This means that in most cases even though the edges changed in the network graphs, the change was not statistically significant. Figure 4-8 present the results of the changes caused by the five crises.

For example, the network constructed after the outbreak of the Global Financial Crisis (Figure 4) is mostly in line with the findings of [Naeem et al. \[2022\]](#). They found that during the crisis grains showed mild connectedness with the other groups, livestock presented strong bi-directional connectedness with other agricultural groups, and softs were rather disconnected. However, after examining the significance of these changes, only the increase in net spillover between grains and energy appears to be statistically significant.

Another similar example is the COVID-19 Pandemic (Figure 7), where similar results were found as well when examining the network after the outbreak. [Naeem et al. \[2022\]](#) noted that oil shocks and agriculture commodities have a high level of connectedness, softs are net information transmitters, while grains are receivers. Moreover, [Farid et al. \[2022\]](#) found that the Pandemic notably increased spillover between commodities: grains became the largest shock transmitter, while metals were the receiver of information. However, when examining the significance of these changes, none of them are considered statistically significant.

V.3 Net connectedness of six commodity groups and the determining factors

Three economic factors', two financial factors', three geopolitical factors' and five crises' impacts are tested on the aggregated net connectedness of the six categories of commodities, and the TCI with and without aggregation of the 33 assets⁷. Information on the starting and end dates of the five crises is provided in Table 9 in the Appendix. The analysis is based on the works of Ugolini et al. [2023], where several determining factors impact was tested on the net connectedness of five asset classes of DeFi, cryptocurrency, stock, and safe-haven.

$$C_t = \beta_t + \beta_1 BDIY_t + \beta_2 S\ pread_t + \beta_3 VIX_t + \beta_4 S\ P500_t + \beta_5 EPU_t + \beta_6 GPR_t + \beta_7 GPA_t + \beta_8 GPT_t + \beta_9 GFC_t + \beta_{10} ES\ DC_t + \beta_{11} OIL_t + \beta_{12} COVID_t + \beta_{13} WAR_t + \varepsilon_t \quad (13)$$

Table 3 presents the result of the OLS regression for the fundamental and non-fundamental factors. The Baltic Exchange Dry Index (BDIY) is found to have a significant negative effect on the aggregated net connectedness of energy, precious metals, and the TCI with and without aggregation, while it positively impacts livestock. Ma et al. [2021] found that BDIY plays the most dominant role in the metal market. The Spread is only significant in the case of grains, demonstrating a positive impact on the category's net connectedness, while Mandaci et al. [2023] found a rather weak impact on the TCI. The Volatility Index (VIX) is found to be one of the top factors in terms of explanatory power, with almost being significant for each connectedness measure, except for industrial metals and grains. The findings are in line with the findings of Hu et al. [2020], Al-Yahyaee et al. [2020], and Ma et al. [2021]. VIX demonstrates a positive impact on energy and the TCI with and without aggregation (Mandaci et al. [2023]), and a negative effect on precious metals, soft, and livestock. The Standard and Poor's 500 stock market index is also a top determining factor. It plays a role in the evolution of the agricultural market (Ma et al. [2021]), except for the group of grains. The U.S. Economic Policy Uncertainty (EPU) Index has also a large explanatory power (Hu et al. [2020], Al-Yahyaee et al. [2020]), being significant across half of the commodity categories, and also in explaining the TCI with and without aggregation. It positively affects energy and the two TCI measures, while having a negative impact on industrial metals and livestock. Finally, the Geopolitical Risk Index (GPR)

⁷Eq. (13) presents the OLS regression. The left-hand side variable (C) presents the various connectedness measures.

is found to be statistically insignificant in all cases as opposed to previous findings (Wang et al. [2022], Mandaci et al. [2023]).

Table 3 The impact of economic, financial, and geopolitical factors on the connectedness

	energy	ind. metals	prec. metals	grains	softs	livestock	TCI(without)	TCI(with)
β	-6.4e-02*** (-6.1e+00)	1.0e-03 (2.1e-01)	2.2e-02*** (4.2e+00)	-4.4e-04 (-6.1e-02)	7.4e-03 (1.5e+00)	3.4e-02*** (3.0e+00)	-5.0e-02*** (-7.4e+00)	-3.9e-02*** (-6.6e+00)
BDIY	-5.9e-05*** (-1.1e+00)	-2.1e-05 (-8.3e-01)	-1.1e-05*** (-4.0e-01)	-1.9e-05 (-5.1e-01)	3.3e-05 (1.3e+00)	7.7e-05*** (1.3e+00)	-3.8e-05*** (-1.1e+00)	-2.4e-05*** (-7.7e-01)
Spread	1.1e-02 (2.2e-01)	5.6e-03 (2.5e-01)	-3.1e-02 (-1.2e+00)	8.0e-02** (2.4e+00)	-2.3e-02 (-9.9e-01)	-4.2e-02 (-8.1e-01)	1.6e-02 (4.9e-01)	4.5e-02 (1.6e+00)
VIX	2.5e-03*** (5.2e+00)	2.1e-04 (9.8e-01)	-9.9e-04*** (-4.1e+00)	4.2e-04 (1.3e+00)	-5.8e-04*** (-2.6e+00)	-1.6e-03*** (-3.0e+00)	2.4e-03*** (7.6e+00)	2.0e-03*** (7.4e+00)
SP500	-7.0e-04*** (-5.3e+00)	9.2e-05 (1.5e+00)	1.2e-04* (1.8e+00)	-1.2e-04 (-1.3e+00)	1.2e-04* (1.9e+00)	4.9e-04*** (3.5e+00)	-2.1e-04** (-2.5e+00)	-1.5e-04** (-2.1e+00)
EPU	1.7e-04*** (3.5e+00)	-4.1e-05* (-1.8e+00)	-1.2e-05 (-4.9e-01)	-3.3e-05 (-9.9e-01)	2.3e-05 (9.9e-01)	-1.1e-04** (-2.0e+00)	7.7e-05** (2.4e+00)	6.3e-05** (2.3e+00)
GPR	5.5e-04 (1.3e+00)	-1.6e-05 (-8.3e-02)	-3.1e-04 (-1.5e+00)	-3.8e-04 (-1.3e+00)	3.7e-05 (1.9e-01)	1.1e-04 (2.6e-01)	3.4e-04 (1.3e+00)	1.5e-04 (6.5e-01)
GPA	-2.9e-04 (-1.6e+00)	3.2e-05 (3.9e-01)	1.4e-04 (1.5e+00)	1.4e-04 (1.1e+00)	-1.0e-05 (-1.2e-01)	-7.4e-06 (-3.9e-02)	-1.5e-04 (-1.3e+00)	-9.4e-05 (-9.5e-01)
GPT	-2.2e-04 (-1.0e+00)	-3.4e-05 (-3.3e-01)	1.3e-04 (1.1e+00)	2.2e-04** (1.5e+00)	-1.6e-05 (-1.5e-01)	-8.0e-05 (-3.4e-01)	-1.8e-04 (-1.3e+00)	-7.2e-05 (-5.7e-01)

