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Quantile time-frequency connectedness analysis between crude oil, gold, financial markets, and macroeconomic indicators: Evidence from the US and EU

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ABSTRACT

This study examines the relationships between various financial and economic sectors using a method called quantile time-frequency connectedness. We use the quantile time-frequency connectedness approach developed by Chatziantoniou et al. (2022) to investigate how commodity markets, such as crude oil and gold, interact with stock markets, currency markets, industrial production indices, and consumer price indices (CPI) in both the United States (US) and the European Union (EU), comparing the differences between crude oil and gold in the US and EU. The main findings of the study reveal that system risk varies over time and quantiles, with dynamic total connectedness being more significant during extreme market conditions (5% and 95% quantiles) and short-term spillovers outweighing long-term spillovers for both the US and the EU. Crude oil consistently serves as the primary net transmitter of shocks in both short-term and long-term dynamics across various quantiles. In contrast, gold's role varies, generally transmitting long-term shocks and receiving short-term shocks. The study also identifies the asymmetric nature of connectedness between bullish and bearish markets in the US, while connectedness in the EU appears more symmetric. Furthermore, different indicators serve as net transmitters or receivers of shocks based on quantiles and time intervals, revealing the sources of market uncertainties and the indicators most vulnerable to shocks. This research is among the first to use this method to study these connections across different domains' indices and macroeconomic and for different situations in both the US and the EU, which can help policymakers and investors obtain a comprehensive understanding of the dynamic quantile time-frequency connectedness between these relationships.

1. Introduction

Connectedness plays a central role in modern risk measurement and management. Understanding the interconnectedness of various financial and economic variables is crucial for assessing systemic risk, contagion effects, and the overall stability of the economic system. Analyzing connectedness helps identify how shocks or disturbances in one part of the system can propagate and impact other components, contributing to a comprehensive risk assessment. This knowledge is essential for investors, policymakers, and financial institutions in making informed decisions about policy responses to systemic crises and implementing effective risk mitigation strategies.

Recently, the global response to the worldwide crisis and geopolitical risk underscores the significance of analyzing the risk of contagion, particularly in times of extreme events. These events have led to a highly volatile market condition, i.e., an extreme market condition, thereby amplifying the systematic risks both at the country-specific level and on a global scale (Sharif et al., 2020; Izzeldin et al., 2023; Antonakakis et al., 2017). Additionally, as noted by Ando et al. (2018), systematic risks tend to be significantly larger during extreme market conditions (i.e., extreme quantiles) than during average median market conditions (i.e., median quantiles). Therefore, the exploration of propagation mechanisms at extreme quantiles holds greater significance than examining the average median quantile. Furthermore, Baruník and Křehlík (2018) underscore the importance of understanding the frequency dynamics of connectedness to gain insights into the origins of spillover effects within an economic system. Understanding the frequency dynamics of connectedness in economic systems is essential, as shocks to economic

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activity can influence variables at different frequencies with varying intensities. The effect of shocks can differ among different frequency bands, with certain frequencies being more susceptible to shocks than others.

In an interconnected global financial landscape, the analysis of interconnections within the multifaceted domain of financial and macroeconomic indicators, encompassing commodity markets, stock markets, currency markets, industrial production indices, and consumer price indices, becomes increasingly crucial because an adverse shock to one part of the financial or macroeconomic domain poses a threat to systemic stability if there are linkages through which it can propagate to other parts of the system (Gkillas et al., 2019; Tang et al., 2010; Miller and Ratti, 2009; Du et al., 2010; Malliaris and Malliaris, 2011; Filis and Chatziantoniou, 2014; Zhu et al., 2023). Crude oil and gold are commonly selected as representative commodities for studying interconnections across financial and economic indicators (Jiménez-Rodríguez and Sánchez, 2005; Kilian, 2009; Kang et al., 2015; Laopodis, 2010; Korhonen and Ledyaeva, 2010; Gokmenoglu and Fazlollahi, 2015). Additionally, their global implication is significant: crude oil's fluctuations influence energy markets, inflation, and the output of industrial production (Kilian, 2009; Yoshizaki and Hamori, 2013; Gokmenoglu et al., 2015), while gold serves as a safe-haven asset and reflects investor sentiment and economic stability (Choudhry et al., 2015; Iqbal, 2017; Triki and Maatoug, 2021). Both commodities possess diverse applications spanning various sectors, and their distinct responses to economic and geopolitical events make for the evaluation of systemic risk.

Here, we provide a concise overview of the theoretical foundation and explanation of the interconnected dynamics between commodity markets, financial sectors (stock market and currency market), and macroeconomic aggregates (consumer price index and industrial production index), aiming to enhance comprehension of the study's motivation and the empirical results. Extreme events and substantial fluctuations in commodity prices are acknowledged as significant sources of risk in financial markets (Demir and Danisman, 2021; Baruník and Křehlík, 2018; Lizardo and Mollick, 2010). Portfolio theory, following Markowitz (1991), underscores diversification as a risk management strategy, enabling investors to optimize risk and return amid variations in commodity prices, extreme events, and stock market conditions (Al-Thaqeb and Algharabali, 2019). From an alternative viewpoint, financial markets respond to diverse extreme events and uncertainties (Karolyi, 2006; Fang et al., 2018). The rare disaster model, introduced by Rietz (1988) and extended by Barro (2006), offers insights into the volatility of stock returns, emphasizing the role of unexpected and rare events in shaping market dynamics and influencing investor behavior. The Capital Asset Pricing Model (CAPM), linking expected returns to systematic risk, establishes a correlation between uncertainties, extreme events, and changes in expected returns. This connection suggests that uncertainties and extreme events may impact not only stock market indices but also extend into macroeconomic aggregates through a contagion effect across diverse asset classes. There exists a relationship between the prices of key commodities (such as oil, gold, or agricultural products) and stock markets (Kilian and Park, 2009; Baruník et al., 2016; Gokmenoglu and Fazlollahi, 2015). Higher commodity prices can impact companies in the commodity production sector, influencing their profitability and stock performance. For commodity-exporting countries, increased commodity prices can boost revenues and stock markets, while commodity-importing countries may face higher costs, potentially affecting stock markets negatively. Changes in commodity prices also impact trade balances, influencing the supply and demand for currencies in the foreign exchange market (Harri et al., 2009; Cashin et al., 2004; Yoshizaki and Hamori, 2013). Countries heavily dependent on a particular commodity may experience currency volatility based on shifts in commodity prices (Golub, 1983; Beckmann et al., 2015; Reboredo and Rivera-Castro, 2013). Commodity prices, especially energy and food prices, contribute to inflationary pressures captured by the consumer price index (Kilian, 2009; Gao et al., 2014). Higher commodity prices can lead to increased production costs and, subsequently, higher consumer prices. Commodity markets are closely linked to industrial production, where fluctuations in oil prices, for instance, can impact production costs for various industries (Kilian, 2009; Jiménez-Rodríguez and Sánchez, 2005; Lardic and Mignon, 2006). Movements in the stock market can influence investor sentiment (Baker and Wurgler, 2007) and impact currency values in the foreign exchange market (Mishra, 2004; Jebran and Iqbal, 2016). A robust stock market may attract foreign investment, potentially leading to a stronger currency, while a declining stock market might have the opposite effect. Stock market movements can also affect business confidence and investment decisions, where a rising stock market may encourage business expansion and investment, positively impacting industrial production (Humpe and Macmillan, 2009). Exchange rate movements influence import and export dynamics, affecting trade balances and, consequently, industrial production (Bampi and Colombo, 2021). A depreciating currency may boost exports but contribute to inflation, while an appreciating currency may have the opposite effect.

The US and the EU, as the world's most substantial and impactful economies, even minor shifts in the commodity markets, stock markets, currency markets, and pivotal macroeconomic indicators like industrial production and consumer prices within these two countries can trigger a ripple effect on international markets and the progress of the global economy (Gkillas et al., 2019). Comprehending the interplay and interconnectedness among these variables, particularly under varying market conditions, holds significance for understanding the potential transmission of shocks, the evolution of risk, and the implications for financial decision-making. The reasons for choosing these two countries, i.e., the US and the EU, are listed as follows: Firstly, the US and the EU are two of the largest economic entities in the world and major players in global trade, investment, and financial stability. Changes in their economic conditions can have spillover effects on other economies. Understanding the risk propagation mechanism in each region aids in assessing the robustness of each region's economic system and can guide policies aimed at enhancing resilience for this region or related economies. Secondly, many investors engage in the equity and foreign exchange markets in both the U.S. and the EU. Investment decisions by investors and portfolio managers are often shaped by their anticipations of economic conditions and movements in financial markets. A comparative analysis between the US and the EU aids investors in understanding the relative risks and opportunities in each region, influencing asset allocation and investment strategies. Thirdly, the Eurozone within the EU represents a unique case of a monetary union with a single currency, the Euro. Analyzing interactions between financial markets and the macroeconomy in the EU provides insights into the functioning and challenges of a currency union, offering lessons for other regions considering such arrangements. Concerning the US dollar, as the most widely used reserve currency globally, the monetary policy decisions of the US Federal Reserve would have global implications. Changes in interest rates and other monetary policy tools can impact global financial markets, capital flows, and borrowing costs. Fourthly, quantile connectedness may reflect variations in the resilience of the US and EU economies to different shocks. Understanding the sources of the systematic risks in each country aids in assessing the robustness of each region's economic system and can guide policies aimed at enhancing resilience.

Therefore, this study encompasses three main objectives. Firstly, it seeks to investigate not only the median quantile (representative of normal market conditions) time-frequency dynamic connectedness but also the extreme quantile (reflective of extreme market conditions such as bearish or bullish markets) time-frequency dynamic connectedness. This investigation particularly focuses on understanding how spillover effects operate within various markets and macroeconomic indicators during diverse extreme market conditions and across different time-frequency bands for both the US and the EU. These markets and indicators include the commodity market, stock market, currency index, industrial production index, and consumer price index. Secondly, the study aims to assess whether the two primary commodities, crude oil, and gold, exert distinct impacts on other variables and whether their roles in transmitting or receiving shocks differ across various extreme market conditions and time-frequency bands. Thirdly, this study aims to identify the sources of the interconnectedness within the systems of the US and EU during different extreme market conditions and across different time-frequency bands, providing insights for investors and policymakers to enhance their risk management strategies and decision-making processes regarding policies.

This study employs the approach of quantile time-frequency connectedness (Chatziantoniou et al., 2022), which is a robust analytical framework that allows us to investigate these interdependencies across different quantiles and different time-frequencies. The quantile time-frequency connectedness approach, introduced by Chatziantoniou et al. (2021) and built upon the work of Ando et al. (2018), traces its roots to the framework of Diebold and Yilmaz (2009); Diebold and Yılmaz (2014). This methodology allows for the examination of quantile propagation mechanisms, particularly during instances of extreme positive or negative structural shocks. In an expanded version of this approach, Chatziantoniou et al. (2022) further integrate the frequency connectedness concept proposed by Barunik and Krehlik (2018) with the quantile connectedness approach proposed by Chatziantoniou et al. (2021). This development enables the approach to account for connectedness measures across various quantiles and time-frequencies. The advantages of this approach become evident when contrasted with the conventional connectedness method introduced by Diebold and Yilmaz (2012); Diebold and Yılmaz (2014). The quantile time-frequency connectedness approach not only demonstrates insensitivity to outliers but also provides more comprehensive insights, particularly in terms of quantile time-frequency considerations. Additionally, this approach facilitates the exploration of how connectedness varies under diverse market conditions, spanning from normal periods to times of extreme turbulence and across various time horizons. Throughout this research, we will examine the dynamics of connectedness and assess how it evolves over time-frequency bands and across quantiles, shedding light on potential vulnerabilities and strengths in the interconnected financial and economic systems of the US and EU.

The study's main findings are as follows: Firstly, concerning the dynamic total connectedness, the research reveals that system risk varies over time and across different quantiles, with dynamic total connectedness being more significant during extreme market conditions (5% and 95% quantiles). Short-term spillovers are more prominent than long-term spillovers for both the US and EU. The dynamics of short-term and long-term total connectedness can diverge, depending on economic and geopolitical events. Secondly, comparing crude oil and gold's impact, crude oil consistently serves as the primary net transmitter of both short-term and long-term shocks in the US and EU networks across various quantiles. In both regions, crude oil transmits shocks primarily to the CPI, followed by the industrial production index and the stock market, while its transmission mechanisms with the currency index depend on quantiles and time-frequency bands. However, gold's role varies; generally, it transmits long-term shocks and receives short-term shocks at different quantiles. Thirdly, with respect to the symmetry or asymmetry in connectedness, the connectedness between bullish and bearish markets is asymmetric in the US, indicating that spillovers behave differently in such market conditions. In contrast, connectedness in the EU appears more symmetric. The averaged short-term TCIs are higher at the upper extreme quantiles, and the averaged long-term TCIs are higher at the lower extreme quantiles, indicating that during economic downturns, long-term total connectedness is more prominent, particularly in the lower extreme quantiles. Fourthly, various indicators serve as net transmitters or receivers of shocks, depending on different quantiles and time intervals. For example, in the 5% extreme lower quantile, US industrial production is the largest overall net transmitter of shocks, while in the 95% extreme upper quantile, US industrial production is the largest net receiver of shocks. These results identify the sources of market uncertainties and the indicators most vulnerable to shocks.

