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Commodity Futures Markets Under Stress and Stress-free periods: Further Insights from a Quantile Connectedness Approach

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Abstract

Most of the academic literature on connectedness focuses on stock markets and commodity spot markets. However, there is still much to say about the connectedness among commodity futures markets at different expiration dates, as this part of the literature is as yet small and inconclusive. This paper build on the existing literature by focusing on connectedness among a set of ten futures commodity markets (including energy, agriculture and metal sectors) at different maturities, the global equity market and three different sources of uncertainty (financial, economic ang geopolitical). In doing so, we estimate quantile connectedness metrics based on the works of Chatziantoniou et al. (2021) and Ando et al. (2022) which enable measuring connectedness under different market circumstances (i.e., low, median and high quantiles). Using daily data spanning from January 4th, 2000, to May 25th, 2022, the analysis provides evidence of the variable aspect of connectedness across commodities and uncertainty measures assessed across different quantiles. The time-varying aspect suggests that quantile connectedness increases during crisis periods. Additionally, the pattern of connectedness at the upper and lower tails differs from the conditional median, implying that connectedness metrics estimated at the conditional median may disguise the evolution of connectedness at high and low quantiles.

Keywords: Commodity futures markets, uncertainty, global equity market, quantile connectedness, stress- and stress-free periods.

1. Introduction

The first quarter of the 21st century was marked by several events – including the global financial crisis of 2008-2009, the US-China trade war, the COVID-19 outbreak and, most recently, the Russian-Ukrainian war – that have shaken the commodity and stock markets, as well as the world economy. As a result of the increasing integration of financial markets and the financialization of commodities, the disruptions in the international financial system are now not only more recurrent, but also more persistent. Indeed, increased financial integration can exacerbate systematic risk, thereby threatening the resilience of the global financial system and the development of economic activity (Cui et al., 2021). For instance, the COVID-19 outbreak has intensified financial and economic uncertainty, which led the WTI prices to drop for the first time in history to a negative level in April 2020. More recently, in its latest World Economic Outlook, the International Monetary Fund notes that the Russian-Ukrainian conflict has been a major shock to commodity markets and has also severely disrupted the global economic outlook, especially since the world economy has not yet recovered from the aftermath of the COVID-19 outbreak (IMF, 2022). Indeed, this conflict has led to substantial disruptions to the production and trade of commodities for which Russia and Ukraine are major exporters. This, in turn, has raised energy and food security concerns, especially for low-income countries (World Bank, 2022).

As it has significant implications not only for market participants and regulators, but also for the decisions of all economic agents, the propagation of shocks between futures commodity markets is a very important mechanism to study. Indeed, the speed and magnitude of the transmission of shocks between markets provides information on the extent to which markets are integrated or segmented. A higher level of market integration would exacerbate the magnitude of comovement between the price dynamics of different financial assets. Thus, it can affect (**i**) the flows of funds within the financial system, (**ii**) the diversification strategies, and (**iii**) the resilience of the financial system, especially during times of market turbulence.

To that end, the objective of this paper is to examine the mechanism of propagation of shocks among a set of ten futures commodity markets (belonging to energy, agricultural and metal sectors) at different maturities, the global financial market and different sources of uncertainty (financial, economic and geopolitical), over the period between January 4th, 2000 to May 25th, 2022, from two different perspectives. First, the paper examines the overall interaction among the considered markets in the time domain. Then, it investigates whether the impact of either bullish and bearish markets is symmetric or not.

As investment in commodity markets has accelerated since the early 2000s, commodities are increasingly viewed as a new asset class alongside stocks and bonds, a process commonly known as the "financialization of commodity markets" (Cheng and Xiong, 2014; Adams and Glück, 2015). This process of financialization of the commodity markets could lead to greater financial integration and thus exacerbate the spread of shocks across financial markets. Given that greater financial integration magnifies systemic risk[1], and that greater systemic risk jeopardizes the resilience of the global financial system as well as the global economy, the empirical financial and economic literature has recently examined in depth how shocks propagate across markets, to further understand to what extent financial markets are integrated or segmented. Higher levels of integration in financial markets imply greater and faster interactions between them.

A large and growing strand of the literature investigates the connectedness among commodity markets because the level of integration of financial markets could affect the investment decisions and positions of investors in both stress and stress-free periods. While greater financial market integration would allow, in stress-free episodes, for better diversification and hedging strategies (King and Wadhwani, 1990; Jayasinghe and Tsui, 2008; James et al. 2012; Fengler and Gisler, 2015; Barunik et al. 2017), it could, in stress episodes, reduce the diversification payoff (Amonlirdviman and Carvalho, 2010), and intensify the effects of systemic shocks (Black, 1976; French et al. 1987; Forbes and Rigobon, 2002; Aït-Sahalia et al., 2015), since co-jumps among financial assets tend to occur just prior to, or during, periods of crisis and market stress (Longin and Solnik, 2001; Lahaye et al. 2011; Chevallier and Ielpo, 2013). Thus, the growing financialization of commodity markets since the turn of the millennium could lead to further financial integration and thereby amplify the magnitude and accelerate the speed of propagation of shocks across markets (Stoll and Whaley, 2010; Cheng and Xiong, 2013; Adams and Glück, 2015).

Studying the connectedness among commodity futures markets has recently received particular attention in the literature (among others: Pindyck and Rotembergn 1990; Booth and Ciner 1997; Booth et al., 1998; Escribano and Granger, 1998; Xu and Fung 2005; Dahl et al., 2020; Kang et al., 2019; Umar et al., 2021; Barbaglia et al., 2020; Mensi et al., 2022). For instance, Pindyck and Rotemberg (1990) use monthly data ranging from April 1960 to November 1985 to study the co-movement among a set of seven largely unrelated commodities. Their results suggest that commodities prices tend to move together, and that this link depends in part on changes in current and expected performances of macroeconomic variables. Similarly, by considering a set of eight largely unrelated commodities together with a set of 184 real and nominal macroeconomic variables from both developed and emerging economies, Le Pen and Sevi (2018) provide evidence on time-varying excess co-movements, which were found to be particularly high in the aftermath of the 2007 crisis. They also find that the excess co-movements of commodity prices (**i**) persists after adjusting for the impact of macroeconomic fundamentals and (**ii**) appears to be related to hedging and speculative pressures, reflecting the significant influence of the financialization of commodity markets. Booth and Ciner (1997) use a vector autoregression (VAR) model to better understand the linkages among corn futures contracts traded in Tokyo Grain Exchange (TGE) and those traded on the Chicago Board of Trade (CBOT) over the period 1993-1995. Their findings support that the dynamics of the TGE

[1] Systemic risk could be defined as the risk that many market operators are affected by important losses at the same time (Benoit et al. 2017).

depend on that of the CBOT. In the same vein, Xu and Fung (2005) employ a bivariate asymmetric GARCH-type model to explore spillovers between gold, platinum and silver futures traded in the U.S. and Japanese commodity markets during the period spanning from November 1994 to March 2001. They find that the U.S. precious metals commodity market seems to lead the Japanese market. Similarly, Booth et al. (1998) find that the Canadian wheat futures market seem to be dependent on the U.S. CBOT. By using various single-equation estimation techniques, Escribano and Granger (1998) reveal a significant and strong long-run simultaneous relationship between silver and gold. Dahl et al. (2020) apply an ARMA (1,0)–EGARCH (1,1) model and the Diebold and Yilmaz (2012) connectedness index on daily data ranging from July 2nd, 1986, to June 3rd, 2016, to investigate the return and volatility spillover among major agriculture commodities and crude oil futures. Their results highlight the existence of bidirectional spillover between crude oil and agricultural commodity futures markets, which becomes stronger in times of financial and economic instability. Kang et al. (2019) use the frequency-connectedness framework of Baruník and Křehlík (2018) to study the connectedness among crude oil and five agricultural commodities. Their results suggest a bidirectional and asymmetric connectedness between oil and agriculture markets at all frequency bands. Furthermore, Umar et al. (2021) use the Granger causality test and the connectedness framework of Diebold and Yilmaz (2012) to explore the linkages between oil price and agricultural commodities over the period spanning from January 2002 to July 2020. They show that the connectedness among the commodities examined intensifies during financial turmoils and that shifts in agricultural commodity prices Granger-cause oil prices. In the same context, Barbaglia et al. (2020) confirms the existence of volatility spillovers between energy and biofuel, as well as between energy and agricultural commodities over the period from January 3rd, 2012, to October 28th, 2016. More recently, Mensi et al. (2022) estimate a bivariate FIAPARCH-DCC model on high-frequency data to investigate the volatility spillovers between the U.S. stock market and a set of commodity markets from April 23rd, 2018, to April 24th, 2020. Their results show that gold offers stronger protection against dropping equity prices than oil before and throughout the COVID-19 outbreak.