Notes: The impact of three economic, two financial, and three geopolitical factors are tested on the net connectedness of each aggregated net connectedness measure of energy, industrial metals, precious metals, grains, soft, and livestock. In addition, each factor's significance is tested on the total connectedness with and without employing aggregation. T-statistics are reported in round brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Next we examine the impact of crises on the connectedness measures, represented as dummy variables, taking the value of one during the given crisis, and zero otherwise. Table 9 in the Appendix presents the starting and end dates of the five crises⁸: GFC, ESDC, OIL, COVID, and WAR. Table 4 presents the regression results. The GFC is found to have the largest impact, having a negative effect on energy and the two TCI measures, and a positive effect on the net aggregated connectedness of the category of precious metals. The ESDC is only significant in the case of energy and the TCI measure without aggregation, and has a negative impact in each case. The decline in crude oil has a positive significant impact on the net connectedness

⁸The dates for the Global Financial Crises, the European Sovereign Debt Crisis, and the COVID-19 Pandemic are based on Badics et al. [2023]. Crude Oil Collapse dates are sourced from Cornell [2015], while the Russo-Ukrainian war dates are from Wu et al. [2023].

of energy, however, it does not affect the other categories nor the TCI measures. This could imply that energy-related shocks only affect the commodities from the group of energy and do not spill over to others. COVID has a weak impact on the connectedness measures (Wang et al. [2022]). The results show a negative impact on the group of energy and the two TCI measures and a positive effect on livestock. Finally, the WAR is found to be statistically insignificant.

Table 4 The impact of five global crises on the connectedness

	energy	ind. metals	prec. metals	grains	softs	livestock	TCI(without)	TCI(with)
β	-6.4e-02*** (-6.1e+00)	1.0e-03 (2.1e-01)	2.2e-02*** (4.2e+00)	-4.4e-04 (-6.1e-02)	7.4e-03 (1.5e+00)	3.4e-02*** (3.0e+00)	-5.0e-02*** (-7.4e+00)	-3.9e-02*** (-6.6e+00)
GFC	-4.1e-02*** (-3.0e+00)	6.7e-03 (1.0e+00)	2.0e-02*** (2.9e+00)	-2.0e-02 (-2.0e+00)	6.4e-03 (9.6e-01)	2.8e-02* (1.8e+00)	-4.2e-02*** (-4.6e+00)	-3.6e-02*** (-4.5e+00)
ESDC	-2.1e-02* (-1.9e+00)	-1.7e-03 (-3.3e-01)	8.7e-03 (1.5e+00)	4.6e-03 (5.8e-01)	7.5e-04 (1.4e-01)	9.1e-03 (7.4e-01)	-1.7e-02** (-2.3e+00)	-1.0e-02 (-1.5e+00)
OIL	5.4e-02*** (2.7e+00)	-1.4e-02 (-1.5e+00)	-1.1e-02 (-1.0e+00)	-1.4e-02 (-9.8e-01)	-2.0e-03 (-2.1e-01)	-1.4e-02 (-6.4e-01)	2.1e-02 (1.6e+00)	1.1e-02 (9.9e-01)
COVID	-3.8e-02*** (-2.8e+00)	9.1e-03 (1.5e+00)	9.2e-03 (1.3e+00)	-6.4e-03 (-6.9e-01)	-1.5e-03 (-2.4e-01)	2.7e-02* (1.9e+00)	-2.2e-02** (-2.5e+00)	-2.4e-02*** (-3.1e+00)
WAR	-1.6e-02 (-1.3e+00)	5.4e-03 (9.7e-01)	2.1e-03 (3.3e-01)	1.6e-03 (1.9e-01)	-6.4e-04 (-1.1e-01)	7.8e-03 (6.0e-01)	-1.2e-02 (-1.5e+00)	-3.2e-03 (-4.7e-01)

Notes: The impact of five global crises (the Global Financial Crisis, the European Sovereign Debt Crisis, the Crude Oil Collapse, the COVID-19 Pandemic, and the Russo-Ukrainian war) are tested on the net connectedness of each aggregated net connectedness measure of energy, industrial metals, precious metals, grains, softs, and livestock. In addition, each factor's significance is tested on the total connectedness with and without employing aggregation. T-statistics are reported in round brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

VI Robustness test

In this section, the robustness of the results are tested. First, the connectedness measure's robustness is assessed with a window size of 200 and 300. Second, the robustness of the OLS regression is tested by defining energy and non-energy-related crises.

First, to test the robustness of the connectedness results, in addition to the 250 day rolling window size, the dynamics of the total spillover index with and without aggregation are constructed with rolling windows of 280 (Figure 11) and 300 (Figure 13) days (Guhathakurta et al. [2020], Hu et al. [2020]). The figures show that the total connectedness indices with and without aggregation do not change, therefore the results are robust with respect to the window size.

Second, the robustness of the OLS regression model is checked by constructing two dummy variables instead of the original five: energy-related shocks (the Crude Oil Collapse and the Russo-Ukrainian War) and non-energy-related shocks (the Global Financial Crisis, the European Sovereign Debt Crisis, and the COVID-19 Pandemic). Table 10 presents the model output and shows that the results do not significantly differ from previous findings.

VII Conclusion

In this study, the static and dynamic connectedness of commodity volatilities was analyzed among 33 assets from all six groups of energy, industrial metals, precious metals, soft, grains, and livestock from 25th August 1998 to 1st of April 2024. In addition, the impact of several influential global events and crises and other fundamental and non-fundamental factors on the connectedness measures were examined.