To the best of our knowledge, this study was the first application of quantile time-frequency connectedness methods to explore the quantile time-varying connectedness and spillover transmission dynamics across commodities (e.g., crude oil and gold prices) and a spectrum of financial and macroeconomic indicators, including stock market indices, currency indices, industrial production indices, and consumer price indices from the US and the EU under different time-frequency ranges and various quantiles (median and extreme quantiles). Secondly, this study represents the pioneering research effort to identify the sources of systemic risk across distinct time-frequency bands and varied market conditions within the financial macroeconomic systems of both the US and the EU. Thirdly, it marks the first attempt to compare the roles (as spillover transmitters or receivers) of crude oil and gold when there are extreme positive or negative structural shocks in the system.

The subsequent sections of this paper are arranged as follows: Section 2 reports the literature review. Section 3 explains the methodology and the data. Section 4 analyzes the empirical results and discusses the findings, encompassing the time-frequency dynamic connectedness and the quantile dynamic connectedness. Section 5 concludes this study and discusses the findings and implications for policymakers and investors.

2. Literature review

The interaction between the crude oil market and various other financial markets and economic indicators has been the focus of extensive research, with numerous scholars employing a range of methodologies to investigate this relationship. This comprehensive body of research includes significant contributions from Ahmad et al. (2020), Beckmann et al. (2015), Belhassine and Karamti (2021), Benlagha and Omari (2022), Chatziantoniou et al. (2023), Chisti et al., 2020, Chen et al. (2013), Chen et al. (2022), Degiannakis et al. (2018), Ding et al. (2021), Engle et al. (2013), Filis and Chatziantoniou (2014), Go and Lau (2021), Hung (2020), Iqbal (2017), Ji et al. (2019), Jiang et al. (2020), Kang et al. (2021), Kumar (2019), Li et al. (2021), Reddy et al. (2019), Shang and Hamori (2023), Smales (2021), Tiwari et al. (2020), Wei et al. (2019), Yang et al. (2017), Yoshizaki and Hamori (2013), Yoshizaki and Hamori (2014), and Zolfaghari et al. (2020).

Chisti et al., 2020 carried out an investigation into the correlation between economic indicators, particularly foreign institutional investments, foreign exchange rates, and crude oil prices, as well as their effects on stock market performance, focusing on the Nifty 50 index in the context of the Indian financial landscape. In his comprehensive approach, Hung (2020) combined wavelet coherence analysis with the multivariate (DCC-GARCH) model. The objective was to examine the time-frequency relationships involving exchange rates, stocks, and the international commodities markets, specifically gold and oil. Six macroeconomic indicators were considered in an in-depth examination by Reddy et al. (2019): inflation, interest rate, gold, silver, crude oil, and exchange rate. The research aimed to uncover the influence of these factors on chosen sectoral indicators, shedding light on the complex interplay between macroeconomic variables and sector-specific performance. Rehman and Vo (2021) delved into an exploration of the integration of returns between precious metal, energy, and industrial metal commodities. Their objective was to unveil the interconnectedness and interdependencies among these diverse categories of commodities. Shah et al. (2021) embarked on an investigation of interconnectedness within and between crude oil, precious metals (including gold, etc.), and foreign exchange markets, employing a comprehensive analysis that spanned both temporal and frequency domains. Tiwari et al. (2020) conducted a comprehensive study on systemic risk and the interdependence among the stock market indicators and the oil market in G7 economies. Wei et al. (2019) used a combination technique to explore the long-term correlations between the Chinese stock market index and the crude oil futures, focusing on the recently occurring financial crises.

The technique of time and frequency connectedness network, which is based on VAR (Vector Autoregression) and forecast error variance decomposition models, has been widely adopted in the field of connectedness investigation. Prominent contributors to this field include Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) and Antonakakis et al. (2020a). Pioneering research in this field has set the stage for subsequent investigations, including those conducted by Antonakakis et al. (2020b), Antonakakis et al. (2017), Jiang et al. (2020), Bouri et al. (2021), Diebold and Yilmaz (2015a), Diebold and Yilmaz (2015b), Li et al. (2021), and Shang and Hamori (2021). Notably, Bouri et al. (2021) presented compelling findings, highlighting a significant transformation in the structure and evolving trends of interconnectedness among various asset classes. These assets encompass gold, crude oil, global equities, currencies, and bonds, particularly during the onset of the COVID-19 pandemic. Jiang et al. (2022) introduced a Time-Varying Parameter Vector Autoregression (TVP-VAR) approach to delve into the complexities of volatility transmission dynamics across diverse financial markets. Their research aimed to elucidate the roles played by these markets in the broader global volatility propagation system. The study encompassed a wide array of financial domains, ranging from natural gas, gold, and crude oil to bitcoin, foreign exchange, and stocks.

Moreover, considering the notable disparities in the pace of information exchange among financial markets across different investment horizons, the adoption of the time-frequency connectedness methodology, as conceived by Baruník and Křehlík (2018), has emerged as a prominent focus of academic exploration. This approach proves especially beneficial when evaluating the dynamic linkages between a wide array of economic and financial indicators at varying time-frequency intervals. It furnishes a nuanced and accurate comprehension of the shifts in these interconnections across diverse timeframes, facilitating the distinction between short-term and long-term. These findings have crucial implications for risk management by enabling the development of strategies tailored to address sudden market shocks in the short term, while also facilitating adjustments to adapt to long-term trends. Traders and investors benefit from a more profound comprehension of the unique dynamics of short-term and long-term connectedness, aiding in effective market timing. Policymakers can formulate more timely and effective responses and enduring policies using this approach. Additionally, it is essential for assessing systemic risk, supporting comprehensive planning, and enhancing forecasting accuracy, ultimately improving decision-making in dynamic markets. Noteworthy contributions to this field include the works of Baruník and Kocenda (2019), Chatziantoniou et al. (2023), Mensi et al. (2021), Mensi et al. (2018), Osah and Mollick (2023), Shah et al. (2021), Wang et al. (2021a), Wang and Wang (2019), Wang et al. (2020), Wang et al. (2021b), and Zhu et al. (2022). For instance, by examining both short- and long-term trends, Kang et al. (2021) investigated the directional connectedness between gold, oil, the stock market, uncertainty indicators, US sector equity ETFs, oil, and gold. Wang et al. (2020) investigated the connectedness of returns spillovers, across four global commodity futures markets, including wheat, gold, copper, and crude oil, while analyzing their interactions in both the frequency and time domains. Wang et al. (2021b) conducted a pioneering study on connectedness both in frequency and time domains and risk-hedge strategies using five hedges, i.e., commodities, gold, crude oil, the US dollar index, and Bitcoin, along with four stock market indicators that involved developed markets and developing markets. Mensi et al. (2018) explored the examination of time-frequency connections involving interest rates and crude oil prices.

On the other hand, an increasingly focused area in academic research is quantile connectedness, as it allows for the investigation of specific interconnections under various tail quantiles or extreme market conditions. The utilization of quantile connectedness holds great importance in the examination of a broad spectrum of financial markets and indicators. This method dissects distinct quantiles, encompassing both typical and extreme market conditions, thereby offering a granular perspective on risk evaluation. Quantile connectedness empowers the formulation of tailor-made risk management tactics that cater to different intensities of market pressure, thus providing a valuable resource for investors to discern bearish and bullish signals. Consequently, this assists in the identification of potential market downturns or upswings, enabling prompt adjustments to investment strategies. Furthermore, it functions as an advanced alert system, aiding in the anticipation of market volatility and significant economic shifts. This proactive approach bolsters portfolio safeguarding and the exploitation of emerging prospects. Policymakers can harness quantile connectedness to craft targeted policies that adapt to varying market circumstances. This approach equips investors, central banks, and governments with the tools to make more informed and adaptable decisions, thereby fostering economic stability. It has also demonstrated its worth in the evaluation of infrequent yet high-impact tail risks, offering a comprehensive standpoint that supports a nuanced scrutiny of market dynamics under an array of scenarios. Noteworthy contributions in this domain encompass the works of Ando and Bai (2020), Ando et al. (2022), Ando et al. (2018), Baruník and Kley (2019), Baumöhl and Shahzad (2019), Du and He (2015), Liu et al. (2021a, 2021b), Rehman et al. (2022), Yang et al. (2021), and Yousaf et al. (2022).

The quantile time-frequency approach, developed by Chatziantoniou et al. (2022), builds upon the integration of time-frequency and quantile connectedness methods. This approach is rooted in the foundational work of Chatziantoniou et al. (2021) and Ando et al. (2018). This innovative approach possesses a unique capacity to explore interrelationships within the time-frequency domain and across diverse quantiles, providing an all-encompassing perspective on the interplay of financial markets and indicators in various scenarios. Significant contributions to this field can be found in the research of Rehman and Vo (2021) and Zhu et al. (2023).

In summary, extensive research has been dedicated to investigating the interplay between the crude oil market and a spectrum of financial and economic indicators, encompassing gold, stock markets, currency exchange rates, industrial production, and consumer price indices. Various analytical methods have been applied to probe the dynamic relationships among these variables within distinct contexts. Time and frequency connectedness analysis, as pioneered by Diebold and Yilmaz (2012, 2014) and Baruník and Křehlík (2018), has proven invaluable in unraveling how these connections evolve across different timeframes and frequencies. Moreover, the introduction of quantile connectedness analysis by Ando et al. (2018) has further enriched our comprehension by segmenting these connections into various quantiles, thereby shedding light on tail risks and exceptional market conditions. Additionally, the quantile time-frequency approach, devised by Chatziantoniou et al. (2022), has provided a comprehensive framework for examining interconnectedness within diverse time-frequency bands and quantiles, thereby enhancing our capacity to fathom market dynamics across a range of scenarios. Our utilization of the quantile time-frequency connectedness approach equips us to scrutinize shifts in interconnections amid varied market conditions, spanning periods of tranquility to phases of heightened turbulence, and across multiple time intervals.

3. Data and methods

3.1. Data

In this research, our focus lies on examining the quantile frequency return interconnections that exist between commodity, stock, and currency markets and the macroeconomic indices within the US and the EU. We employed the monthly indices of all variables from April 1991 to July 2023, collecting them from various databases such as the Federal

Reserve Bank of St. Louis, Investing.com, and OECD Stat.

The datasets encompassed several variables, including the West Texas Intermediate (WTI) crude oil spot price, the Brent crude oil price, gold price, stock market indices, currency indices, industrial production indices, and the consumer price indices of the US and EU. We depict the prices and indices in Fig. 1.

Upon acquiring the raw data, we proceeded to compute the returns of these prices and indices by taking the first difference of their logarithms. Fig. 2 presents the returns of these prices and indices graphically.

Table 1 provides a comprehensive overview of the statistical characteristics of all the return series utilized in this research. It is essential to acknowledge that, owing to constraints related to data availability, the euro index data for the EU does not extend back to March 1991. Several noteworthy points emerge from the statistical descriptions of the return data:

1. The mean values across all the return series are positive, suggesting a prevailing upward trend in the data.
2. WTI and Brent returns exhibit the highest standard deviations, indicating that crude oil prices are more volatile compared to other prices and indices.
3. Industrial production, along with consumer price indices, displays the least volatility, implying that industrial activities in the US are relatively stable.
4. Except for gold, the USD index, and the EU's CPI, other returns are left-skewed.
5. The kurtosis values highlight that the industrial production indices of both the US and the EU are characterized by extremely high leptokurtic distributions.
6. The results of the unit root test reveal that all the return series demonstrate stationarity at the 1% significance level, apart from the CPI of the EU.