In light of extreme events in recent decades, there is a growing interest in understanding how the extreme downward and upward market conditions alter the structural dynamics of financial markets (e.g., Naeem et al., 2021; Cui et al., 2021; Farid et al., 2022). Therefore, another strand of the literature focuses on the tail dependence structure among commodity markets. For instance, Bouri et al. (2022) investigate extreme spillovers among realized volatilities of many commodities using high-frequency (5 minutes) data of energy, metals, and agricultural commodities from September 23rd, 2008, to June 1st, 2020. By using quantile-based connectedness measures, they show that realized volatility shocks spread more strongly during extreme events, such us the COVID-19 outbreak, than during stress-free periods. Likewise, Chen et al. (2022) explore the connectedness among fossil energy, clean energy, and metals commodity markets over the period June 25th, 2009, to December 31st, 2020. Their results reveal that connectedness is much higher during extreme events, both positive and negative. In the same way, Farid et al. (2022) estimate the quantile connectedness among 34 commodities including energies, metals, grains and oilseeds, livestock, and softs for the period from January 2nd, 2006, to October 10th, 2020. Their results unveil that the degree of tail-dependence between energy, metals, and agricultural commodities varies over time. They also depict strong transmission of shocks between energy, metals, and agriculture commodities during the COVID-19 outbreak. Besides, Jena et al. (2021) estimate the quantile connectedness among six fuel markets. Their findings reveal that the connectedness during periods of extreme negative and positive returns (5^{th} and 95^{th} quantiles) is stronger than in normal periods (50^{th} quantile).

Apart from the empirical evidence on the interdependencies among commodity markets, the effect of uncertainty measures on commodity prices has piqued the interest of many academics. Huang et al. (2021) investigate the interaction between commodity futures prices and uncertainty indicators including economic policy uncertainty (EPU), macroeconomic uncertainty (MU), equity market uncertainty (EMU), and stock market volatility (VXO) using a time-varying parameter vector autoregression (TVP-VAR) model. Their results reveal that the impact of UPR, VXO, and EMU shocks on commodity prices is time-varying, and that this impact is relatively more pronounced for agricultural commodities than for metals and energy markets. Furthermore, Naeem et al. (2021) evaluate the effect of several factors including the U.S. economic policy uncertainty index (EPU), the U.S. geopolitical risk index (GPR) and the VIX fear index on the propagation between crude oil WTI and other commodity uncertainties. Their results show that factors considered have a significant causal effect between crude oil WTI and other commodity uncertainty indices (including gold, silver, platinum, palladium, aluminum, copper, zinc, lead, nickel, wheat, corn, soybean, coffee, sugar, cocoa, and cotton). Based on time-varying spillover indices derived from TVP-VAR model, Mokni et el. (2020) demonstrate that economic policy uncertainty has a significant influence on the nexus between oil shocks and the gold market.

Regardless to the fact that several studies have investigated interdependencies among commodities using various methodologies, few research document the interdependencies among commodity futures markets in extreme market conditions. In this backdrop, our analysis uses the quantile vector autoregressive process (QVAR) and generalized forecast error variance decomposition (GFEVD), to explore the quantile connectedness among a set of futures commodity markets including energy, grains and oil seeds, and metals, three different sources of uncertainty, and the global stock market. The quantile-based connectedness metrics provide useful insights in terms of asset allocation and risk management and allow for a better understanding of the propagation of extreme returns among the underlying commodities and the various uncertainty indicators.

While a strand of the existing literature investigates cross commodity linkages, as well as the linkages between commodity and stock markets, studying the connectedness among commodity futures markets across different maturities and different quantiles is broadly neglected. Thus, and as market participants operate in both short- and long-term futures maturities markets, this paper examines the extreme connectedness among a set of commodity futures (across different nearest-to-maturities), the global financial market and a set of indicators of uncertainty.

A better understanding of the connectedness among commodity markets helps to identify potential systematic risks, improve the productive use of funds, and provide guidance in structuring appropriate investment strategies (Caporale et al., 2002; Erb and Campbell, 2006; Liu et al., 2019). Yet, while most of the existing literature is devoted to the connectedness between stock and/or commodity markets, little attention is given to commodity futures markets at different maturities. Indeed, there are very few articles such as Buyuksahin and Robe (2014), Isleimeyyeh (2020), and Ben Amar et al. (2022) that study the connectedness among commodity markets across different maturities, and thus emphasize the importance of paying attention to short- and long-term maturities.

To empirically explore the connectedness among financial markets, Diebold and Yilmaz (2009) first proposed a spillover index as a measure of the average overall interdependence among different markets. Then, Diebold and Yilmaz (2012) exploit the generalized VAR framework proposed by Koop et al. (1996) and extended by Pesaran and Shin (1998), which produces generalized impulse responses invariant to the order of variables in the vector of endogenous variables, to define a more robust connectedness index that overcomes the inadequacies of the potentially order-dependent results due to the Cholesky factorization in the initial work of Diebold and Yilmaz (2009). Since then, not only a large body of the literature has used the Diebold and Yilmaz (2012) model to examine the connectedness among financial markets, but also this model has undergone several evolutions and extensions that have helped refine the analysis of the transmission of shocks between markets. For this reason, we employ the quantile connectedness approach developed by Ando et al. (2022) and Chatziantoniou et al. (2021) to investigate the quantile propagation mechanism among a set of futures commodity markets and the different sources of uncertainty.

Our findings reveal many interesting insights, which can be summarized as follows. First, the time-varying total connectedness metric shows that the level of connectedness peaked during crisis and stress periods – the global financial crisis; the 2011 Arab Spring; the 2014-2016 oil price crash period; the COVID-19 outbreak; the 2022 Russo-Ukrainian conflict. Second, the net connectedness metric reveal that natural gas is rather a net recipient of volatility shocks. However, crude oil and heating oil appears to broadly net transmitters. As for agricultural commodities, the highest net connectedness levels were recorded during the global financial crisis and the ongoing Russian-Ukrainian war. Regarding precious metals, they are rather net transmitters most of the time. Moreover, economic and geopolitical uncertainties turn out to be net receivers. As for the fear index as well as the global equity market, they are net receivers during the global financial crisis, and net transmitters during COVID-19 outbreak and the Russian-Ukrainian war. Third, when investigating the quantile connectedness, the results highlight not only the high sensitivity of commodity markets and uncertainty proxies to extreme shocks, but also that the overall connectedness peaks at all quantiles during stress periods. Fourth, the quantile net total directional connectedness results show that return spillovers prove to be higher during the bullish and bearish phases, compared to spillovers at the 50^{th} quantile. Furthermore, while crude oil and heating oil were steadily net transmitters to all other commodity markets at all quantiles, regardless of the maturity, natural gas was mostly a net receiver. It is worth mentioning that the quantile net directional transmission is less important for agricultural commodities compared to energy commodities especially at median quantiles.

The main contributions of this paper to the existing literature are fourfold. First, it fills the gap in the literature by presenting evidence on the extreme connectedness network of major commodities including energy, grains and oil seeds, and metals. Second, for the sake to detect possible interdependencies between commodity futures with different maturities, this paper considers for each commodity the shortest maturity to the longest maturity in the year, as this may contain useful information for market participants. Third, this paper discusses the extreme connectedness among commodities considered and several indicators representing global stock market, economic policy uncertainty, financial uncertainty, and geopolitical risk. Fourth, the period examined includes several well-known episodes of increased uncertainty including the Global Financial Crisis, the COVID-19 outbreak, the recent Russian-Ukrainian war, and different phases of stability, rise and fall in oil prices. This allows us to examine the connectedness during stress and stress-free periods. The analysis of connectedness is performed from two different perspectives: (i) within Diebold and Yilmaz (2012) framework for an aggregated investigation of the interaction among the considered markets, then (ii) within the Ando et al. (2022) and Chatziantoniou et al. (2021) quantile connectedness framework for a more detailed analysis of the transmission of shocks between the markets considered.

Our findings can be useful for market participants, both investors and policy makers. Indeed, in a context of increasing economic openness and financial integration, it is crucial for market participants to understand the extent to which commodity markets are integrated or segmented and how they are sensitive to different sources of risk. This information helps to (**i**) deal with the propagation of financial risks, and (**ii**) make a more efficient resource allocation.

The rest of the paper is organized as follows. Section 2 discusses the data and presents the methodology. Section 3 analyzes the results as well as their practical implications. Section 4 concludes.

2. Data and Methodology

a. Data

Our underlying datasets are daily observations of the MSCI ACWI & Frontier Markets index [**MXWD**], which is a representative global stock market index, the Economic Policy Uncertainty index [**EPU**], which is a representative measure of the U.S. policy-related uncertainty (Baker et al., 2015), the VIX implied volatility index [**VIX**], which is used to proxy financial uncertainty (Bloom, 2009; Ludvingson et al., 2019), the Geopolitical Risk index [**GPRD**], which track adverse geopolitical events and associated risks (Caldara and Matteo, 2022), and a set of commodity futures prices (WTI crude oil [**WTI**], natural gas [**NGAS**], heating oil [**HOIL**], wheat [**WHT**], soybean oil [**SOIL**], soybean [**SOYB**], corn [**CORN**], copper [**COPR**], silver [**SILV**], and gold [**GOLD**]) for different maturities. The nominated commodity futures are traded on the NYMEX (New York Mercantile Exchange) and the CBOT (Chicago Board of Trade)[2]. The data are collected from Bloomberg, except for the GDPR data which are downloaded from https://www.matteoiacoviello.com/gpr.htm, and cover the period running from January 4th, 2000 to May 25th, 2022, providing a sample of 5843 trading days. The period studied is informative in terms of market development because it contains both stress and stress-free periods in which shocks can be transmitted between commodities with different intensities.