The results show a relatively weaker level of inter-group connectedness and a strong level of intra-group connectedness. The aggregated categories of grains and energy turned out to be the main shock transmitters, while livestock, followed by precious metals are the main receivers. The connectedness measures are shown to have time-varying features, with an increased level of connectedness during times of crisis. The BDIY, the VIX, and the S&P 500 are all proven to have a significant impact on the net aggregated group connectedness measures as well as on the total connectedness measures. Finally, the GFC and the COVID-19 Pandemic are found to be key factors in explaining the connectedness measures. However, after testing the significance of several previously identified changes in the connectedness network graph due to crisis events, - employing the moving-block bootstrap method - the results show only a few key differences.

Furthermore, the findings have important implications for market regulators. First, acknowledging that all assets are connected both on the micro and macro levels, allows policymakers to assess systematic risk and potential risk spillovers during financial downturns. Second, identifying the key information transmitters and receivers in the commodity network provides great insight into the dynamics of commodities.

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Appendix

Table 5 Summary of the literature review

Author(s)	Time series	Regularization	Crisis	Aggregation	Determinants	Number of assets
Batten et al. [2015]	return + volatility	no	no	no	no	4
Barunk et al. [2015]	volatility	no	no	no	no	3
Kang et al. [2017]	return + volatility	no	no	no	no	6
Diebold et al. [2017]	volatility	yes	no	yes	no	19
Ji et al. [2018]	return	no	no	no	no	5
Kang et al. [2019]	return	no	no	no	no	6
Uddin et al. [2019]	return + volatility	no	no	no	no	4
Zhang and Broadstock [2020]	return	no	GFC	no	no	7
Yip et al. [2020]	volatility	no	no	no	no	4
Dahl et al. [2020]	return + volatility	no	oil regimes	no	no	11
Barbaglia et al. [2020]	volatility	yes	no	no	no	10
Hu et al. [2020]	volatility	no	no	no	EPU, ESI, DEF, SI, VIX, GPR	3
Guhathakurta et al. [2020]	volatility	no	5 structural breaks in oil prices	yes	no	17
Al-Yahyaee et al. [2020]	volatility	no	no	no	EPU, VIX	6
Hung [2021]	return	no	COVID-19	no	no	7
Gong et al. [2021]	volatility	no	no	no	no	4
Balcilar et al. [2021]	return	no	no	no	no	12
Umar et al. [2021]	return + volatility	no	no	no	no	11
Caporin et al. [2021]	volatility	no	no	yes	no	12
Maitra et al. [2021]	volatility	no	no	no	no	23
Ma et al. [2021]	return	no	GFC	yes	Financialization, US Dollar Index, VIX, BDI, DEF, S&P500	21
Naeem et al. [2022]	return + frequency	no	GFC, Shale Oil Revolution, COVID-19	yes	no	20
Tiwari et al. [2022]	volatility	no	COVID-19	no	no	10
Zhou et al. [2022]	return + volatility + skewness + kurtosis	no	no	no	no	9
Farid et al. [2022]	return	no	COVID-19	yes	no	37
Just and Echaust [2022]	return	no	no	no	no	5

Author(s)	Time series	Regularization	Crisis	Aggregation	Determinants	Number of assets
Gong and Xu [2022]	volatility	no	no	no	GPR, GPA, GPT	5
Jiang and Chen [2022]	frequency	no	COVID-19	no	no	7
Gong et al. [2022]	volatility + skweness + kurtosis	no	no	no	no	6
Wang et al. [2022]	return + volatility	no	no	no	GPR, COVID-19	16
Ghosh et al. [2023]	return	no	no	no	no	3
Wu et al. [2023]	volatility	no	COVID-19, Russo-Ukrainian war	no	no	7
Mandaci et al. [2023]	return	no	no	no	GPR	12
Furuoka et al. [2023]	frequency	no	no	no	no	7
Lu et al. [2023]	return	no	no	no	GPR	4
Hu et al. [2023]	return	no	no	no	no	6
Jiang and Chen [2024]	return	no	Russo-Ukrainian war	no	no	7
Cui and Maghyreh [2024]	skweness, kurtosis	no	no	no	GPR, FSI	17