3.2. The quantile time-frequency connectedness approach

In our research, we adopt the quantile connectedness approach utilized by Chatziantoniou et al. (2021) to investigate the propagation mechanism across commodity, stock, currency markets, and macroeconomic variables at different quantile levels. This approach, known as the quantile time-frequency connectivity method, builds upon the connectedness framework initially proposed by Diebold and Yilmaz (2012); Diebold and Yılmaz (2014), Baruník and Křehlík (2018), and Ando et al. (2018). To clarify the methodology further, Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) laid the foundation for a framework based on multivariate vector autoregression in the time domain, incorporating generalized variance decomposition. Subsequently, the time-varying parameter vector autoregressive (TVP-VAR), as advanced by Antonakakis et al. (2020a), extended this framework by employing Kalman filter estimation within the conceptual framework proposed by Koop and Korobilis (2014). In contrast, Baruník and Křehlík (2018) introduced similar measures of connectedness but extended the analysis to encompass different frequency bands, allowing for a more detailed examination of how interconnections vary across different time frequency bands, such as the high-frequency band (short-term connectedness) and the low-frequency band (long-term connectedness). Meanwhile, Ando et al. (2018) introduced the quantile connectedness method, which focuses on measuring the relationships and dependencies among variables at different quantile levels, providing a nuanced perspective on extreme events and their impact on the interconnections among variables. The quantile connectedness approach could measure connectedness under different market situations, such as the median (normal market), extreme high quantile (bullish market), and extreme low quantile (bearish market), to assess whether there is strong coherence among the variables depending on the strength and direction of the shock (i.e., whether it is a high or low quantile). This methodology allows for a nuanced examination of how extreme events impact the interconnections among variables.

4. Empirical results

This section presents the quantile time-frequency time-varying connectedness analysis results between commodity, stock, and currency markets with the macroeconomic indicators of the US and the EU. Through these results, one can acknowledge the dynamic connectedness between these prices and indices and the macroeconomic indices in various time-frequency to distinguish whether the events had a relatively prolonged impact on the variables by discriminating the short-run (1–6 months)[1] and long-run (6–infinite months) connectedness, and in different quantiles to get a comprehensive understanding of the different quantile co-movements within different market situations, such as bullish or bearish, strong growth or weak market, as well as the normal market.

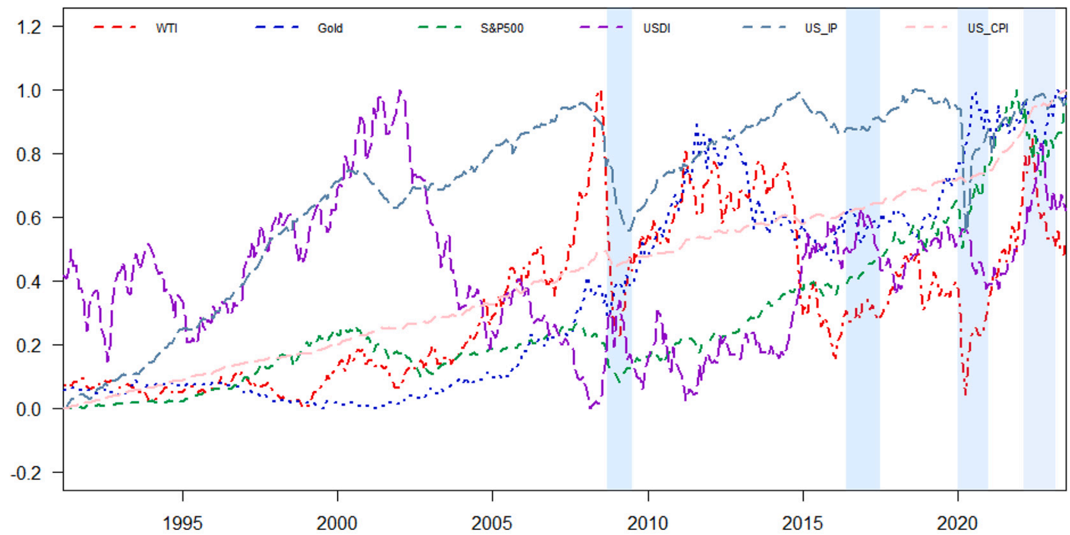
4.1. Time-frequency dynamic connectedness analysis results in the median quantile

4.1.1. Average median connectedness

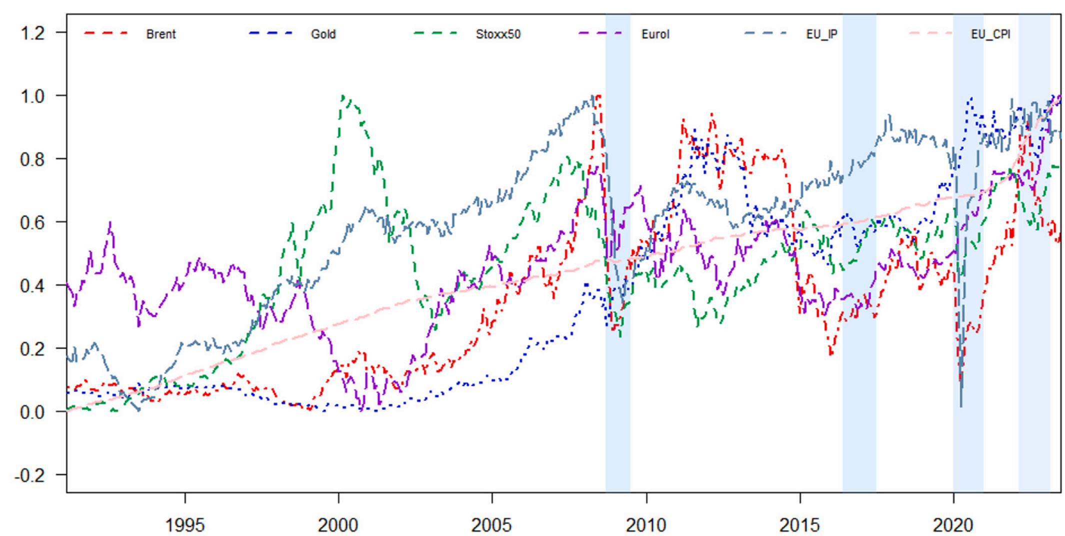
We present our results, starting with the average dynamic connectedness. The average median results cover the whole sample period and do not account for the dynamic effects of events that happened at specific moments in time. These findings are summarized in Table 2 (US) and Table 3 (EU), which include the time-domain values as well as the short-term and long-term connectedness values presented in parentheses.

Table 2 presents the US's average median dynamic connectedness report, revealing that the WTI has 67.47% own-variance share spillovers. Of this total, 59.47% are short-term own-variance spillovers, with the remaining 8.00% exhibiting long-term own-variance spillovers. Therefore, all other factors contribute to 32.53% of the WTI forecast error variance. In-depth analysis reveals that the prices of gold, S&P 500, USD index, US industrial production index, and US CPI have a respective impact of 2.51%, 5.58%, 6.02%, 4.57%, and 13.85% on WTI prices. These influences can be disintegrated into spillovers occurring in the short and long terms. The US CPI, which impacts the WTI the most, is responsible for 12.39% of short-term spillovers and 1.46% of long-term spillovers. In total, WTI influences the other variables by 41.23% and is influenced by other variables to the extent of 32.53%, indicating that it is a net transmitter of shocks with a net transmission of 8.70%. It is both a short-term and long-term transmitter of shocks, with the highest short-term net spillovers of 4.54% and the highest long-term net spillovers of 4.16%. The WTI stands out as the primary transmitter of shocks among all the analysis series, with the USD Index coming in second at 4.32%. The appearance of WTI as a major transmitter of shocks in the entire system is not unexpected, as price changes in WTI oil could result in ripple effects throughout the financial system, directly influencing inflation and production expenses, thus affecting the US CPI and Industrial Production Index (Filis and Chatziantoniou, 2014; Shang and Hamori, 2020; Yoshizaki and Hamori, 2013). Sharp oil price changes may trigger financial market risk aversion, which impacts assets such as gold and the S&P 500 (Beckmann et al., 2015; Degiannakis et al., 2018). Investors may seek safe-haven assets such as gold during periods of market turbulence and uncertainty, which contributes to the sensitivity of gold to oil shocks. Additionally, crude oil is usually priced in US dollars, implying that fluctuations in oil prices may lead to changes in the value of the USD. Also, the USD Index, which exhibits a strong

[1] Due to the use of monthly frequency data, our definition of "short-term" in this study differs from the conventional short-term classification employed in previous research. In accordance with the classification in Wei et al. (2023), we designate a 6-month period as the short-term horizon, which aligns with their classification of "medium-term."



(**US**) prices and indices

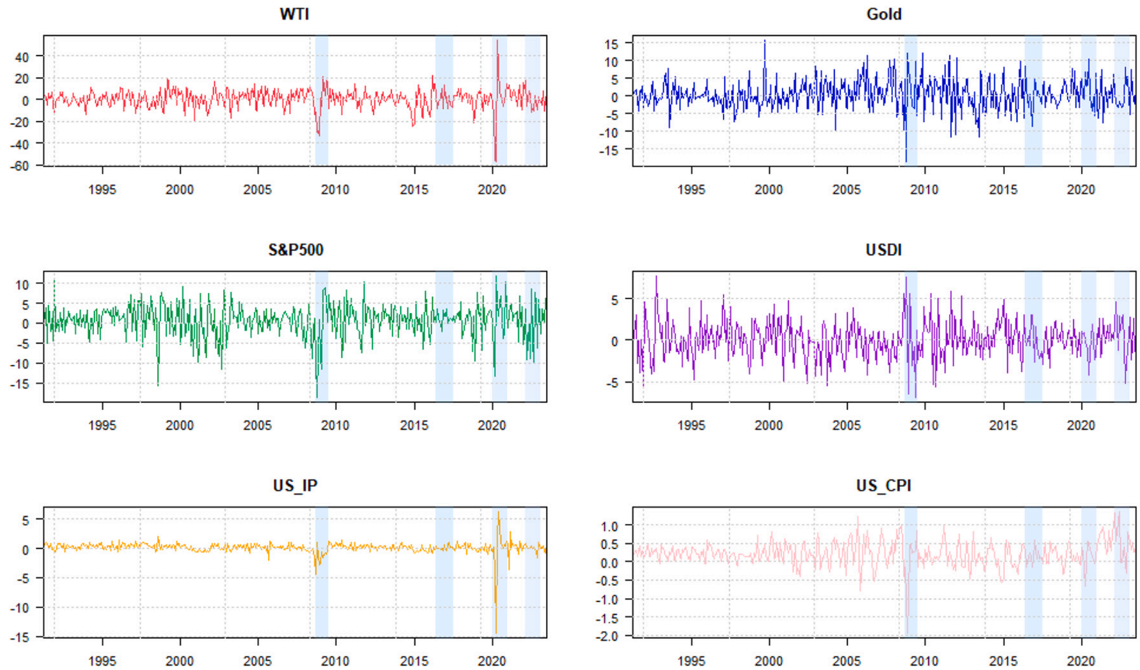


(**EU**) prices and indices

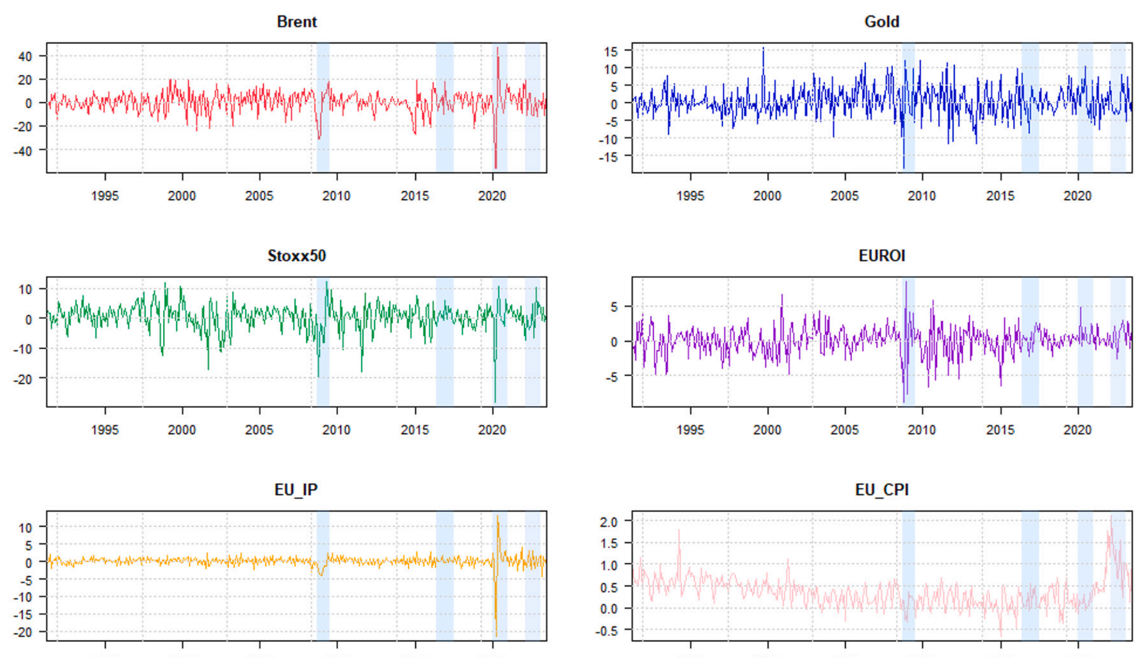
Fig. 1. Historical evolution of prices and indices for the US and EU.
Notes: The columns (**US**) include the WTI spot prices, gold prices, the S&P 500 index for the stock market, the US Dollar Index (USDI), the US Industrial Production Index (US_IP), and the US Consumer Prices Index (US_CPI). The columns (**EU**) include Brent spot prices, gold prices, the Stoxx 50 index for the stock market, the Euro Index (EUROI), the EU Industrial Production (EU_IP), and the EU Consumer Prices Index (EU_CPI). There are four baby blue areas, corresponding to the 2008 Global Financial Crisis, the 2016 Brexit Referendum, the 2020 COVID-19 pandemic, and the 2022 Russian invasion of Ukraine.

transmission of shocks (4.32%), plays a significant role as the primary short-term transmitter (2.87%). In contrast, the US CPI, characterized as the primary short-term net receiver of shocks (−5.00%) and long-term net receiver of shocks (−7.00%), serves as the predominant shock absorber (−12.00%). Finally, when considering the average TCI, it is noteworthy that short-term momentum (23.01%) is more than five times greater than long-term spillover (3.93%). These values represent average measures of connectedness, which may obscure time-varying and time-specific effects. Therefore, our analysis will proceed to examine dynamic connectedness plots to provide a more comprehensive understanding of these interconnected relationships.