Table 1. Summary of commodity futures markets

	Commodity		Exchange	Maturities											
				1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
ENERGY	Crude Light (WTI)	**CL**	NYMEX	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Natural gas	**NG**	NYMEX	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Heating oil	**HO**	NYMEX	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
GRAINS AND OILSEEDS	Wheat	**W**	CBOT			✓		✓		✓		✓			✓
	Corn	**C**	CBOT			✓		✓		✓		✓			✓
	Soybeans	**S**	CBOT	✓		✓		✓		✓	✓	✓		✓	
	Soybean oil	**BO**	CBOT	✓		✓		✓		✓	✓	✓	✓		✓
METALS	Copper	**HG**	COMEX	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓*	✓	✓
	Silver	**SI**	COMEX			✓		✓		✓		✓			✓
	Gold	**GC**	COMEX		✓		✓		✓		✓		✓		✓

Note: Table 1 summarizes the exchange market where the commodity futures are traded and the delivery months. The ticker for each commodity is in bold. Abbreviations: NYMEX, New York Mercantile Exchange; CBOT, Chicago Board of Trade; COMEX, Commodity Exchange. * Due to the lack of data going back to the year 2000 for the 11- and 12-month maturities for copper, the 10-month maturity was used.

For each commodity, there are several delivery dates per year, e.g., monthly delivery for **WTI**, **NGAS**, **HOIL** and **COPR** futures, 5 times per year for **WHT**, **CORN**, and **SILV** futures, 6, 7, and 8 times for **GOLD**, **SOYB**, and **SOIL** futures, respectively (see Table 1). Thus, in order to detect possible interdependencies between commodity futures of different maturities, we consider in this study the shortest and the longest maturities in the year (see Table 1). All series are in U.S. dollars. Apart from **VIX**, **EPU**, and **GPRD** which are expressed in natural logarithms, the daily log-returns are computed for all commodity futures as well as the global stock index.

b. Methodology

[2] Gold is traded on Commodity Exchange (COMEX), which is a division for trading futures and options in NYMEX.

We employ the quantile connectedness (hereafter QC) approach proposed by Ando et al. (2022) and Chatziantoniou et al. (2021), which is based on the quantile vector autoregressive process (QVAR) and generalized forecast error variance decomposition (GFEVD), to investigate the quantile propagation mechanism among the futures commodity markets considered and the different sources of uncertainty. Thus, to calculate the QC metrics we first estimate a K-variables QVAR(p) model $y_t = \mu(\tau) + \sum_{i=1}^{p} \alpha_i(\tau) y_{t-i} + e_t(\tau)$, with y the vector of endogenous variables, $\tau \in [0,1]$ represent the quantiles examined, p the order of the QVAR model, $\mu(\tau)$ the conditional mean vector, $\alpha_1(\tau), \dots, \alpha_p(\tau)$ the QVAR coefficient matrices, and $e_t(\tau)$ the vector of errors. The quantile moving-average process representation, QVMA(∞), of this QVAR process is given by $y_t = \mu(\tau) + \sum_{i=0}^{\infty} Z_i(\tau) e_{t-i}(\tau)$. Since $Z_i(\tau)$ includes an infinite number of lags, it should be approximated with the moving average coefficients Z_h computed at $h = 1, \dots, H$ horizons (Wold, 1954). By using the GFEVD[3] framework of Koop et al. (1996) and Pesaran and Shin (1998), which measures how much of the variance forecast error of variable q, at horizon h, is due to shocks in variable i, the total connectedness index, TCI, which measures the overall interconnectedness among variables in the system, as

$$TCI = \frac{\sum_{\substack{i,q=1 \\ i \neq q}}^{K} \tilde{\lambda}_{iq}^{G}(H)}{K-1} \text{ with } \tilde{\lambda}_{qj}^{G}(H) = \frac{\lambda_{iq}^{G}(H)}{\sum_{q=1}^{K} \lambda_{iq}^{G}(H)}$$

where $\lambda_{iq}^{G}(H)$ is the H-step-ahead GFEVD and $\tilde{\lambda}_{iq}^{G}(H)$ is the directional pairwise connectedness from variable q to variable i at horizon H. The TCI could be split into directional connectedness indices. Specifically, it enables computing the directional spillovers to variable i received from all remaining variables, $CI_{i\leftarrow\bullet}^{H}$, and the directional spillovers transmitted from variable i to all remaining variables, $CI_{i\rightarrow\bullet}^{H}$. The difference between $CI_{i\rightarrow\bullet}^{H}$ and $CI_{i\leftarrow\bullet}^{H}$ results in the net total directional connectedness (NCI), which indicates whether a market i is a net receiver or a net transmitter of volatility shocks.

3. Results

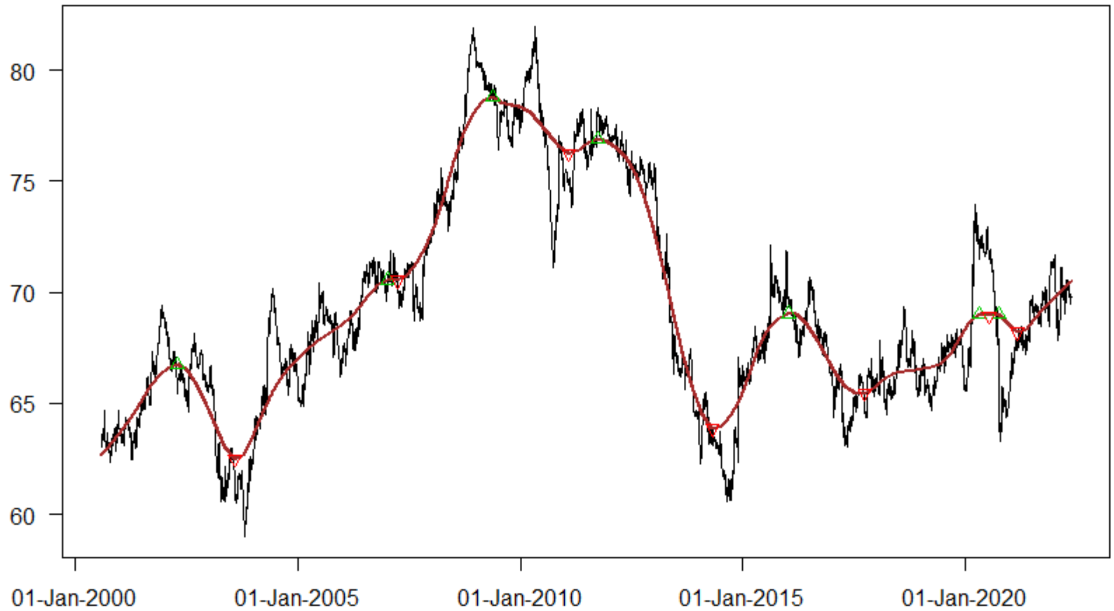
In this section, we assess the connectedness among the considered commodity futures markets and uncertainty indices by investigating their spillover effects. We start with an aggregated investigation of the interaction among the considered markets by using the Diebold and Yilmaz (2012) methodology (hereafter ***DY***-connectedness). Then we use the Ando et al. (2022) and Chatziantoniou et al. (2021) recently developed quantile connectedness approach (hereafter ***Q***-connectedness), which enables us to capture whether the impact of either bullish and bearish markets is symmetric or not.

[3] The H-step-ahead GFEVD, $\lambda_{iq}^{G}(H)$, is given by $\lambda_{iq}^{G}(H) = \frac{\sigma(\tau)_{qq}^{-1} \sum_{h=0}^{H-1} (\varepsilon_i' Z_h(\tau) \Sigma(\tau) \varepsilon_q)^2}{\sum_{h=0}^{H-1} (\varepsilon_i' Z_h(\tau) \Sigma(\tau) Z_h'(\tau) \varepsilon_i)}$ with ε_i is a $K \times 1$ selection vector with ones as the i^{th} elements and zeros otherwise.

3.1. DY-connectedness analysis

Before analyzing the *Q*-connectedness, we start with an aggregated investigation of the connectedness *à la* Diebold and Yilmaz (2012), to further understand how the interdependencies among the considered assets and uncertainty proxies has evolved over time. We thus estimate the time-varying **DY** connectedness index using a 150-days rolling window and 10-days-ahead forecast horizon.

Fig.1 Time-varying total connectedness



Notes: results are based on 150-days rolling window VAR(1) model and 10-days-ahead forecast horizon. The Bayesian information criterion was used to select the order of the VAR model. Alternative rolling windows (100- and 200-days) and different forecast horizons (15- and 20-days) were used to check robustness, and the results remained largely unchanged. Unreported results are available upon request.