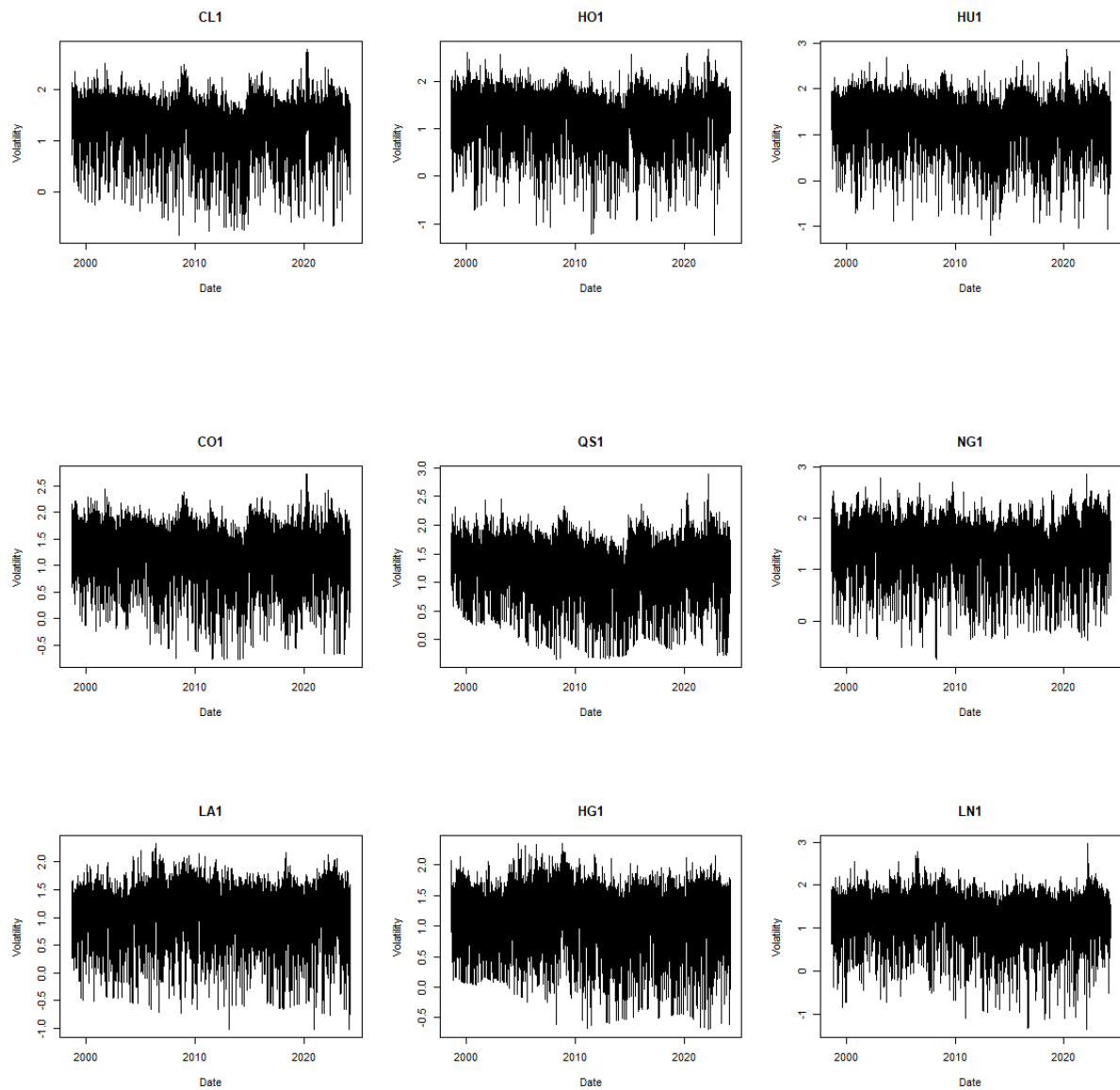
Notes: The contents of the Literature review section are summarized in this table. The author, the type of the time series used for modelling (return, volatility, skewness, kurtosis, and frequency), whether regularization methods were employed (yes, no), crises were examined utilizing connectedness tables or graphs before and after the crisis event, aggregation methods were employed (yes, no), and the impact of various determinants were tested on the connectedness. Finally, it states the number of assets included in the study.