Table 3 provides the average median dynamic connectedness report for the EU. It highlights that Brent accounts for 70.80% of its own-variance share spillovers. This share is further divided into 62.94% for short-term own-variance spillovers and 7.86% for long-term own-variance spillovers. Consequently, the remaining factors collectively contribute to 29.20% of the Brent forecast error variance. Specifically, various factors influence Brent prices, with Gold, Stoxx 50, Euro Index, EU Industrial Production Index, and EU CPI contributing 2.56%, 6.64%, 5.59%, 4.79%, and 9.62%, respectively. These influences are categorized into short-term and long-term spillovers. The EU CPI has the most significant impact on Brent, accounting for 8.77% of short-term spillovers and 0.86% of long-term spillovers. Conversely, Brent has the greatest influence on the EU CPI, at 17.89%. In total, Brent serves as a net transmitter of shocks, with a net transmission of 7.85%. It functions as both a short-term and long-term transmitter of shocks, contributing 4.77% to short-term net spillovers and 3.08% to long-term net spillovers. Among all the analysis series, the Euro Index emerges as the primary transmitter of shocks, notably impacting Gold (8.40%) and the Stoxx 50 (7.39%). Conversely, the EU CPI serves as the main short-term and long-term net receiver of shocks, with values of −6.14% and −5.06%, respectively, making it the predominant shock receiver



(**US**) returns of prices and indices



(**EU**) returns of prices and indices

Fig. 2. Historical evolution of the returns of prices and indices for the US and EU.
Notes: The columns (US) include the returns for the WTI spot prices, gold prices, the S&P 500 index for the stock market, the US dollar index (USDI), the industrial production index (US_IP), and the consumer prices index (US_CPI) of the US. The columns (EU) include the returns for Brent spot prices, gold prices, the Stoxx 50 index for the stock market, the Euro index (EUROI), the industrial production index (EU_IP), and the consumer prices index (EU_CPI) of the EU.

(−11.20%). When evaluating the average TCI, it's worth noting that short-term momentum (19.32%) greatly exceeds long-term spillover (3.28%).

In summary, the total connectedness for the median quantile is not that high (when comparing with 5% and 95% quantiles) at 26.94% with short-term at 23.01% and long-term at 3.93% for the US, and similar low extent at 22.60% with short-term at 19.32% and long-term at 3.28% for the EU, indicating that the connectedness in the US and EU are both contributed by the short-term spillover. We can see that the median TCI of the US is a little higher than that of the EU, indicating that during normal market and economic conditions, there are more risks and uncertainties in the US system than in the EU network. Comparing the

Table 1
Data statistical descriptions.

	WTI	Gold	S&P500	USDI	US_IP	US_CPI	Brent	Stoxx50	EUROI	EU_IP	EU_CPI
Mean	0.35	0.44	0.65	0.03	0.14	0.21	0.37	0.39	0.08	0.07	0.36
Std. dev.	9.53	4.35	4.30	2.28	1.08	0.34	9.81	4.59	2.07	1.85	0.35
Skewness	−0.88	0.07	−0.75	0.11	−6.23	−0.62	−0.99	−1.20	−0.34	−3.36	0.99
Kurtosis	11.39	4.04	4.49	3.52	90.43	7.69	9.23	7.92	5.01	58.31	6.20
J-B test	1189***	18***	72***	5.15*	126079***	381***	691***	484***	73***	50186***	228***
ERS	−6.64***	−8.68***	−7.41***	−8.08***	−7.89***	−8.52***	−8.89***	−5.56***	−4.71***	−6.43***	−1.72*

Notes: The J-B test stands for the Jarque-Bera test (Jarque and Bera, 1980), which is usually used for the normality test. The ERS test refers to the ERS unit root test (Elliott et al., 1996). USDI represents the US dollar index collected from Investing.com, while EUROI denotes the Euro index collected from Investing.com. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2
Average Median Dynamic Connectedness for the US.

	WTI	Gold	S&P500	USDI	US_IP	US_CPI	FROM
WTI	67.47	2.51	5.58	6.02	4.57	13.85	32.53
	(59.47, 8.00)	(2.31, 0.20)	(4.57, 1.01)	(4.79, 1.23)	(3.79, 0.78)	(12.39, 1.46)	(27.85, 4.68)
Gold	2.81	76.03	1.18	12.63	2.72	4.63	23.97
	(2.68, 0.14)	(71.95, 4.08)	(1.05, 0.13)	(12.24, 0.39)	(2.5, 0.21)	(4.48, 0.15)	(22.95, 1.02)
S&P500	6.30	2.48	76.85	8.33	4.85	1.19	23.15
	(5.07, 1.23)	(2.32, 0.16)	(68.84, 8.01)	(7.25, 1.08)	(4.02, 0.84)	(1.05, 0.14)	(19.69, 3.46)
USDI	4.33	11.62	8.59	70.33	3.17	1.96	29.67
	(3.69, 0.64)	(10.67, 0.94)	(7.86, 0.73)	(65.07, 5.26)	(2.87, 0.30)	(1.66, 0.30)	(26.74, 2.92)
US_IP	5.37	2.37	4.55	2.38	83.32	2.01	16.68
	(4.48, 0.89)	(1.99, 0.37)	(3.91, 0.64)	(2.22, 0.16)	(72.66, 10.66)	(1.81, 0.20)	(14.43, 2.25)
US_CPI	22.42	3.93	2.42	4.63	2.24	64.36	35.64
	(16.47, 5.94)	(3.06, 0.87)	(1.86, 0.57)	(3.11, 1.52)	(1.88, 0.36)	(51.81, 12.55)	(26.38, 9.25)
TO	41.23	22.91	22.33	33.98	17.55	23.64	
	(32.39, 8.84)	(20.35, 2.55)	(19.25, 3.08)	(29.61, 4.37)	(15.06, 2.49)	(21.38, 2.25)	**TCI**
Net	8.70	−1.06	−0.82	4.32	0.87	−12.00	**26.94**
	(4.54, 4.16)	(−2.60, 1.53)	(−0.44, −0.38)	(2.87, 1.45)	(0.64, 0.23)	(−5.00, −7.00)	**(23.01, 3.93)**

Notes: Average dynamic connectedness for returns based on a 100-month rolling-window QVAR. The values enclosed within the first and second sets of parentheses () signify the connectedness measures corresponding to short-term and long-term frequencies, respectively. The ij-th item of the upper-left 6 × 6 submatrix offers the ij-th pairwise directional connectedness, i.e., the percentage of the 12-month-ahead forecast error variance of variable i due to shocks from variable j. The rightmost ("FROM") column displays total directional connectedness, i.e., row sums ("from all others to i"). The bottom ("TO") row presents total directional connectedness, i.e., column sums ("to all others from j"). The difference in total directional connectivity is shown in the bottom-most ("NET") row (TO–FROM). Total connectedness (mean "from" connectedness, or equivalently, mean "to" connectedness) is the bottom-right element (in boldface). USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively.

average median connectedness results between the US and EU, the similarities are listed as follows:

- The highest pairwise connectedness is both found between the crude oil and CPI.
- The stock market indices are both impacted by the currency indices, followed by crude oil.
- The currency indices are both impacted by gold the most, and vice versa.
- Either industrial production or the CPI are both influenced by crude oil the most.
- The crude oil in either the US or the EU influences the stock market, industrial production index, and CPI more than the influences from gold.
- In terms of the Net median connectedness, both crude oil and currency indices in the US and the EU are characterized as the median quantile spillover transmitters, while both CPIs are characterized as the median quantile spillover receivers across various time horizons, encompassing overall, short-term, and long-term connectedness.
- Gold in both the US and the EU serves as the net receiver of median quantile spillovers in terms of overall and short-term connectedness; however, it is the net transmitter of spillovers in the context of long-term connectedness, indicating that gold mainly exerts prolonged influence in the long run.
- The industrial production indices in both the US and the EU exhibit the lowest TO median quantile connectedness, suggesting that they have the least impact within the network. In contrast, both crude oil prices in the US and the EU display the highest TO median quantile connectedness, confirming their most influential status in this interconnected system.

Subsequently, the differences are listed as follows:

- The WTI contributes more to the US_CPI than the Brent contributes to the EU_CPI, indicating that the US_CPI receives more spillover from crude oil returns than it does in the EU.
- The Brent contributes more to the EU industrial production than the WTI contributes to the US_IP, indicating that there is a possibility

Table 3
Average Median Dynamic Connectedness for the EU.

	Brent	Gold	Stoxx50	EUROI	EU_IP	EU_CPI	FROM
Brent	70.80	2.56	6.64	5.59	4.79	9.62	29.20
	(62.94, 7.86)	(2.29, 0.27)	(5.51, 1.13)	(4.55, 1.04)	(4.28, 0.51)	(8.77, 0.86)	(25.41, 3.79)
Gold	2.27	84.17	1.46	8.40	2.23	1.47	15.83
	(2.20, 0.07)	(79.62, 4.55)	(1.33, 0.12)	(8.04, 0.36)	(2.12, 0.11)	(1.33, 0.13)	(15.03, 0.80)
Stoxx50	6.33	1.62	79.12	7.39	3.37	2.16	20.88
	(5.59, 0.74)	(1.40, 0.22)	(68.78, 10.34)	(5.79, 1.60)	(3.12, 0.25)	(1.58, 0.58)	(17.49, 3.39)
EUROI	3.17	6.68	5.94	80.84	1.29	2.07	19.16
	(2.74, 0.43)	(6.10, 0.58)	(5.20, 0.75)	(74.36, 6.48)	(1.21, 0.08)	(1.72, 0.35)	(16.97, 2.18)
EU _IP	7.39	2.38	6.92	2.91	78.20	2.19	21.80
	(6.63, 0.76)	(2.3, 0.08)	(5.58, 1.34)	(2.71, 0.21)	(73.88, 4.33)	(2.13, 0.06)	(19.34, 2.45)
EU_CPI	17.89	2.01	2.18	4.51	2.13	71.28	28.72
	(13.01, 4.87)	(1.73, 0.28)	(1.64, 0.53)	(3.38, 1.13)	(1.92, 0.22)	(58.18, 13.10)	(21.68, 7.04)
TO	37.05	15.25	23.14	28.81	13.81	17.51	
	(30.18, 6.88)	(13.83, 1.42)	(19.27, 3.88)	(24.47, 4.34)	(12.65, 1.16)	(15.54, 1.98)	**TCI**
Net	7.85	–0.58	2.27	9.65	–7.99	–11.20	**22.60**
	(4.77, 3.08)	(–1.20, 0.62)	(1.78, 0.49)	(7.50, 2.16)	(–6.70, –1.29)	(–6.14, –5.06)	**(19.32, 3.28)**

Notes: Average dynamic connectedness for returns based on a 100-month rolling-window QVAR. The values enclosed within the first and second sets of parentheses () signify the connectedness measures corresponding to short-term and long-term frequencies, respectively. The ij-th item of the upper-left 6×6 submatrix offers the ij-th pairwise directional connectedness, i.e., the percentage of the 12-month-ahead forecast error variance of variable i due to shocks from variable j. The rightmost ("FROM") column displays total directional connectedness, i.e., row sums ("from all others to i"). The bottom ("TO") row presents total directional connectedness, i.e., column sums ("to all others from j"). The difference in total directional connectivity is shown in the bottom-most ("NET") row (TO–FROM). Total connectedness (mean "from" connectedness, or equivalently, mean "to" connectedness) is the bottom-right element (in boldface). EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively.

that industrial production in the EU is more reliant on crude oil and more sensitive to changes in crude oil prices.