Figure 1 shows the pattern of total connectedness over time. An initial global visual inspection of the connectedness plot reveals that the overall connectedness index exhibits periods of smooth evolutions and periods of high jumps, which is quite expected as the period under study covers almost 22 years and includes both stress and stress-free periods in which shocks can propagate through the markets considered with different magnitudes. The intensity of the connectedness ranges from about 60 to 80%, with a substantial variation over the period examined. Specifically, and broadly consistent with the findings of Cui et al. (2021), Figure 1 shows that the level of connectedness peaked during five episodes: (i) the global financial crisis, (ii) the 2011 Arab Spring, (iii) the 2014-2016 oil price crash period, (iv) the COVID-19 outbreak, and (v) the 2022 Russo-Ukrainian conflict. Indeed, starting in mid-2006, the connectedness index began to display an upward momentum, before peaking at almost 80% towards late 2008, which might be attributed to the global financial crisis that exacerbated risk and uncertainty in all financial markets around the world (Gamba-Santamaria et al., 2019; Cui et al., 2021), and the rise in oil prices in 2007-2008. The second spike (in late 2011) was driven, at least in part, by increased energy market uncertainties induced by political and social unrest in the Middle East and North Africa (MENA) region. In addition, connectedness increased to about 70% towards the end of 2015, along with the oil price crash from about $106 in June 2014 to approximately $37 in December 2015. Following the COVID-19 outbreak, the total connectedness increased to over the 70% mark in the first half of 2020. More recently, the Russian-Ukrainian conflict seems to have exacerbated systematic risk in all financial markets and, thus, significantly influenced the interdependence between commodity and purely financial markets, which is currently on an upward trend.

[**Insert Fig.2 about here**]

The time-varying net connectedness indices (NCI), which measure whether an asset i is a net receiver ($NCI < 0$) or a net transmitter ($NCI > 0$) of volatility shocks at each time point, are plotted in Figure 2. The goal is to capture the dynamics of the net contribution of the assets and uncertainty proxies considered to the system. We find that commodity futures markets show no discernible trend throughout the whole sample period, implying that there is a bidirectional and asymmetric connectedness across all commodity futures except natural gas (**NGAS**), which is almost always negative, which means that this commodity is rather a net recipient of volatility shocks if a few small outliers, notably during 2015-2016 timeframe, are excluded. This result is consistent with the results of Ji et al. (2018) who show that natural gas markets act as net receiver in a system including natural gas and oil markets. Aside from **NGAS**, commodities net connectedness indices are not only highly volatile, but also evolve in both the positive ($NCI > 0$) and negative ($NCI < 0$) zones, depending on the nature of the commodity and the circumstances and market conditions. For instance, the net connectedness plot reveals that **WTI** (WTI.1 and WTI.12) and **HOIL** (HOIL.1 and HOIL.12) become broadly net volatility transmitters (**i**) in 2007-2008 with the run-up of oil prices (from $56 to $138 per barrel of Brent crude and from $58 to almost $140 of WTI crude)[4], (**ii**) towards the end of 2011, with the increase of uncertainties in the energy market induced by the Arab Spring and the resulting unrest in the Middle East and North Africa (MENA) region, and (**iii**) following the oil price plunge of 2014-2016[5]. The results also suggest a decoupling between the short- and the longer-term net behaviour of crude oil during the COVID-19 outbreak and the Russo-Ukrainian conflict. Indeed, during the COVID-19 outbreak, the short-term crude oil market (**WTI.1**) was rather a net receiver of volatility, while the longer-term crude oil market (**WTI.12**) was rather a net transmitter. However, the opposite was detected during the first phase of the ongoing war between Russian and Ukraine, *i.e.*, **WTI.1** was rather net transmitter of volatility, and **WTI.12** was rather net receiver. This decoupling between the net position of the short-term crude oil

[4] The 2007–2008 oil price spike was due to high demand combined with stagnant global production. We refer readers who are interested in the causes and consequences of this oil price spike to Hamilton (2009).

[5] In June 2014, as the U.S. Federal Reserve was exiting its Quantitative Easing program, the European Central Bank (ECB) was doing the opposite. Indeed, on June 5, 2014, at a press conference, former ECB President Mario Draghi began preparing the markets by announcing that the ECB would start its Quantitative Easing program. The consequence of this announcement was a strong increase in the value of the U.S. dollar and, consequently, a sharp drop in oil prices. In addition to monetary policy considerations, the collapse of oil prices also reflects the imbalances in the oil market due mainly to (**i**) a global oversupply resulting mainly from the increase in U.S. oil production and OPEC's decision to keep its production level; (**ii**) a decline in global demand, resulting in particular from the deceleration of the economic activity in China economy and other emerging economies and the expectation of lower demand in Europe; and (**iii**) the return of Iran to the oil market.

market and the net position of the longer-term crude oil market can be explained by the nature of each of these two shocks. While the COVID-19 pandemic had a large impact on oil demand (World Bank, 2020), the Russian invasion of Ukraine has severely disrupted the supply of oil (World Bank, 2022).

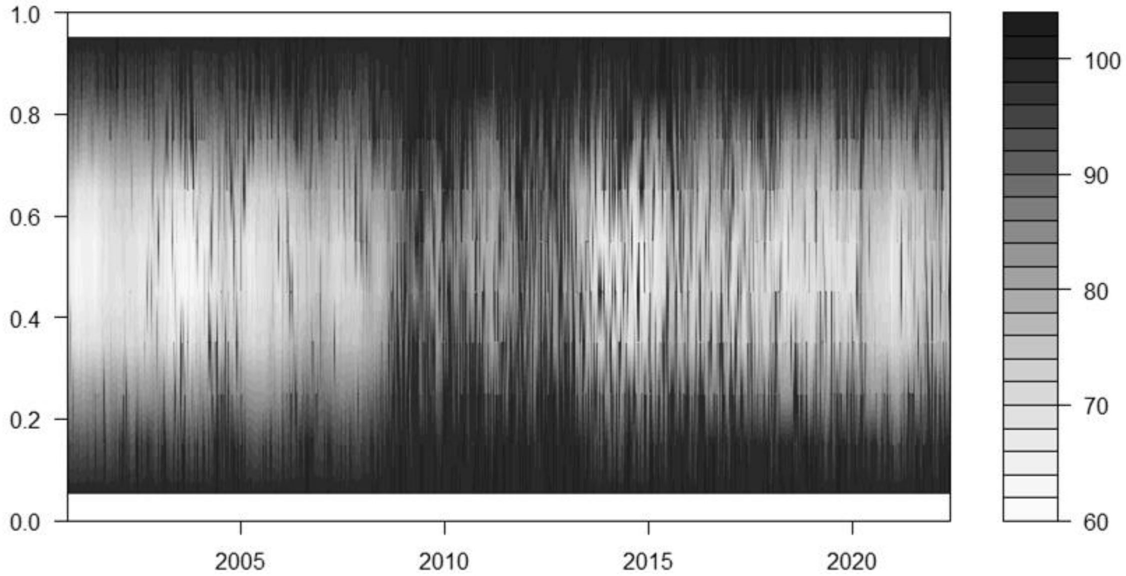
Regarding agricultural commodity markets, the highest net connectedness levels (in absolute values) were recorded during the global financial crisis and during the ongoing Russo-Ukrainian war. During the global financial crisis, the results reveal that the mechanism of net transmission follows broadly the same dynamics for both short and the longer maturities; wheat and corn are net receivers from the system, while soybean is a net transmitter of spillovers to the system. As far as the Russian-Ukrainian conflict is concerned, our results show that the propagation mechanism for both maturities, short and long, evolve towards opposite trends. Indeed, **CORN.1** and **SOYB.1** (respectively **WHT.1** and **SOIL.1**) are net transmitters (respectively net receivers), while **CORN.5** and **SOYB.7** (respectively **WHT.5** and **SOIL.8**) are net receivers (respectively net transmitters) of spillovers. Interestingly, the momentum of the net positions of precious metals – silver and gold – is broadly insensitive to maturity: while they are positive most of the time, which means that these assets are rather net volatility transmitters, gold becomes a net receiver of volatility in times of market stress. In addition, our findings show that **EPU** and **GPRD** are net receivers, which is in line with Geng et al., (2019) and Gao et al., (2021). This can be explained by the fact that market participants include information about economic and geopolitical uncertainties in their investment decisions before these are reflected in the uncertainty indicators themselves and this is due to the methodology of construction of economic and geopolitical uncertainties. Thus, commodity prices react to economic and financial uncertainties faster than uncertainty indicators, and not the other way around. Indeed, Baker et al. (2015) construct the EPU index from three components: (i) the newspaper coverage of policy-related economic uncertainty from ten large U.S. newspapers, (ii) the number of federal tax code provisions set to expire in future years, and (iii) the disagreement among forecasters as regards the outlook for inflation and budget balances. In the same vein, Caldara and Iacoviello (2022) construct a measure of adverse geopolitical events based on newspaper articles covering geopolitical tensions. However, the **MXWD** and **VIX** show a bidirectional and asymmetric net connectedness. They are receivers of spillovers during the global financial crisis, while they are transmitters during COVID-19 outbreak and the Russian-Ukrainian war. Overall, the results report an increase in the levels of the net connectedness metric during the major crises which is largely consistent with the results of Umar et al. (2021), Mensi et al. (2021), Zang et hamori (2021) and Cui et al. (2021).

Our results seem to be valuable and complete the existing literature in two ways. First, previous studies deal mostly with the connectedness among commodity markets considering the nearest maturity (Kang et al., 2017; Bacilar et al., 2021). Indeed, our study deals with spillovers among commodities considering the nearest and the longest maturity in the year to provide some useful insights for investors and policy makers. Moreover, the incorporation of various uncertainty proxies into the system makes our results original compared to previous studies.