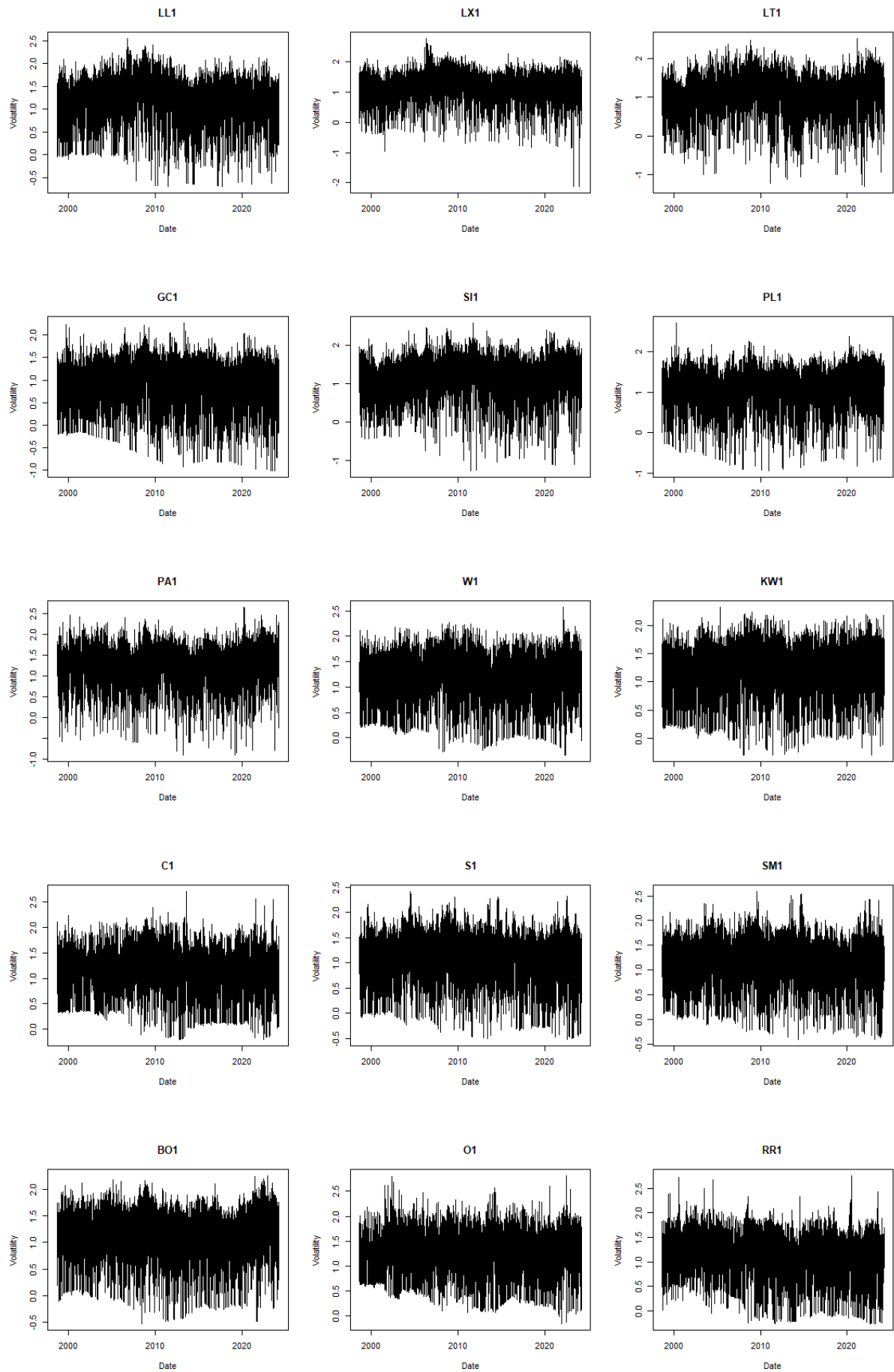
Table 7 Commodity assets' description

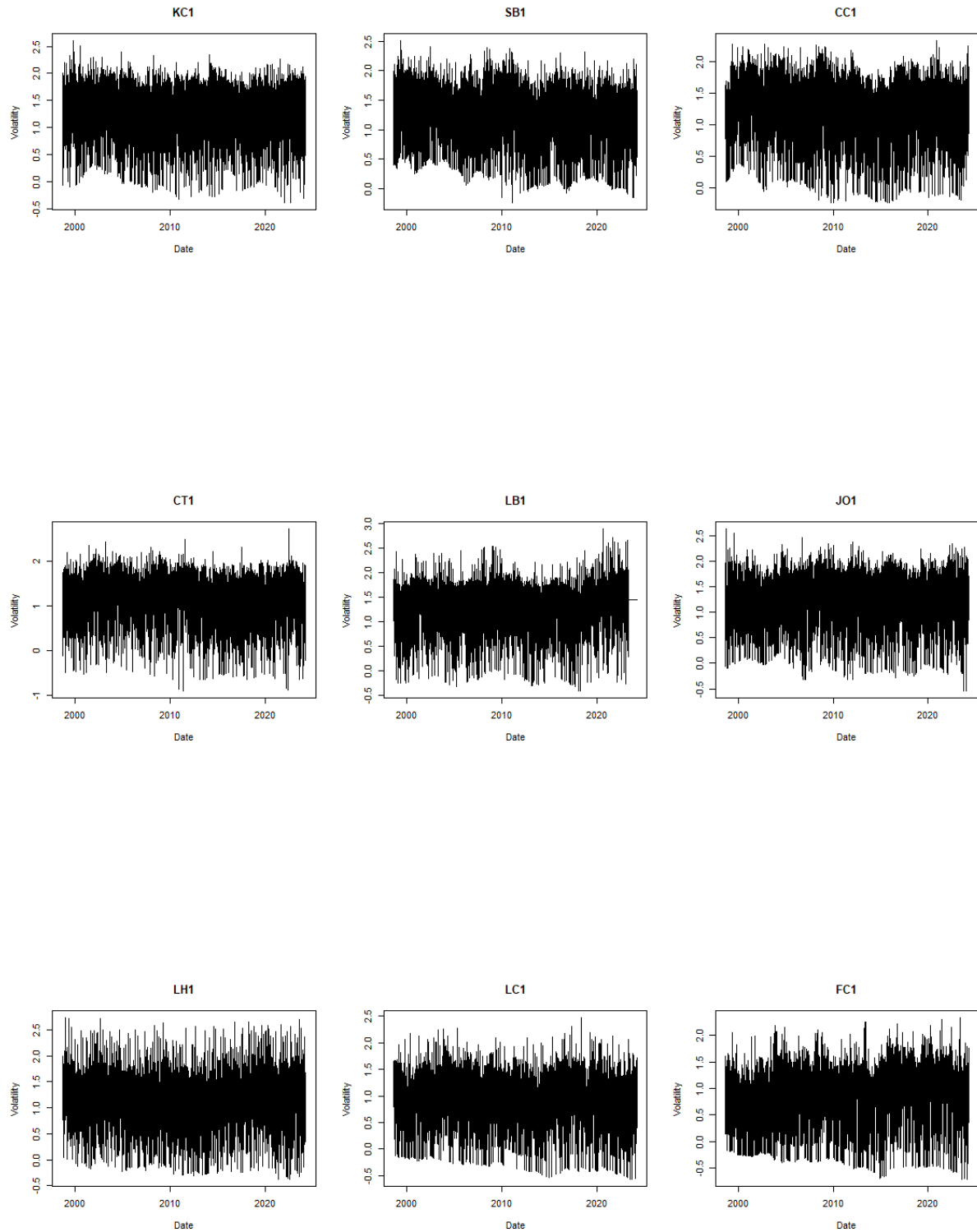
Group	Commodity	Exchange	Bloomberg Ticker	First Date	Last Date
Energy	WTI	NYMEX	CL	1993.01.04	
	Heating oil	NYMEX	HO	1993.01.04	
	Gasoline	NYMEX	HU	1993.01.04	2006.05.10
	RBOB Gasoline	NYMEX	XB	2005.10.03	
	Brent Crude oil	ICE-Europe	CO	1993.01.04	
	Gasoil	ICE-Europe	QS	1993.01.04	
	Natural gas	NYMEX	NG	1993.01.04	
Industrial Metal	Aluminium	LME	LA	1997.07.23	
	Copper	Comex	HG	1993.01.04	
	Nickel	LME	LN	1997.07.23	
	Lead	LME	LL	1997.07.23	
	Zinc	LME	LX	1997.07.23	
	Tin	LME	LT	1997.07.23	
Precious Metal	Gold	Comex	GC	1993.01.04	
	Silver	Comex	SI	1993.01.04	
	Platinum	NYMEX	PL	1993.01.04	
	Palladium	NYMEX	PA	1993.01.04	
Grains	Chicago wheat	CBoT	W-	1993.01.04	
	Kansas (red) wheat	CBoT	KW	1993.01.04	
	Corn	CBoT	C-	1993.01.04	
	Soybeans	CBoT	S-	1993.01.04	
	Soymeal	CBoT	SM	1993.01.04	
	Soyoil	CBoT	BO	1993.01.04	
	Oats	CBoT	O-	1993.01.04	
	Rough Rice	CBoT	RR	1993.01.04	
Softs	Coffee	ICE-US	KC	1993.01.04	
	Sugar	ICE-US	SB	1993.01.04	
	Cocoa	ICE-US	CC	1993.01.04	
	Cotton	ICE-US	CT	1993.01.04	
	Lumber	CME	LB	1993.01.04	
	Orange Juice	ICE	JO	1993.01.04	
Livestock	Lean hogs	CME	LH	1993.01.04	
	Live Cattle	CME	LC	1993.01.04	
	Feeder cattle	CME	FC	1993.01.04	

Notes: This table reports the 33 commodity assets from each of the six categories, lists the exchange, the Bloomberg ticker and the first and last date of the prices that were obtained.

Figure 9: Volatilities of 33 commodity futures







Notes: Each of the 33 subplots reports the daily volatilities of the individual assets, computed using the squared of returns methodology from 25th August 1998 to 1st of April 2024.