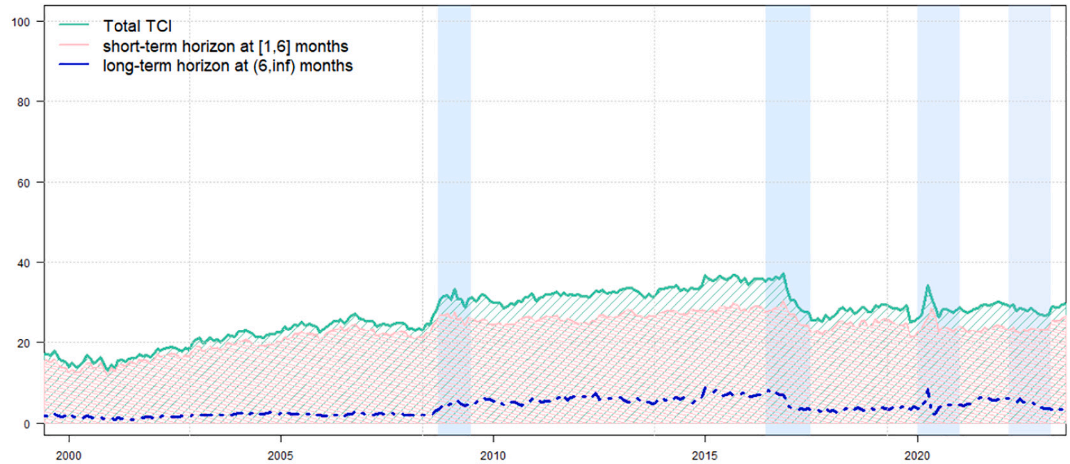
- The USD index is highly influenced by the gold ($\widetilde{C}^{H}_{USDI\leftarrow Gold} = 11.62\%$), almost two times more than the pairwise connectedness from the gold to the Euro index ($\widetilde{C}^{H}_{EUROI\leftarrow Gold} = 6.68\%$), implying that the two conventional risk hedges (USD and gold) have a higher connection with gold than the ones between Euro and gold.
- In terms of the Net median connectedness, in the US, the industrial production index acts as the transmitter of median quantile spillovers, while the stock market index serves as the receiver of spillovers across the overall, short-term, and long-term timeframes. In contrast, in the EU, the roles of these two indices are reversed. This suggests that the industrial production and stock market indices between the US and the EU generally exhibit opposite responses to shocks originating from other variables.
- Concerning the FROM median connectedness, the CPI in the US received the largest number of spillovers within the interconnected system, suggesting that the US CPI is more sensitive to system risks or uncertainties within the network. On the other hand, the Brent crude oil price in the EU received the highest spillovers among the variables.

4.1.2. Median dynamic total connectedness

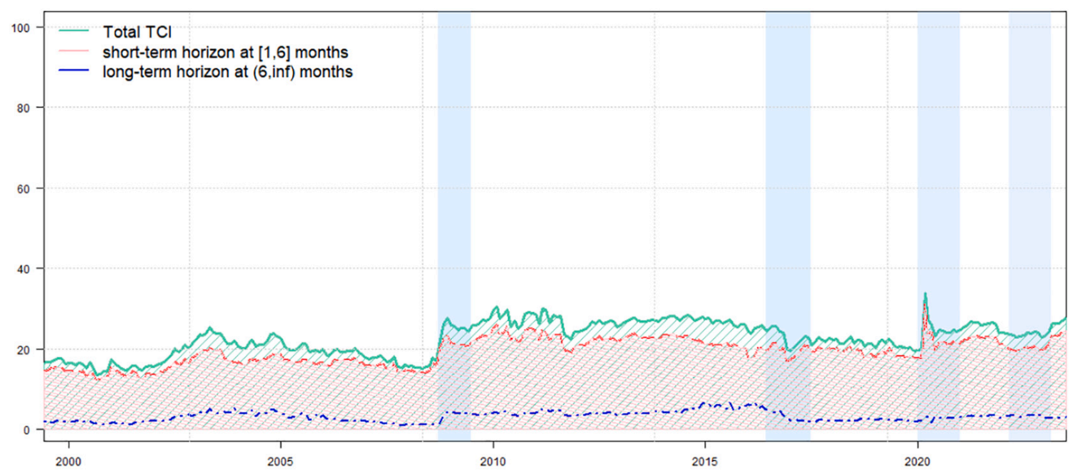
Fig. 3 illustrates the Total Return Connectedness Index (TCI), where the prediction horizon for the underlying variance decomposition is configured at 12 periods, a setup aligned with Antonakakis et al. (2020a). Taking a comprehensive view of the total connectedness plot within Fig. 3 reveals several noteworthy patterns.

Here, we will now delve into the interpretation of the short-term, long-term, and total dynamic connectedness. Overall, we see total spillovers start increasing substantially from 2008 GFC within the US' system until 2016. After 2016, the long-term, short-term, and overall TCIs experienced a decline and stabilized at approximately 30% until the conclusion of 2019. A subsequent upsurge is observed at the beginning of 2020, corresponding to COVID-19, which only caused a transitory risk upswing within the US system. Afterward, we see that all three TCIs return to the previous level of around 30% in the next two years until the 2023 US banking crisis (three small- and mid-size banks broke) decouples the short-term and long-term spillover. The short-term and overall TCI increased, whereas the long-term TCI decreased, indicating this banking crisis impacts the total connectedness index mainly in the short run.

Concerning the EU short-term, long-term, and overall TCI results, the overall and short-term TCI did not show a continuing rise like the US but rather frequent changes during 2011–2012, which corresponds to the Greek debt crisis, afterwards staying steady during 2013–2016. Another observation is that the short-term TCI shows significant volatility, whereas the long-term TCI shows a relatively long swing and is steady. Thus, it's crucial to examine short-term and long-term dynamics separately. Focusing solely on the total TCI might obscure the sources of these fluctuations. In 2020, we can observe a substantial surge during the outbreak of the COVID-19 pandemic, indicating that the pandemic only caused a transitory risk upswing within the EU system. The frequency analysis emphasizes that the rise in the total TCI is primarily attributed to short-term dynamics rather than long-term dynamics. It's worth noting that a significant change in long-term TCI typically signifies a profound alteration in the overall market structure, as discussed in Chatziantoniou et al. (2021). This analysis underscores the effectiveness of the QVAR approach, particularly when dealing with anomalies, and underscores the importance of decomposing the total TCI into short-term and long-term components to enhance our understanding of the fluctuations in total TCI. Additionally, the insight into short-term and long-term TCI dynamics demonstrates that the overall TCI has been primarily influenced by short-term dynamics, which are more volatile than long-term dynamics.



(US)



(EU)

Fig. 3. Median Quantile Total Spillovers for the US and the EU.
Notes: Results are based on the quantile time-frequency connectedness. Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.

In summary, the median quantile overall TCIs in both the US and the EU are predominantly influenced by short-term TCI (Ding et al., 2021; Tiwari et al., 2022), indicating that risks or uncertainties in the system are processed rapidly. Furthermore, there are several notable fluctuations in the median time-varying frequency TCI plots:

1. The first significant jump occurred in 2008–2009, coinciding with the 2008 Global Financial Crisis.
2. A notable decline was observed in both the US and EU. The drop in the EU was linked to the 2016 Brexit referendum, while the decline in the US was associated with the 2016 US presidential election.
3. Another surge is observed in the TCI plots during the 2020 COVID-19 pandemic.
4. The TCI plots show an ascending trend at the beginning of 2023.

These results highlight that while the TCIs in the median quantile may be relatively lower, they provide valuable insights into how risks evolve over time and across different frequencies, particularly during global crises.

4.1.3. *Median dynamic net total connectedness*

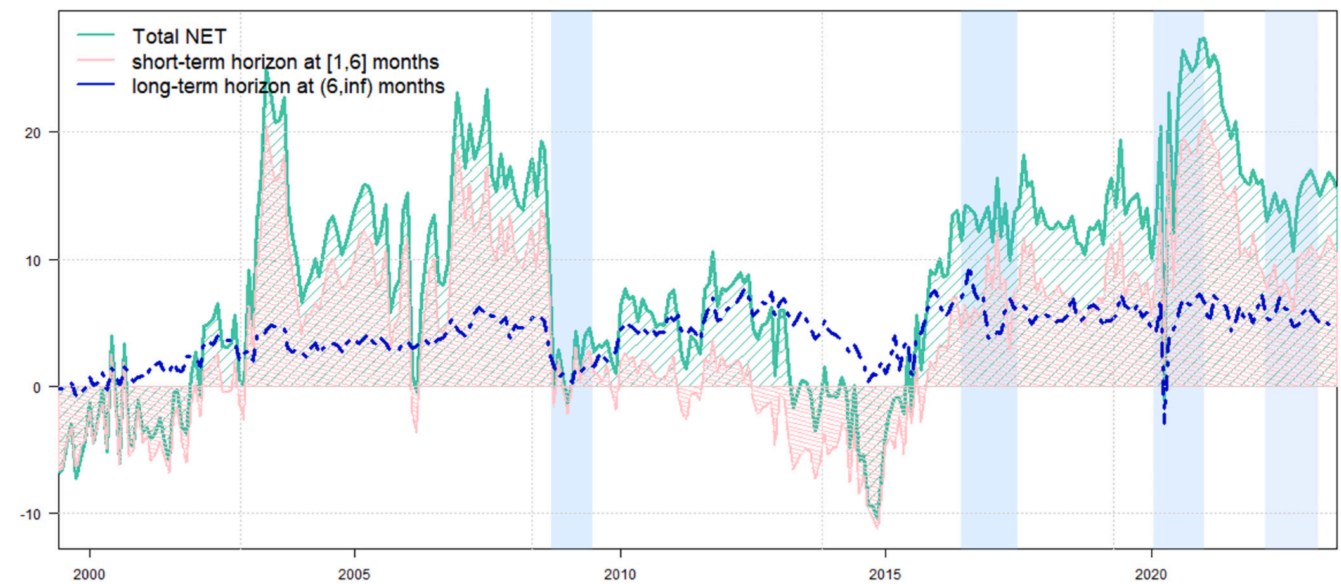
The results related to the net transmission power of each series hold significant importance in the field of connectedness research, here, we focus on the median quantile dynamic net connectedness, which depicts the spillover transmission for the normal market or economy condition. Furthermore, breaking down the net total directional connectedness into short-term and long-term dynamics reveals that the long-term dynamics exclusively determine whether each of the four series acts as a net transmitter or receiver of shocks. In contrast, the short-term net transmission mechanism offers a much clearer perspective.

These results are presented in Fig. 4 (US) and Fig. 5 (EU). It's important to note that positive values indicate that these variables are net transmitters of shocks into the system, whereas negative values signify that they are net receivers of shocks. The dynamic analysis reveals that the roles of variables in the network may change over time. Additionally, the green-shaded area corresponds to total connectedness, while the pink-shaded area and blue-dashed line represent the breakdown of the analysis into short- and long-run connectedness results, respectively.