3.2. Q-connectedness analysis

To further our discussion, we investigate the connectedness between the markets considered at different quantiles. This decomposition attempts to capture the quantile propagation mechanism and, in particular, the extent to which the spread of shocks is symmetric or asymmetric. Fig.3 illustrates the quantile-time-varying total connectedness index. The light-coloured time-quantile areas are spaces where the total connectedness (TCI) is low. Areas with high connectedness level are those in dark color. The darker the color is, the more integrated the markets considered are. A first visual inspection of the Q-connectedness plot reveals that the connectedness among the markets considered seems to be symmetric. Indeed, the *TCI* is very strong both for extreme negative and extreme positive returns, *i.e.,* below the 20th quantile and above the 80th quantile, respectively. The strong connectedness at both extreme tails highlights the sensitivity of commodity markets and uncertainty proxies to extreme shocks, which is in harmony with the existing literature revealing that connectedness among commodities intensifies during severe positive and negative events (e.g., Farid et al., 2022, Jena et al.,2021). The median quantile connectedness (50th quantile), which corresponds to the total average connectedness, tend to be higher in some specific time-intervals, which stem that the overall connectedness level among the markets considered is quantile- and time-varying, and highly event-driven. In fact, it indicates that connectedness among markets becomes stronger during crisis periods, when the total connectedness increases to relatively high levels, than during tranquil periods, when connectedness falls to relatively low levels, which is in line with the results of section 3.1. For instance, we notice that the connectedness at the 50th quantile become significant in the wake of the global financial crisis, the Arab spring (2011), the European debt crisis (2011–2013), the fall in oil prices (2014-2016), the COVID-19 epidemic (2020) and towards the end of our sample, together with the outbreak of the war between Russia and Ukraine. Specifically, Figure 3 shows that the total connectedness index started to increase at all quantiles as early as mid-2006, in tandem with the increasing market stress due to the Federal Open Market Committee's decision to further tighten monetary policy, before reaching substantially high levels between 2008 and the end of 2009, in tandem with the depreciation of the U.S. dollar, rising oil prices and other developments following the global financial crisis, as outlined by Gamba-Santamaria et al. (2019) and Antonakakis et al. (2018). The connectedness stayed at fairly high levels until the beginning of 2012. The European debt crisis as well as a series of poor economic indicators in both Europe and the United States and heightened uncertainties in the energy market (induced by geopolitical unrest in MENA countries) are potential explanations for the persistence of the total connectedness at quite high levels at all quantiles. After a rather stress-free phase from 2013 to mid-2014, marked by relatively low interdependency among markets, a second high connectedness phase was detected. Indeed, the Q-connectedness map displays a high level of connectedness among markets between mid-2014 and mid-2016, which reflects the market tensions that occurred in the wake of the Chinese stock market turmoil (from June 2015 to February 2016) and the drop in oil prices by approximately 65% (from about $106 in June 2014 to $37 in December 2015), one of the four largest and most prolonged oil price drops in modern history (World Bank, 2018)[6]. Following the COVID-19 outbreak, commodity markets have experienced another round of heightened connectedness at all quantiles. Specifically, the TCI began to increase in late January 2020. Indeed, attention to the novel strain of coronavirus increased tremendously (i) when Chinese authorities reported that the COVID-19 could potentially be transmitted between humans (January 20, 2020) and (ii) when the Italian government unexpectedly imposed a region-wide lockdown in Lombardy, Italy's most populous region, and surrounding provinces (February 2020). Consequently, the total connectedness began to increase rapidly, which is consistent with the findings of NT Hung (2021) and Farid et al. (2022). More recently, the recent Russian-Ukrainian war appears to have significantly exacerbated the interdependence between commodity markets.

Fig.3 Quantile-time-varying total connectedness



Notes: Time appears in the x-axis, while quantiles on the y-axis. The color scale depicts the magnitude of total connectedness (TCI) at each quantile. The light-colored time-quantile areas are spaces where the TCI is low. Areas with high connectedness level are those in dark color. The darker the color is, the more integrated the markets considered are. Results are based on 200-days rolling window QVAR(1) model and 20-days-ahead forecast horizon. The Bayesian information criterion was used to select the order of the QVAR model. Alternative rolling windows (100- and 150-days) and different forecast horizons (10- and 15-days) were used to check robustness, and the results remained largely unchanged. Unreported results are available upon request.

Figures 4 to 7 illustrate the quantile- and time-varying net total directional connectedness results. The color scale represents the net position: it ranges from blue (which indicates net receiver) to red (which indicates net transmitter). First and foremost, the results show that return spillovers remained higher during the bullish and bearish phases, depicted respectively by the 20th and 80th quantiles, compared to spillovers at the 50th quantile. That justifies our interest in studying spillovers among different quantiles where we can differentiate between mechanisms of spillovers during tranquil and turbulent periods, which may be relevant for investors and policy makers. This result was expected given evidence of strong markets

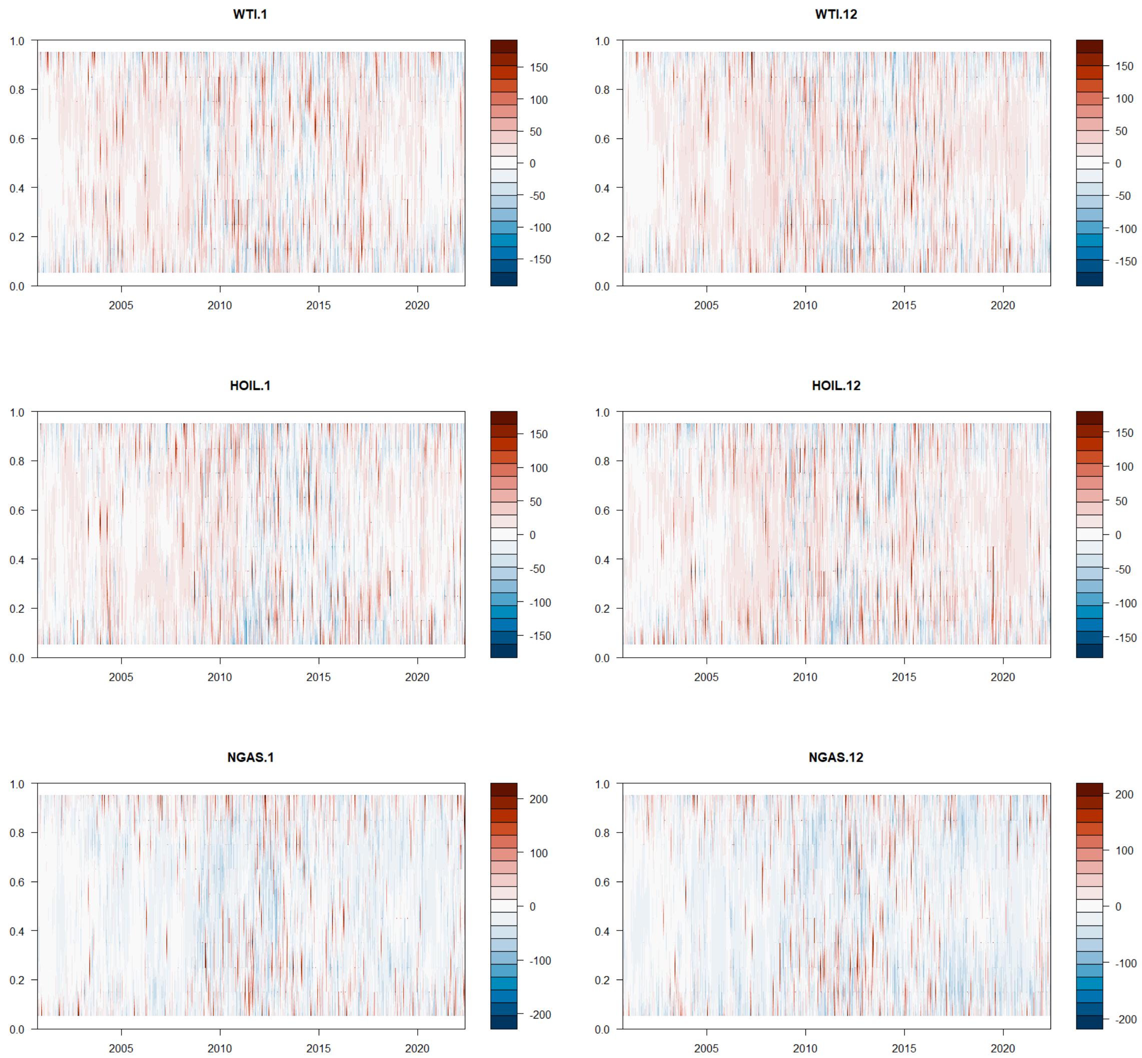
[6] The drop in oil prices from mid-2014 to early 2015 was primarily driven by supply-side factors, including the U.S. oil supply surge, diminishing geopolitical uncertainties, and OPEC's policy shift. Nevertheless, the deteriorating the demand outlook also played a role, particularly from mid-2015 to early 2016.

connectedness under extreme conditions (e.g., Farid et al., 2022, Jena et al.,2021). However, it is worth mentioning that the net spillovers among markets and uncertainty proxies fluctuate greatly under the two-tail estimation.