Table 8 Descriptive statistics of the 33 commodities

Commodity	Minimum	Maximum	Mean	Std. dev.	Skewness	Kurtosis	ADF
CL1 Comdty	-0.85	2.79	1.33	0.49	-0.93	4.37	-10.57***
HO1 Comdty	-1.25	2.67	1.29	0.50	-1.05	4.80	-11.99***
HU1 Comdty	-1.20	2.87	1.34	0.50	-1.07	4.90	-12.96***
CO1 Comdty	-0.77	2.73	1.28	0.49	-0.89	4.13	-11.48***
QS1 Comdty	-0.35	2.89	1.29	0.48	-0.74	3.52	-10.82***
NG1 Comdty	-0.75	2.86	1.49	0.49	-0.95	4.33	-11.64***
LA1 Comdty	-1.03	2.34	1.10	0.47	-0.97	4.33	-13.23***
HG1 Comdty	-0.70	2.35	1.15	0.48	-0.76	3.66	-12.25***
LN1 Comdty	-1.37	2.97	1.30	0.51	-1.06	5.24	-13.59***
LL1 Comdty	-0.71	2.55	1.22	0.48	-0.79	3.80	-11.32***
LX1 Comdty	-2.14	2.78	1.20	0.49	-0.92	4.66	-10.48***
LT1 Comdty	-1.32	2.52	1.10	0.52	-0.79	4.06	-11.75***
GC1 Comdty	-1.02	2.27	0.94	0.50	-0.75	3.65	-12.21***
SI1 Comdty	-1.27	2.57	1.17	0.52	-0.87	4.27	-11.45***
PL1 Comdty	-0.95	2.72	1.14	0.48	-0.96	4.41	-12.11***
PA1 Comdty	-0.91	2.65	1.27	0.48	-0.89	4.22	-12.54***
W1 Comdty	-0.35	2.58	1.29	0.44	-0.80	3.66	-13.46***
KW1 Comdty	-0.31	2.33	1.26	0.44	-0.76	3.42	-14.04***
C1 Comdty	-0.21	2.71	1.21	0.44	-0.53	3.09	-11.91***
S1 Comdty	-0.53	2.42	1.13	0.46	-0.70	3.50	-12.78***
SM1 Comdty	-0.42	2.59	1.20	0.45	-0.65	3.46	-13.46***
BO1 Comdty	-0.54	2.26	1.17	0.45	-0.85	3.79	-12.36***
O1 Comdty	-0.17	2.82	1.31	0.44	-0.43	2.99	-14.16***
RR1 Comdty	-0.27	2.76	1.16	0.45	-0.56	3.25	-13.86***
KC1 Comdty	-0.40	2.61	1.30	0.46	-0.74	3.50	-15.19***
SB1 Comdty	-0.25	2.51	1.29	0.45	-0.63	3.12	-13.21***
CC1 Comdty	-0.24	2.34	1.25	0.46	-0.77	3.47	-13.28***
CT1 Comdty	-0.91	2.72	1.19	0.50	-0.87	3.93	-13.35***
LB1 Comdty	-0.42	2.89	1.33	0.46	-0.84	3.92	-12.61***
JO1 Comdty	-0.55	2.64	1.26	0.47	-0.71	3.40	-15.03***
LH1 Comdty	-0.38	2.74	1.17	0.50	-0.43	3.38	-12.93***
LC1 Comdty	-0.58	2.48	0.97	0.47	-0.61	3.37	-13.18***
FC1 Comdty	-0.72	2.33	0.88	0.49	-0.46	3.15	-13.64***