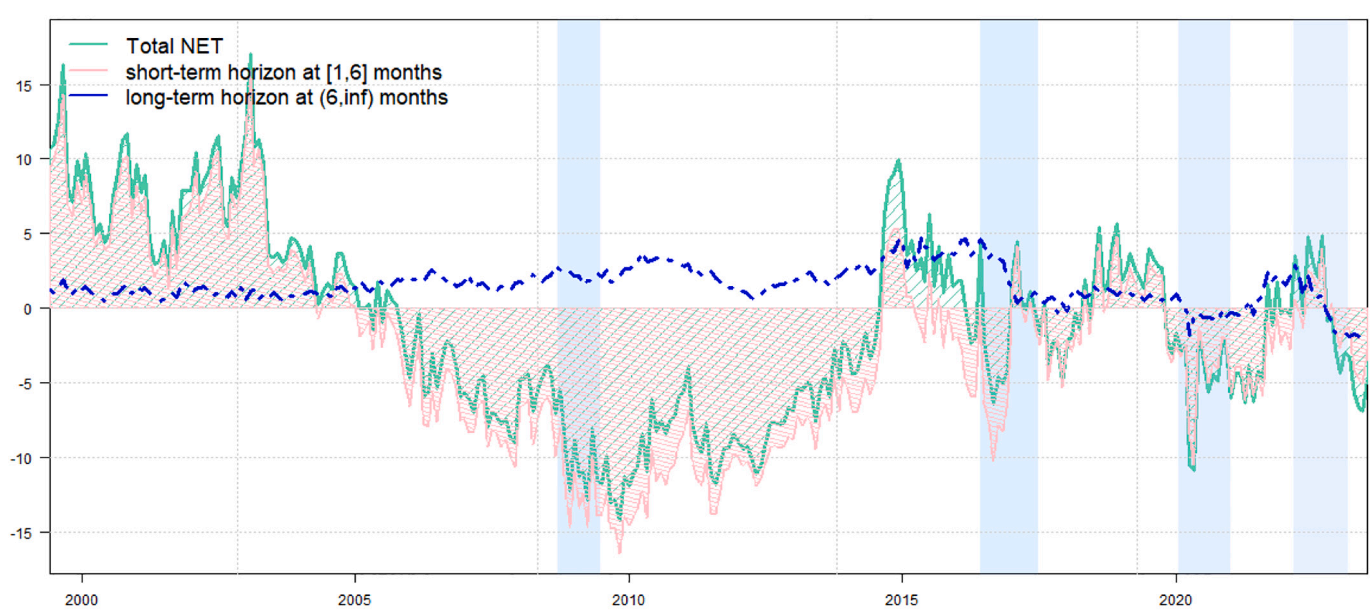
In the context of WTI, our analysis reveals that within the median quantile, the long-term dynamics consistently position it as a net transmitter of shocks across the observation period. However, prior to 2008 and after 2015, it assumed the role of a net receiver of short-term spillover shocks. This long-term transmitter characteristic offers valuable insights for financial advisors and investors due to its relative stability.

Gold exhibits a predominantly long-term net transmitter role, except during the 2020 COVID-19 pandemic outbreak and the 2022 Russian invasion of Ukraine, when it transitions into a long-term receiver. Additionally, for most of the observed periods, gold operates as a short-term spillover receiver. This spans various intervals, notably from 2005 to 2015, during the 2016 US presidential election, the 2020 COVID-19 pandemic, and the 2022 Russian invasion of Ukraine.

With respect to the S&P 500, the period following the 2008 GFC was characterized by a substantial decline in the US stock market, implying that the stock market in the US primarily acted as a shock recipient rather than a shock transmitter in both the short-run and long-run (Osah and Mollick, 2023; Jiang et al., 2020), and this crisis greatly weakened its influence in the system. Furthermore, the stock market's significant

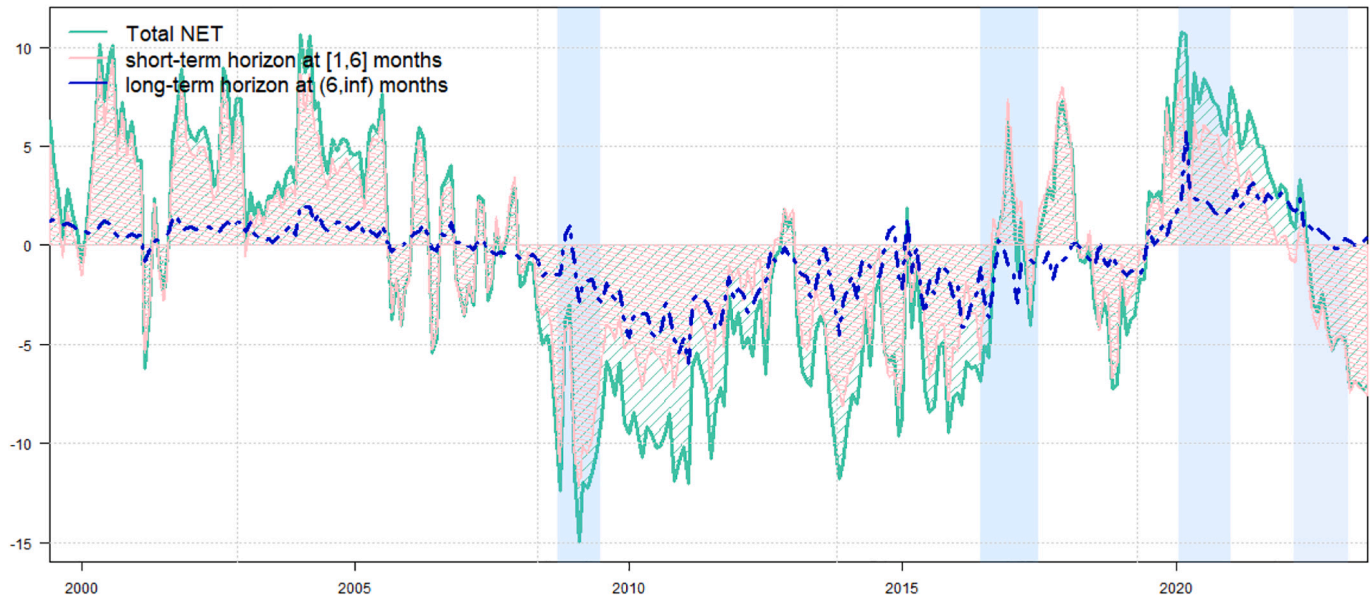


(WTI)

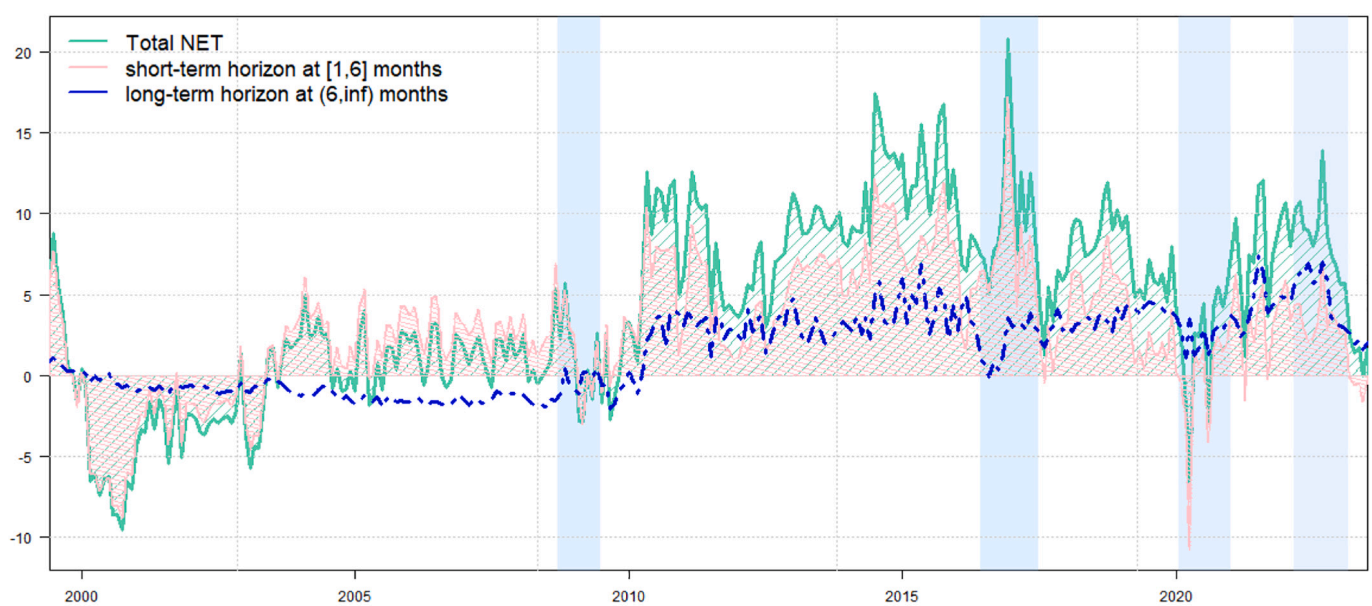


(GOLD)

Fig. 4. Median Quantile Net Spillovers for the US.
Notes: Results are based on the quantile time-frequency connectedness. USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively.

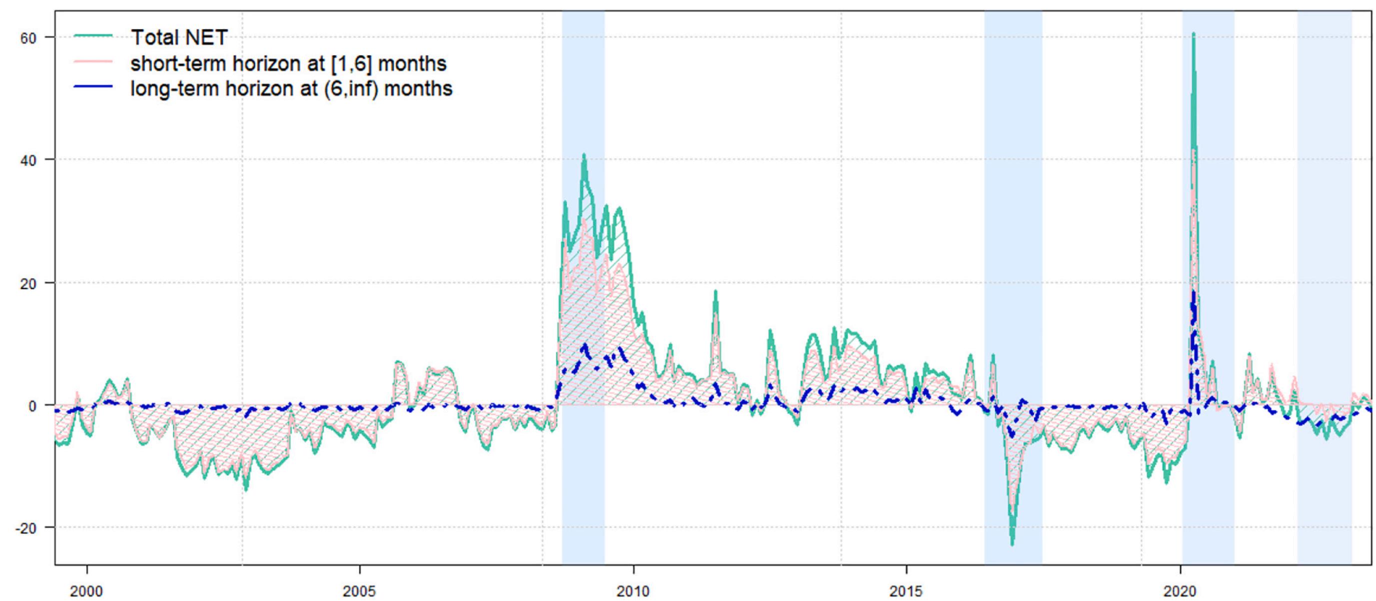


(**S&P500**)

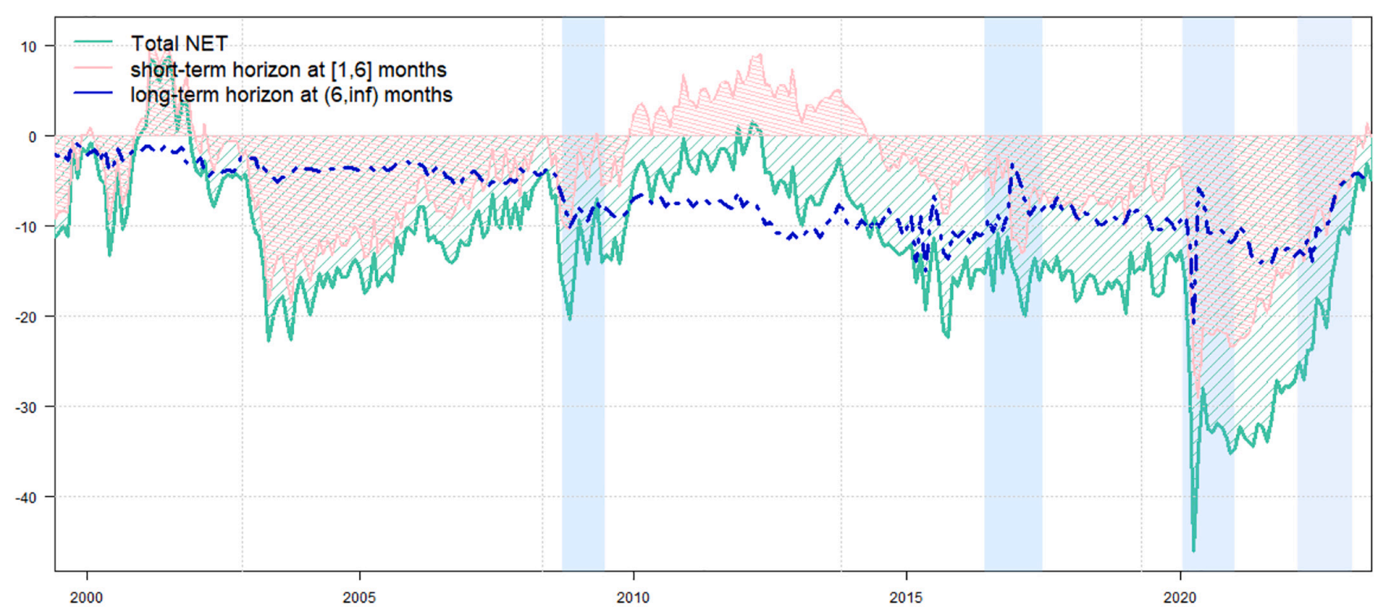


(**USDI**)

Fig. 4. (*continued*).