Figure 4 shows that while **WTI** and **HOIL** were steadily net transmitters to all other commodity markets at all quantiles, regardless of the maturity, **NGAS** was mostly a net receiver. This result is concordant with the findings of Zhang and Wei (2010), Guhathakurta et al. (2020) and Ben Amar et al. (2022) who suggest that crude oil and heating oil are net transmitters to other commodities including agricultural and metal commodities, whereas natural gas is a net receiver all the time and whatever the maturity. The dynamic net connectedness of the **WTI** and **HOIL** increased drastically during the global financial crisis, the Arab spring, the European Sovereign Debt Crisis, the 2014-2016 oil price collapse, the COVID-19 outbreak and the ongoing Russian-Ukrainian War, indicating that net spillovers intensify during major destabilizing episodes. However, it is noteworthy that **WTI** and **HOIL** tend to be mainly net receivers of spillovers in the extremely lower and higher quantiles (*i.e.*, below the 20^{th} quantile and above the 80^{th} quantile) compared to 50^{th} quantile. Moreover, the role of each of these commodity markets shifts over time and becomes a net receiver at specific episodes and quantiles, including (i) the onset of the European debt crisis (2009), (ii) the political unrest in the MENA region in the wake of the Arab spring (2011), and (iii) the oil price drop (2014-2016). As for **NGAS**, it tends to be mainly net receiver of shocks throughout the sample period at median quantile, especially during the period between 2009 and 2013, coinciding specifically with the European sovereign debt crisis and the political upheavals in the MENA region. However, for extreme events (*i.e.*, below the 20^{th} and above the 80^{th} quantiles), the net volatility spillover pattern is dissimilar since the trend of transmissions is not clear and fluctuates between net transmitting and net receiving for the entire period. Yet, we can notice that the **NGAS** turn to be significantly a net transmitter. Yet, we can notice that the NGAS turn to be significantly a net transmitter at the lower tails in 2011 and at the upper tails between 2012 and 2014. This may be due to several events that have shaken the natural gas supply during these periods including the Arab uprising and the Libyan civil war in 2011, beside to the halting of the Russian natural gas exports in February 2012 (Jadidzadeh et Serletis. (2017)). Overall, our results provide evidence that the direction or the strength of connectedness among energy commodities is strongly event dependent.

Findings show that energy products (excluding **NGAS**) dominate the spillover transmission in our system, operating as net information transmitters in tranquil periods (median quantile) and swinging between net transmitters and receivers of spillovers during extreme quantiles which is consistent with the findings of (Cui et al., 2022).

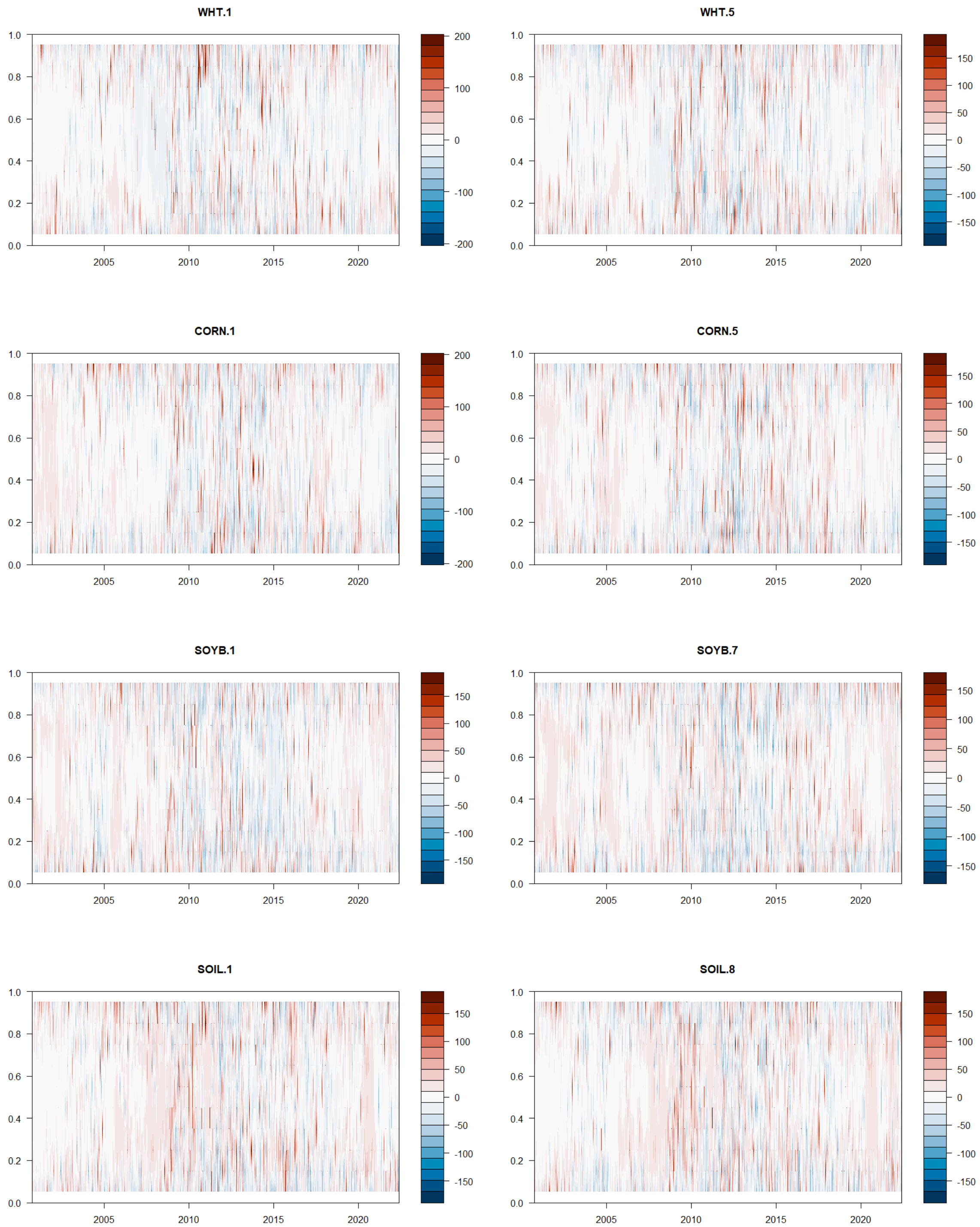
Fig.4. Quantile-time-varying net total directional connectedness - Energy Commodities



Notes: Time appears in the x-axis, while quantiles on the y-axis. The color scale depicts the magnitude of the net total connectedness at each quantile. The color scale depicts represents the magnitude of net reception or net transmission of volatility. Red time-quantile areas represent the spaces where the asset is a net transmitter. Areas where the asset is a net receiver of volatility shocks are those containing the blue color. Results are based on 200-days rolling window QVAR(1) model and 20-days-ahead forecast horizon. The Bayesian information criterion was used to select the order of the QVAR model. Alternative rolling windows (100- and 150-days) and different forecast horizons (10- and 15-days) were used to check robustness, and the results remained largely unchanged. Unreported results are available upon request.