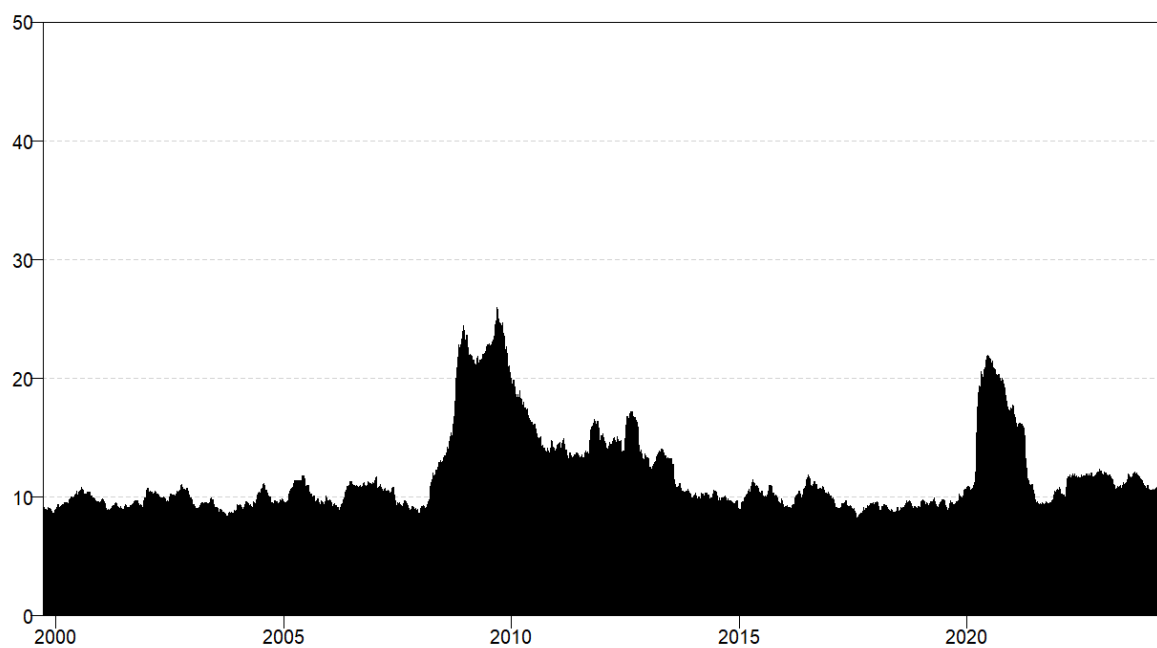
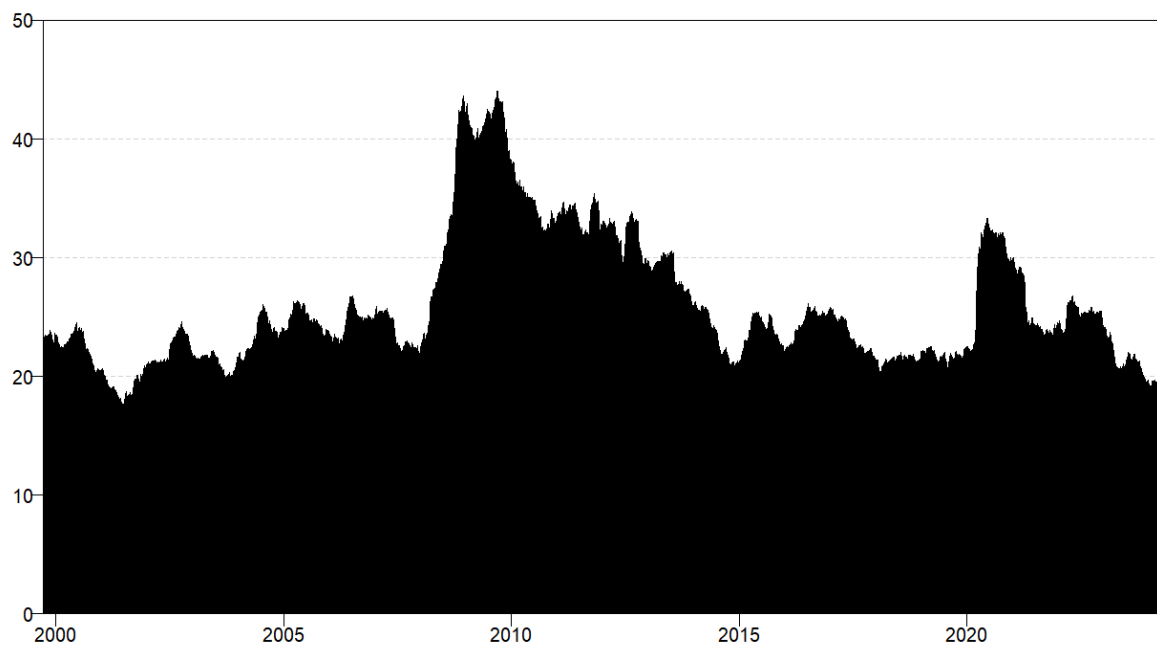
Notes: The descriptive statistics of asset volatilities are presented. The minimum, maximum, mean, standard deviation, skewness, and kurtosis are stated. T-statistics for the Augmented Dickey and Fuller stationary test are reported in round brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9 Crisis starting and end dates

Crisis	Start date	End date
Global Financial Crisis (GFC)	09-15-2008	07-21-2010
European Sovereign Debt Crisis (ESDC)	11-21-2010	03-13-2013
The Decline in Crude Oil (OIL)	07-31-2014	03-16-2015
The COVID-19 Pandemic (COVID)	01-20-2020	12-31-2021
The Russo-Ukrainian War (WAR)	02-24-2022	04-01-2024

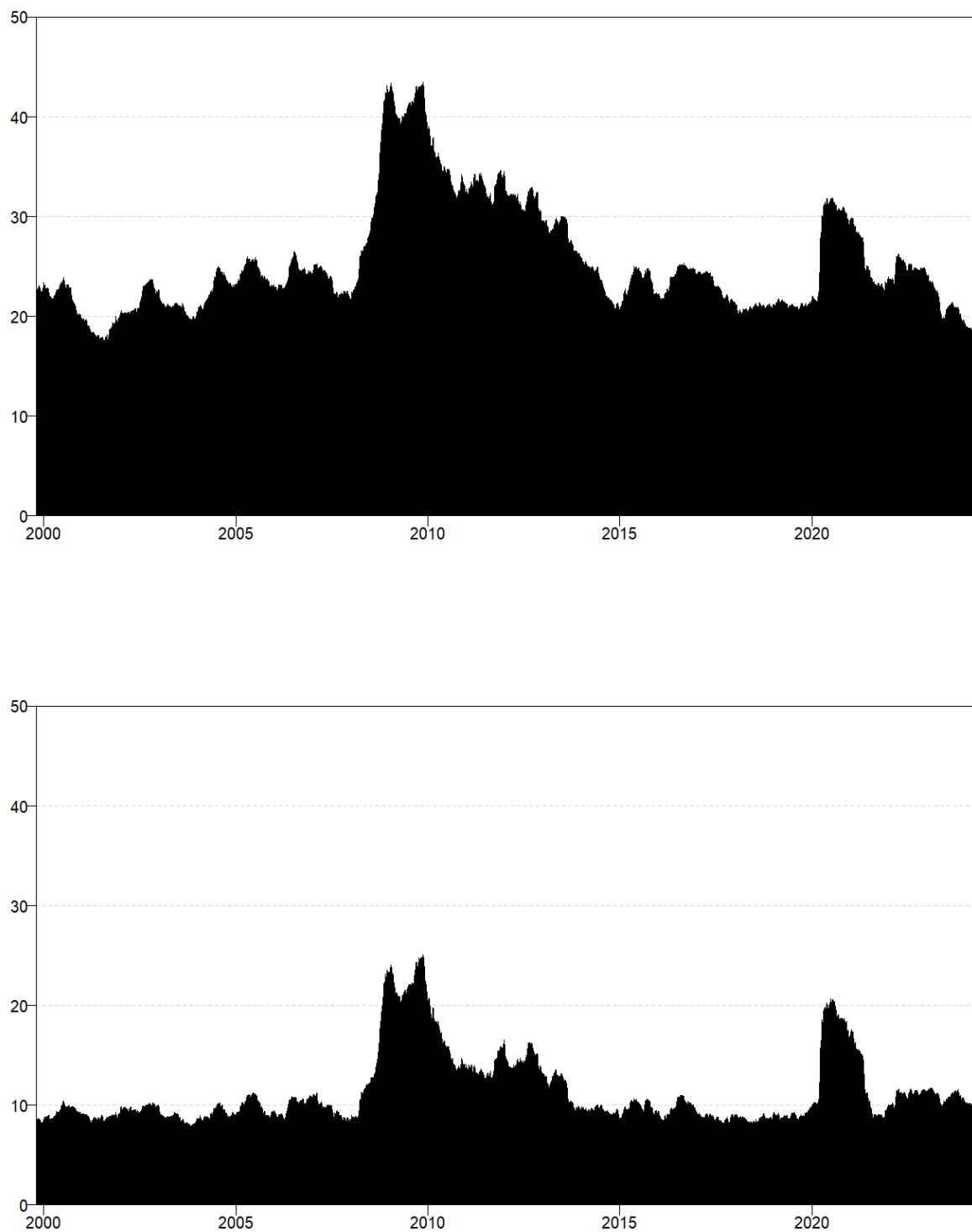
Notes: This table presents the starting and end dates for each of the five crises examined (the Global Financial Crisis, the European Sovereign Debt Crisis, the Crude Oil Decline, the COVID-19 Pandemic, and the Russo-Ukrainian War). The five crises' impact was tested on various connectedness measures employing OLS regression.