(US_IP)



(US_CPI)

Fig. 4. (*continued*).

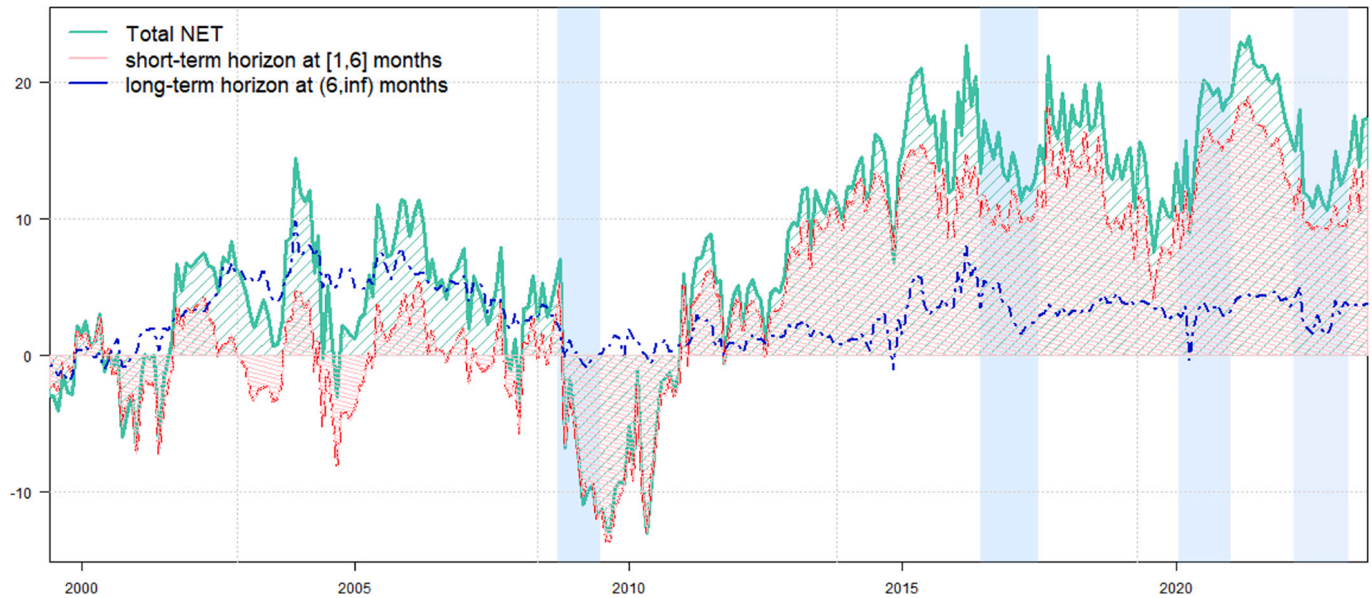
drop in 2011 corresponds to the 2011 US Debt Ceiling Crisis, demonstrating the profound impact of this event on the US stock market. However, this scenario underwent a transformation after the outbreak of the 2020 COVID-19 pandemic, with the S&P 500 assuming the role of a net transmitter of shocks, marking a historical peak in both short-term and long-term contexts. Nevertheless, it reverted to being a net short-term shock receiver, and both short-term and long-term spillovers diminished following the 2022 Russian-Ukrainian conflict.

Following the GFC in 2008, the USD index consistently assumed the role of an overall, short-term, and long-term net transmitter of shocks, with reaching its zenith during the 2016 US presidential election. However, this short-term net spillover role briefly shifted to receiver during the 2020 COVID-19 pandemic and at the onset of the 2023 US banking crisis. This pattern signifies that after the 2008 GFC, the USD index continuously held a prominent position as a contributor to risks and shocks within the system, particularly in the long-term frequency domain.

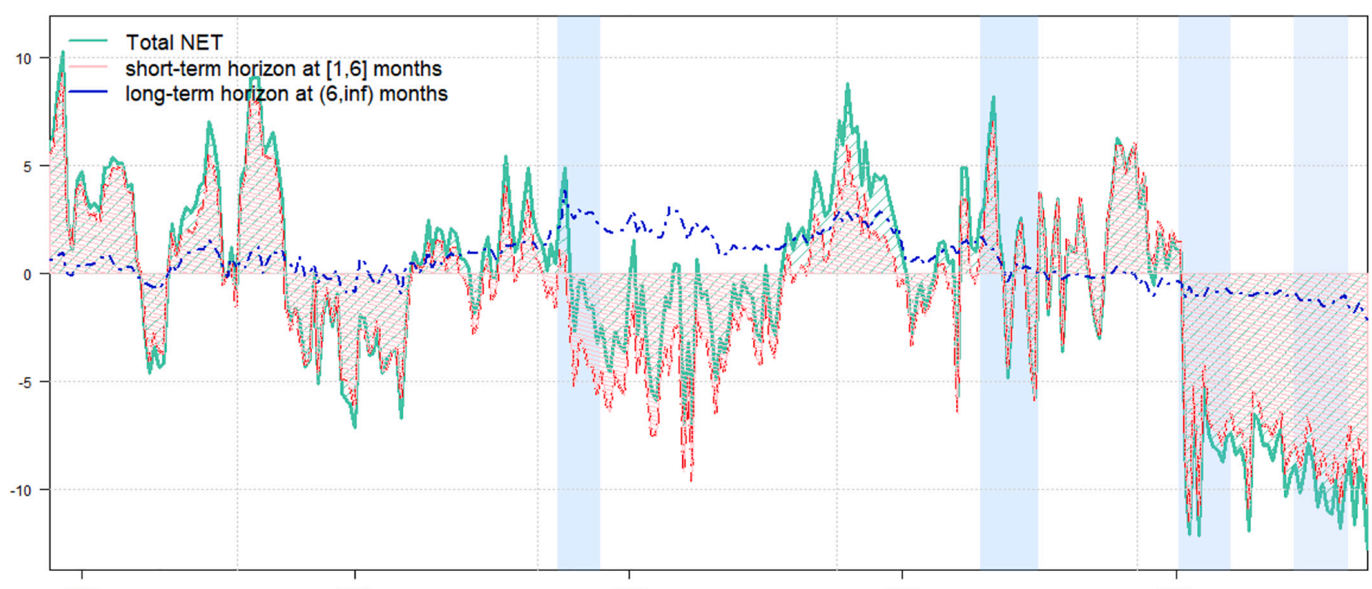
In terms of the US industrial production index, its role varies consistently over time, with no clear positioning; nevertheless, two significant spikes are discernible. The first corresponds to the 2008 GFC, while the second relates to the 2020 COVID-19 pandemic. It is notable that the impact of the former is more persistent than the latter, extending for nearly three years and exerting a sustained effect on both short-term and long-term spillover propagation. On the other hand, the substantial drop in 2016 is believed to be a result of the 2016 US presidential election.

Regarding the US CPI, it predominantly functions as a recipient of net spillovers across the overall, short-term, and long-term throughout most of the entire sample period. There are certain exceptions to this pattern, notably during 2010–2014, when it transitions to a short-term transmitter role.

In the context of Brent crude oil, it is noteworthy that, under median quantile conditions, an overarching long-term trend suggests its role as a net transmitter of shocks, with a shift toward being a net receiver of short-term spillover shocks, particularly after 2011. Additionally, the extent of overall, short-term, and long-term net total connectedness of Brent exhibited a notable increase after 2013, highlighting its influential capacity to transmit spillover effects within the EU system. There are three distinct periods of decline that warrant attention. The first corresponds to the 2016 Brexit referendum, the second occurs at the end of

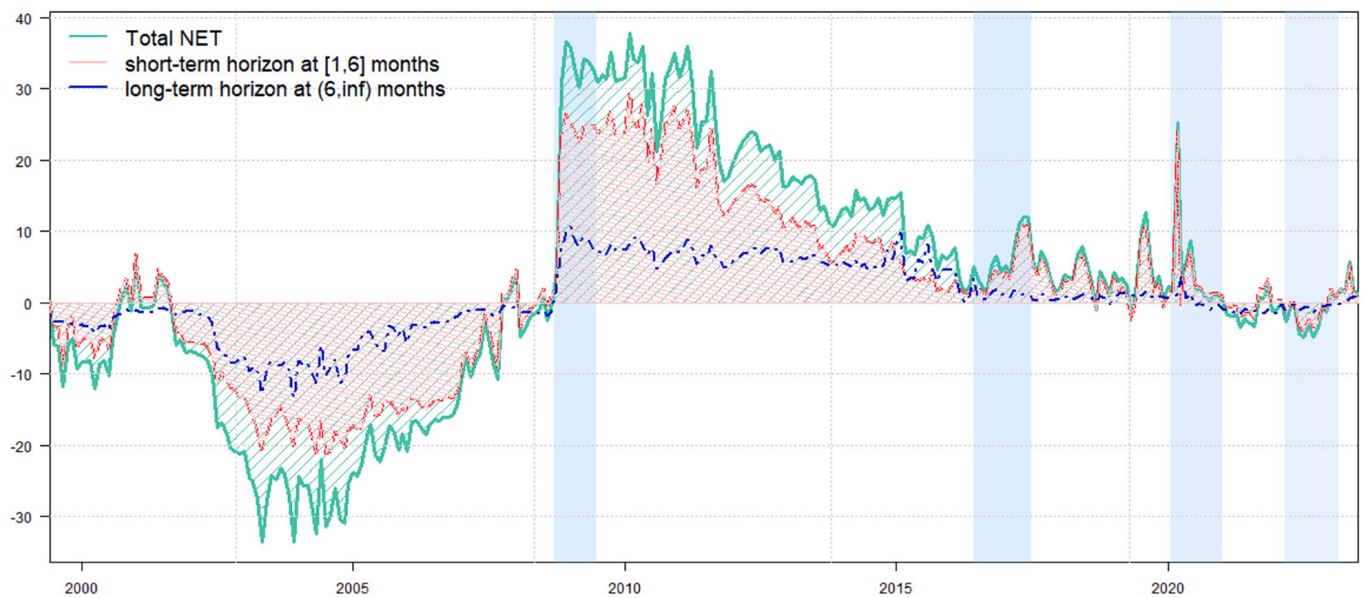


(Brent)

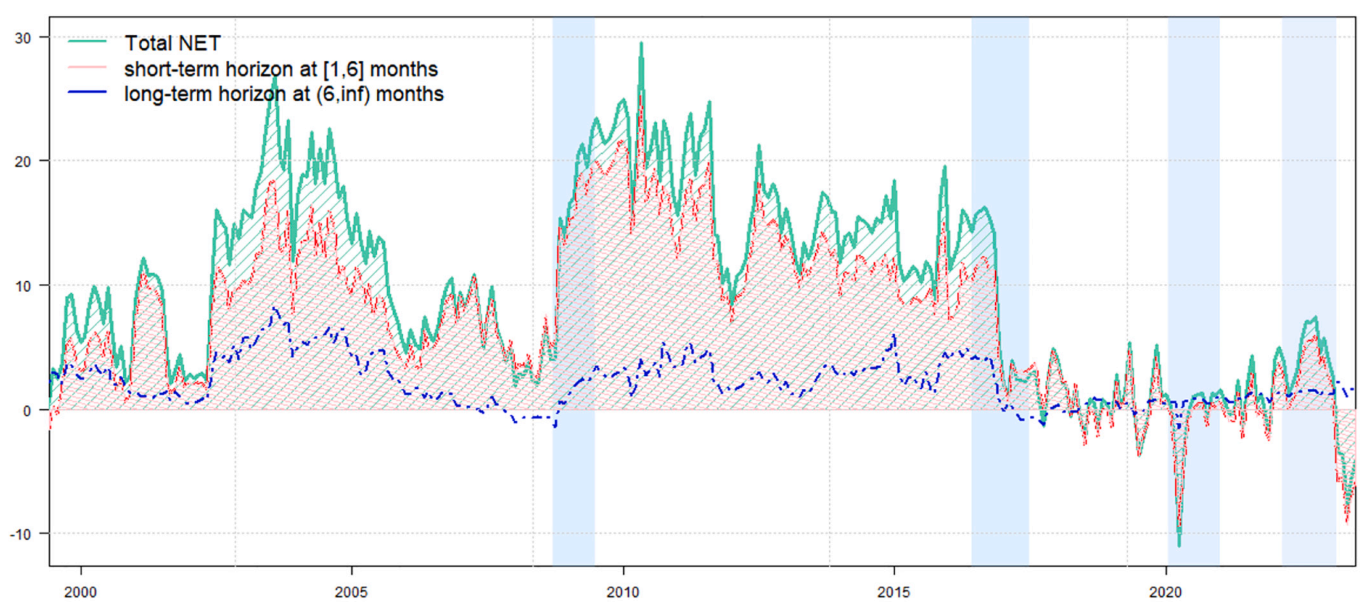


(GOLD)

Fig. 5. Net Spillovers for the EU.
Notes: EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively.