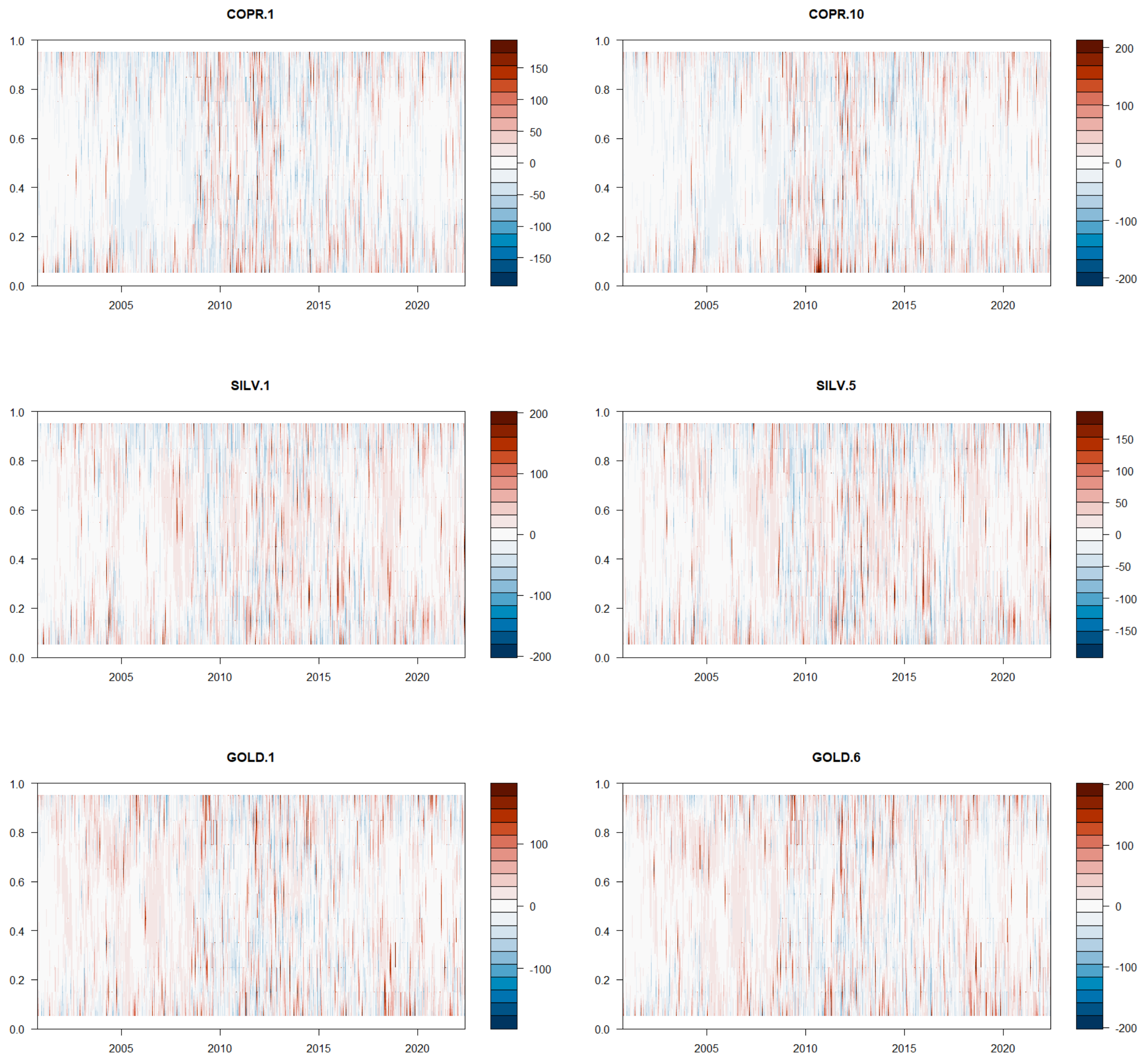
Figure 5 depicts the quantile net connectedness for agricultural commodities. The empirics illustrate that under extreme events occurrences (i.e., at lower and higher quantiles), the net connectedness positions of agricultural commodities shifts across time between a net transmitting and a net receiving role. It is worth mentioning that net directional transmission is less important for agricultural commodities compared to energy especially at median quantiles. However, we notice that the net connectedness has been intensified after the global financial crisis; This is basically owing to the increased financialization of commodities that have increased the degree of integration of commodity markets (Nazlioglu et al., 2013), but also to the severe drought in several countries around the world (World Food Programme, 2010). Considering the net spillovers across all quantiles, **WHT** receive relatively the highest spillovers during the 2007-2009 financial crisis and in the aftermath of the Arab Spring. However, at high quantiles (i.e., above the 80^{th} quantile), **WHT.1** assumes a net transmitting role between 2010 and 2011, which coincide with extreme weather events that adversely impacted major crop exporters; especially the unusual heavy rains in Canada that have lowered wheat yields by about a quarter (Giulia Soffiantini.,2020). **CORN** assumes mainly net receiving role across all quantiles from late 2012 to 2013, which coincides with the European debt crisis, and towards the end of our sample, concomitant with the Russian-Ukrainian war. This later has caused significant interruptions in the production and trade of commodities, notably agricultural commodities, for which Russia and Ukraine are major exporters (World Bank, 2020). These results are in line with Kang et al. (2017) who found that corn and wheat futures were net receivers of spillovers during the European debt crisis. For extreme quantiles, net connectedness of **SOY** and **SOIL** tend to be mostly negative (i.e., net receivers) especially after the global financial crisis. Moreover, we note that in the aftermath of the GFC and during the COVID-19 outbreak, precisely in 2009 and 2020, **SOIL** ~~is~~ become a net transmitter

Fig.5. Quantile-time-varying net total directional connectedness - Agricultural commodities



Notes: Time appears in the x-axis, while quantiles on the y-axis. The color scale depicts the magnitude of the net total connectedness at each quantile. The color scale depicts represents the magnitude of net reception or net transmission of volatility. Red time-quantile areas represent the spaces where the asset is a net transmitter. Areas where the asset is a net receiver of volatility shocks are those containing the blue color. Results are based on 200-days rolling window QVAR(1) model and 20-days-ahead forecast horizon. The Bayesian information criterion was used to select the order of the QVAR model. Alternative rolling windows (100- and 150-days) and different forecast horizons (10- and 15-days) were used to check robustness, and the results remained largely unchanged. Unreported results are available upon request.

Fig.6. Quantile-time-varying net total directional connectedness - Metals



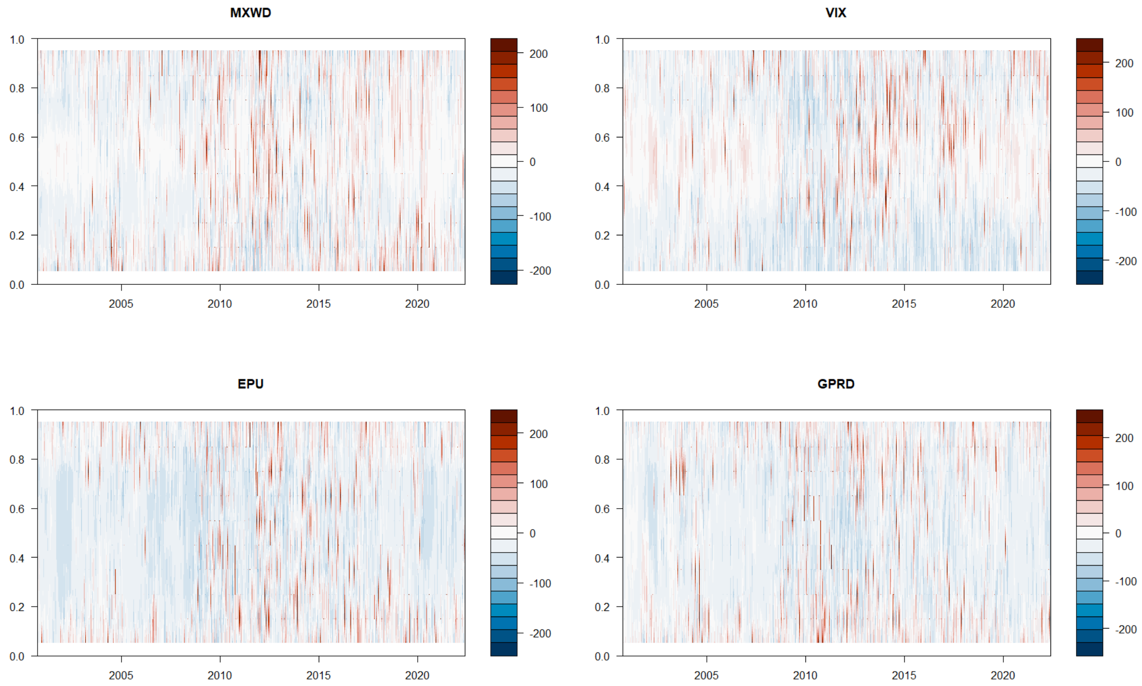
Notes: Time appears in the x-axis, while quantiles on the y-axis. The color scale depicts the magnitude of the net total connectedness at each quantile. The color scale depicts represents the magnitude of net reception or net transmission of volatility. Red time-quantile areas represent the spaces where the asset is a net transmitter. Areas where the asset is a net receiver of volatility shocks are those containing the blue color. Results are based on 200-days rolling window QVAR(1) model and 20-days-ahead forecast horizon. The Bayesian information criterion was used to select the order of the QVAR model. Alternative rolling windows (100- and 150-days) and different forecast horizons (10- and 15-days) were used to check robustness, and the results remained largely unchanged. Unreported results are available upon request.

Figure 6 highlight relatively high net connectedness at extreme quantiles especially for **COPR** and **SILV**. This is in line with evidence from prior studies stemming that the spillover effect estimated at median quantile is not necessarily similar to that estimated at upper or lower quantiles (e.g., Chatziantoniou et al., 2021; Jena et al., 2021). At median quantile (i.e., during relatively tranquil periods), **GOLD** and **SILV** transmit more spillovers to the system compared to **COPR** who tend to be rather a net receiver of volatility. However, no clear trend in transmitting or receiving spillovers is detected at extreme quantiles.

The net connectedness at different quantiles of uncertainty proxies is depicted in Figure7. Our findings demonstrate that the net connectedness of the **VIX** increased after the GFC, which is explained by the fact that the GFC altered the global financial environment and exacerbated global economic uncertainty. During the 2009-2011 timeframe, VIX mostly assumes a net receiving role at all quantiles, indicating that there is an increase of uncertainty in financial markets and a considerable rise in investors' risk aversion in the aftermath of the global financial period. However, **VIX** merges as a net transmitter at extreme positive quantile during the COVID-19 outbreak, in which U.S. financial markets has reached unprecedented volatility levels (**VIX** jumps to 80 on 16th March 2020, breaking its 2008 record).