Figure 11: Robustness test: connectedness measure (A)



Notes: The two figures serve as a robustness test for the computation of the connectedness measures. The figure on the top is the total connectedness without aggregation. In contrast, the figure on the bottom is the total connectedness with aggregation using a rolling window size of 280 days, LASSO regression and a forecast horizon of 10 days.

Figure 13: Robustness test: connectedness measure (B)



Notes: The two figures serve as a robustness test for the computation of the connectedness measures. The figure on the top is the total connectedness without aggregation. In contrast, the figure on the bottom is the total connectedness with aggregation using a rolling window size of 300 days, LASSO regression and a forecast horizon of 10 days.

Table 10 Robustness test: the impact of crises, fundamental and non-fundamental factors on the connectedness

	energy	industrial metals	precious metals	grains	softs	livestock	TCI(without)	TCI(with)
β	-5.8e-02*** (-5.7e+00)	-1.1e-03 (-2.5e-01)	2.0e-02*** (3.9e+00)	2.4e-03 (3.5e-01)	6.6e-03 (1.4e+00)	3.0e-02 (2.8e+00)	-4.5e-02*** (-6.9e+00)	-3.5e-02*** (-6.1e+00)
BDIY	-6.0e-05 (-1.1e+00)	-2.0e-05 (-8.0e-01)	-1.2e-05 (-4.4e-01)	-1.8e-05 (-4.8e-01)	3.2e-05 (1.3e+00)	7.8e-05 (1.3e+00)	-3.6e-05 (-1.0e+00)	-2.3e-05 (-7.6e-01)
Spread	1.1e-02 (2.3e-01)	5.6e-03 (2.5e-01)	-3.1e-02 (-1.3e+00)	7.9e-02** (2.4e+00)	-2.3e-02 (-9.9e-01)	-4.2e-02 (-8.0e-01)	1.6e-02 (5.0e-01)	4.4e-02 (1.6e+00)
VIX	2.3e-03*** (5.1e+00)	2.9e-04 (1.4e+00)	-8.4e-04*** (-3.8e+00)	1.7e-04 (5.7e-01)	-5.1e-04** (-2.4e+00)	-1.4e-03 (-2.9e+00)	2.1e-03*** (7.2e+00)	1.7e-03*** (6.9e+00)
SP500	-7.1e-04*** (-5.4e+00)	9.6e-05 (1.6e+00)	1.2e-04* (1.9e+00)	-1.3e-04 (-1.4e+00)	1.2e-04** (2.0e+00)	5.0e-04 (3.5e+00)	-2.2e-04*** (-2.6e+00)	-1.6e-04** (-2.2e+00)
EPU	1.6e-04 (3.4e+00)	-3.5e-05 (-1.6e+00)	-1.8e-05 (-7.6e-01)	-2.0e-05 (-6.3e-01)	1.7e-05 (7.7e-01)	-1.0e-04 (-2.0e+00)	8.5e-05*** (2.8e+00)	6.8e-05*** (2.6e+00)
GPR	6.2e-04 (1.5e+00)	-3.4e-05 (-1.8e-01)	-3.1e-04 (-1.5e+00)	-4.2e-04 (-1.5e+00)	4.2e-05 (2.2e-01)	1.0e-04 (2.3e-01)	3.6e-04 (1.3e+00)	1.5e-04 (6.4e-01)
GPA	-3.1e-04* (-1.8e+00)	3.5e-05 (4.4e-01)	1.4e-04 (1.6e+00)	1.5e-04 (1.3e+00)	-1.1e-05 (-1.3e-01)	-8.4e-06 (-4.4e-02)	-1.5e-04 (-1.3e+00)	-8.8e-05 (-8.9e-01)
GPT	-2.8e-04 (-1.3e+00)	-1.6e-05 (-1.6e-01)	1.3e-04 (1.2e+00)	2.5e-04 (1.6e+00)	-2.0e-05 (-1.9e-01)	-6.4e-05 (-2.7e-01)	-2.0e-04 (-1.4e+00)	-7.5e-05 (-6.0e-01)
energy_shock	1.6e-03 (1.5e-01)	2.8e-04 (5.7e-02)	-9.1e-04 (-1.7e-01)	-2.2e-03 (-3.1e-01)	-8.0e-04 (-1.6e-01)	2.1e-03 (1.8e-01)	-4.0e-03 (-5.8e-01)	4.2e-04 (7.0e-02)
non_energy_shock	-3.0e-02*** (-3.4e+00)	3.1e-03 (7.8e-01)	1.2e-02*** (2.7e+00)	-5.3e-03 (-8.9e-01)	1.7e-03 (4.0e-01)	1.9e-02 (2.0e+00)	-2.4e-02*** (-4.3e+00)	-2.1e-02*** (-4.2e+00)

Notes: The results for the robustness test are presented. The impact of three economic, two financial, and three geopolitical factors are tested on the net connectedness of each aggregated net connectedness measure of energy, industrial metals, precious metals, grains, soft, and livestock and the TCI with and without aggregation. In addition, the effect of energy-related (Crude Oil Decline, Russo-Ukrainian War) and non-energy-related (the Global Financial Crisis, the European Sovereign Debt Crisis, and the COVID-19 Pandemic) crises. T-statistics are reported in round brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.