Furthermore, the findings unveil that **MXWD** emerges as net transmitter between 2009 et 2012 (i.e., in the European dept Crisis), and during the first phase of the worldwide spread of the coronavirus. However, it merges as net receiver during the Russian-Ukrainian war. As far as **EPU** and **GPRD** are concerned, they display a net transmitting role at extreme quantiles, while they turn to be net receivers at median quantiles especially during the 2007-2008 GFC, the COVID-19 outbreak, the Russian-Ukrainian war which is in line with Geng et al. (2019) who found that **EPU** serves as information receiver of net return spillover from energy and stock markets.

Fig.7. Quantile-time-varying net total directional connectedness - MXWD & uncertainty indices



Notes: Time appears in the x-axis, while quantiles on the y-axis. The color scale depicts the magnitude of the net total connectedness at each quantile. The color scale depicts represents the magnitude of net reception or net transmission of volatility. Red time-quantile areas represent the spaces where the asset is a net transmitter. Areas where the asset is a net receiver of volatility shocks are those containing the blue color. Results are based on 200-days rolling window QVAR(1) model and 20-days-ahead forecast horizon. The Bayesian information criterion was used to select the order of the QVAR model. Alternative rolling windows (100- and 150-days) and different forecast horizons (10- and 15-days) were used to check robustness, and the results remained largely unchanged. Unreported results are available upon request.

4. Concluding remarks and policy implications

This paper investigates the connectedness among a set of ten futures commodity markets – crude oil, natural gas, heating oil, wheat, corn, soybean, soybean oil, copper, silver, and gold – at different maturities, the global equity market and three different sources of uncertainty (financial, economic ang geopolitical), over the period January 2000-May 2022, from two different perspectives: (i) in the time-domain, then (ii) at different quantiles. Indeed, we first use the Diebold and Yilmaz (2012) methodology to investigate the connectedness among the markets under consideration. Then, and in order to surpass the mean-based connectedness metrics of Diebold and Yilmaz (2012), we use the Chatziantoniou et al. (2021) and Ando et al. (2022) approach which enable measuring the connectedness at different quantiles.

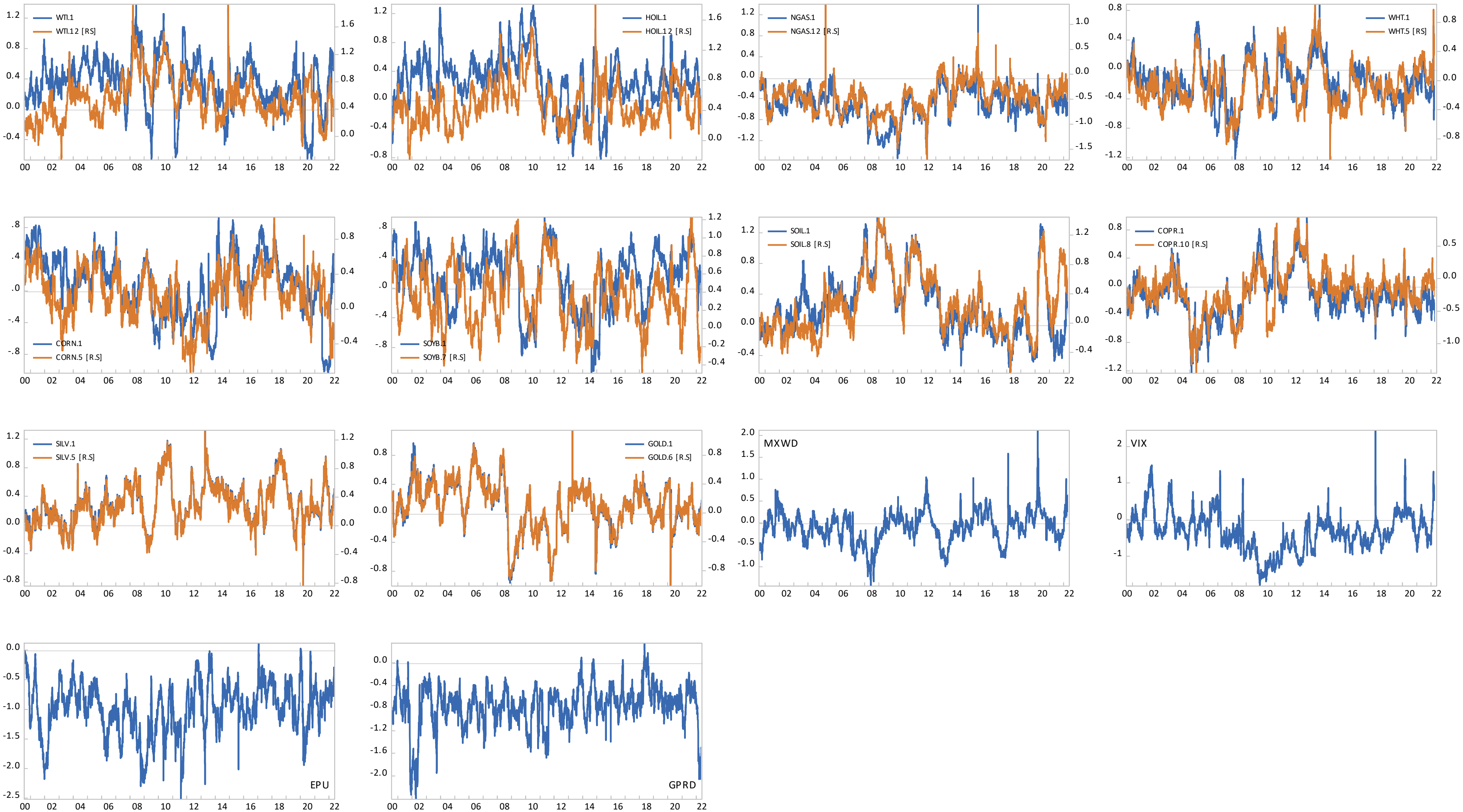
Regarding empirical results, we provide a set of stylized facts on the magnitude of connectedness among the markets under consideration, as well as on the heterogeneity of the impact of the different stress- and stress-free periods examined at different quantiles. The results show that the total Diebold and Yilmaz (2012) connectedness index peaked to relatively high levels during crisis and stress periods – the global financial crisis; the 2011 Arab Spring; the 2014-2016 oil price crash period; the COVID-19 outbreak; the ongoing Russian-Ukrainian conflict. As for the net connectedness metric, it reveals that crude oil and heating oil, including both the longest and shortest maturity within the year, are broadly net volatility transmitters during the global financial crisis, the Arab spring, the oil price crash, while there is a decoupling between the net position of the shortest and the longest maturity during COVID-19 outbreak and the Russian-Ukrainian war. However, natural gas appears to be rather a net recipient of volatility shocks. Regarding agricultural commodities, corn and wheat are net receivers during the global financial crisis, while soybean is a net transmitter: the highest net connectedness levels were recorded during the global financial crisis and the ongoing Russian-Ukrainian war. In addition, the results show that silver and gold, which are broadly insensitive to maturity, are rather net transmitters most of the time, while economic and geopolitical uncertainties seem to be net receivers. As for the fear index as well as the global equity market, they are net receivers during the global financial crisis, and net transmitters during COVID-19 outbreak and the Russian-Ukrainian war.

The results of the quantile connectedness provide evidence of the varying feature of connectedness across different quantiles among commodities and the uncertainty measures considered. The time-varying analysis highlights not only the high sensitivity of commodity markets and uncertainty proxies to extreme shocks, but also that the overall connectedness peaks at all quantiles during stress periods. Moreover, the pattern of connectedness at both the higher and lower tails display different feature comparing to the conditional median, implying that connectedness metrics calculated at the conditional median disguise the evolution of connectedness at tails. Consequently, the results regarding extreme connectedness measures in the upper and lower tails provide a more comprehensive picture of the impact of tail risk propagation within commodities and uncertainty proxies. The quantile net total directional connectedness results show that return spillovers prove to be higher during the bullish and bearish phases, compared to spillovers at the 50^{th} quantile. Interestingly, while crude oil and heating oil were steadily net transmitters to all other commodity markets at all quantiles, regardless to maturity, natural gas was mostly a net receiver. While the net connectedness of agricultural commodities has been strengthened after the global financial crisis and shifts at extreme quantiles across time between a net transmitting and a net receiving role, it is worth mentioning that the quantile net directional transmission is less important for agricultural commodities compared to energy commodities especially at median quantiles. At median quantiles, gold and silver transmit more spillovers to the system compared to copper who tends to be rather a net receiver of volatility. Besides, economic and geopolitical uncertainties display a net transmitting role at extreme quantiles, while they turn to be net recipient at median quantiles.

These findings provide useful insights for investors, portfolio managers, and policy makers. Particularly, they entail implications for market participants and regulators aiming to adjust their investment strategies and political decisions according to different market circumstances. In this way, the empirical findings related to extreme connectedness among commodities at different quantiles (i.e., the upper, middle, and lower quantiles) allow investors to better positioning in the market especially during crisis periods and emphasize the need of regulators to pay special attention to set appropriate regulations in order to mitigate the detrimental repercussions of severe shock that may impact risk hedging and portfolio diversification.

One of our analysis's drawbacks is that it only employs the shortest and the longest maturity in the year. Future studies might include further maturities in order to detect spillovers among commodities with different maturities. This would provide a more detailed understanding of the connectedness across futures markets with short-, medium-, and long- term maturities.

Fig.2 Time-varying net connectedness



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