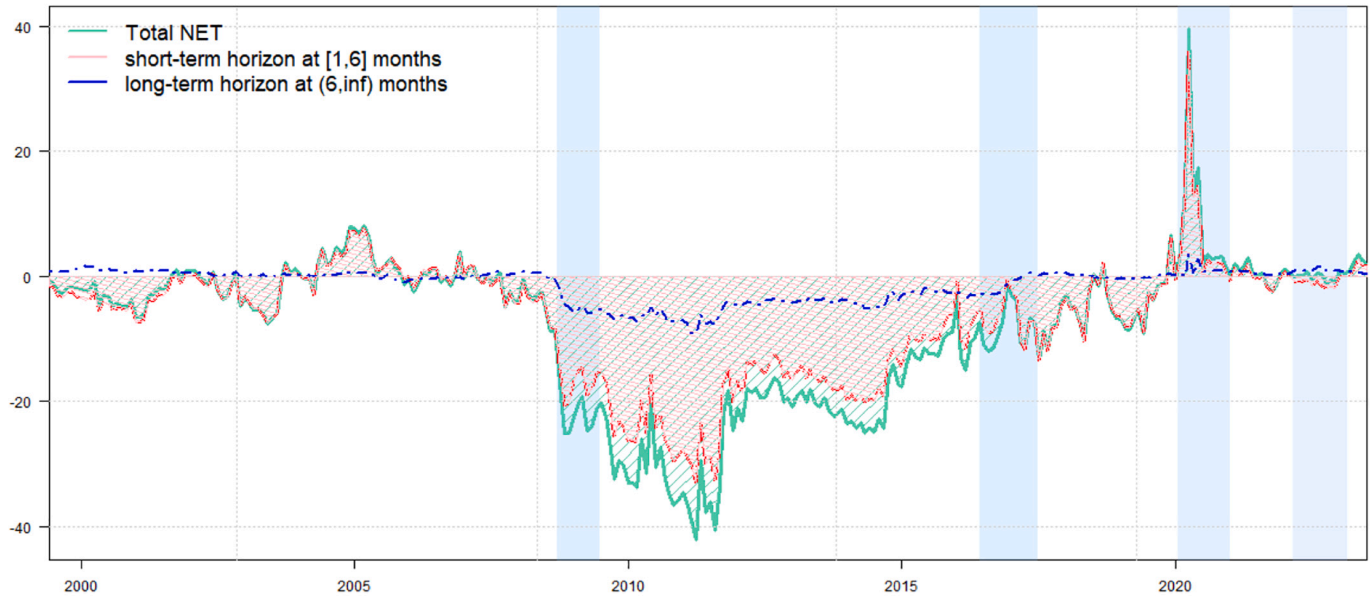


(Stoxx50)

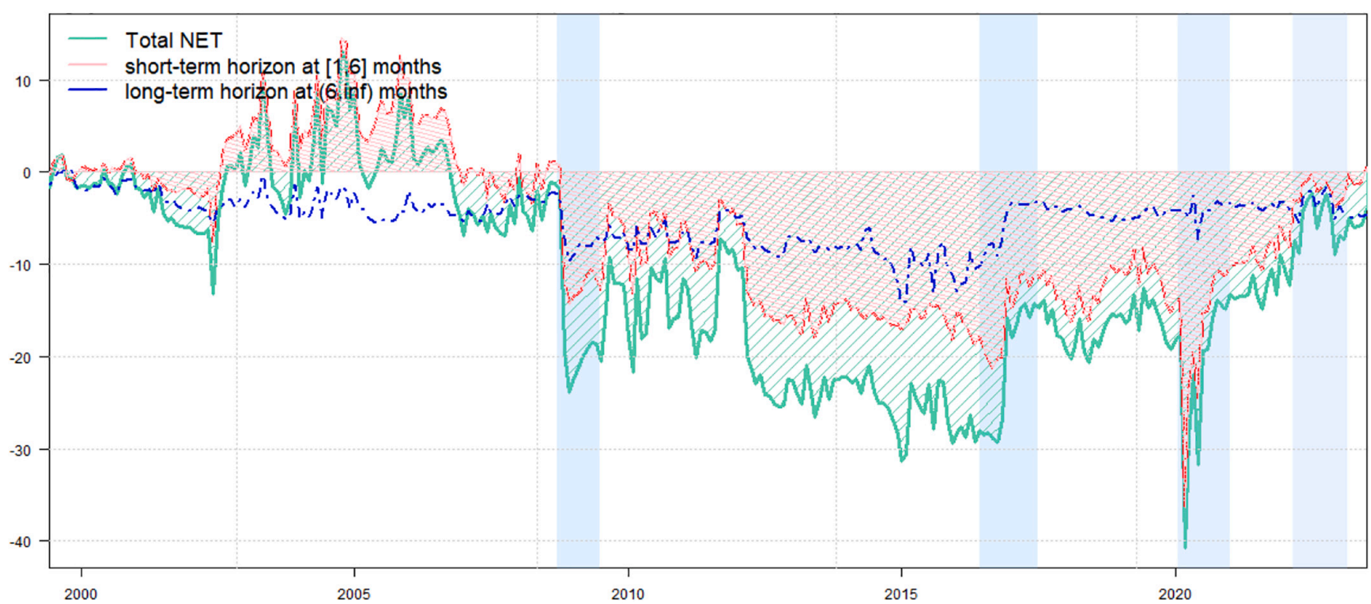


(EUROI)

Fig. 5. (*continued*).



(EU_IP)



(EU_CPI)

Fig. 5. (*continued*).

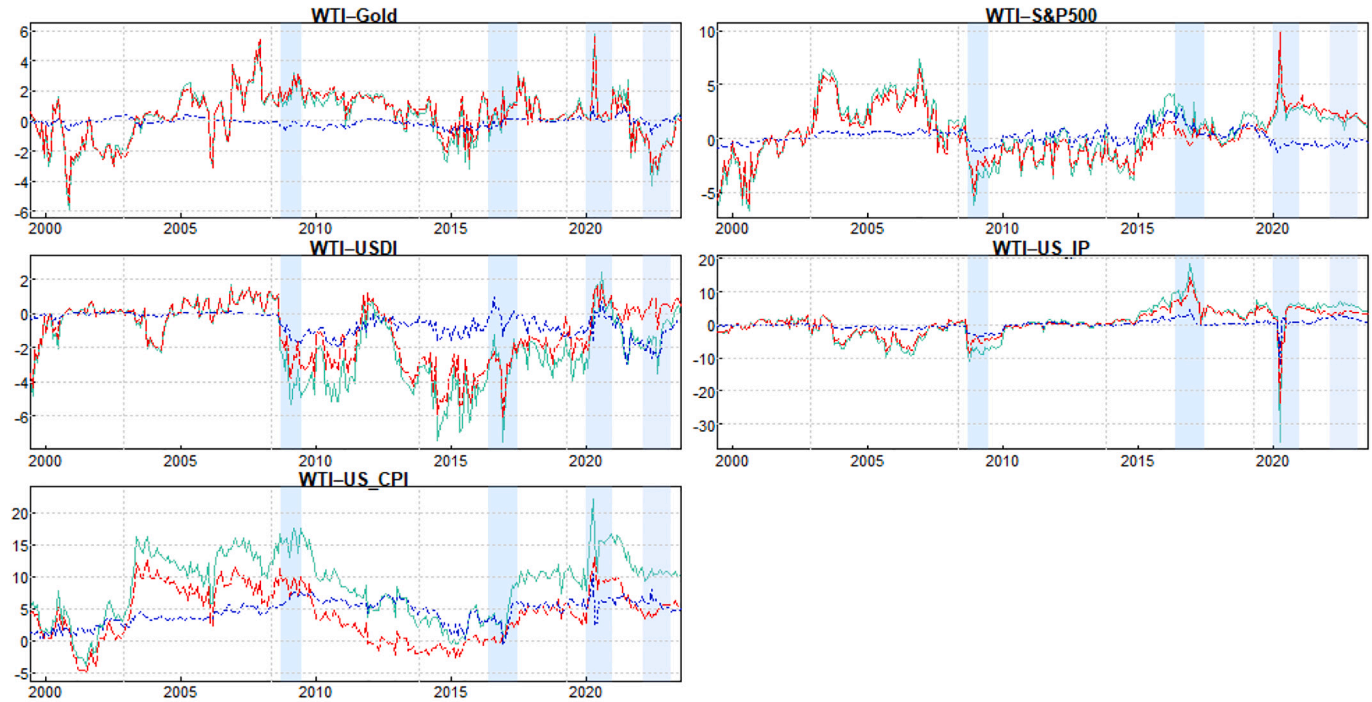
2019, and the third occurs during the 2022 Russian invasion of Ukraine. These events resulted in significant reductions in connectedness. However, it's worth noting that these declines, although noteworthy, do not mirror the extent of the decline observed during the 2008 Global Financial Crisis (GFC), which led to a reversal in the role of Brent from a short-term spillover transmitter to a receiver, a scenario that was also witnessed during the 2010 European Sovereign Debt Crisis.

In our analysis of both the US and EU systems, gold has been a subject of consideration. However, it's important to note that gold displays varying patterns of net total connectedness over time and across different frequency bands within these two systems. Gold acts as a long-term net spillover transmitter during the period from 2005 to 2016, and after 2016, it shifts to being a long-term net spillover receiver until the end of the observation sample. The role of gold varies consistently over time, with no clear positioning. However, three significant clustered plummets are discernible. The first corresponds to the period of 2004–2005, when ten new countries joined the EU, and several of them also adopted the euro as their official currency, thereby affecting gold. The second cluster begins with the 2008 GFC and extends until 2013, corresponding to the Greek debt crisis. The third cluster relates to the

2020 COVID-19 pandemic. Notably, the impact of the 2020 COVID-19 pandemic is more persistent, extending for nearly three years and exerting a sustained effect on both short-term and long-term spillover propagation. It seems that the 2020 COVID-19 has fundamentally changed the role of gold in the EU system.

In the context of the Stoxx 50, the post-2008 GFC period witnessed a notable surge in the EU stock market, indicative of its role as a primary shock transmitter in both short-term and long-term contexts. This crisis significantly amplified its influence within the system. However, a shift in this dynamic occurred following the onset of the 2020 COVID-19 pandemic. During 2021 and 2022, the Stoxx 50 temporarily assumed the role of a short-term net receiver of shocks. Nevertheless, it reverted to being a net spillover transmitter in both short-term and long-term contexts after 2023.

Concerning the Euro index, it functioned as the overall, short-term, and long-term spillover transmitter before 2016. However, after 2016,



(WTI)

(Gold)

Fig. 6. Net Pairwise Spillovers for the US.
Notes: USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively. Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.

its role exhibited frequent variations over time without a clear, consistent positioning. Two periods of substantial upswings in net total connectedness across different frequency bands are discernible. The first occurred around 2004, and the second extended from 2008 until 2016. Furthermore, the Euro index temporarily assumed the role of a short-term spillover receiver at the beginning of 2020 and again in 2023, with a significant decline in connectedness.

In the context of the EU industrial production index, it primarily assumes the role of a net total connectedness receiver in the short term after the 2008 GFC. In the long term, its influence is not as pronounced as it was before 2016. A noticeable surge in its role can be seen during the 2020 COVID-19 pandemic, followed by consistent variations in its role over time without a clearly defined positioning.

As for the EU CPI, there's a marked shift observed after the 2008 GFC, with the EU CPI predominantly acting as a recipient of net spillovers across the overall, short-term, and long-term frequencies. Notably, a significant drop in its role can be observed during the 2020 COVID-19 pandemic, reaching its historically lowest extent.

In summary, despite the time-varying nature of net total connectedness results across different time-frequency intervals, certain overarching trends can be delineated. Both WTI and Brent crude oils have predominantly served as spillover transmitters for both short-term and long-term spillovers since the onset of the global financial crisis in 2008. Gold, in the US context, has exhibited a role as a short-term spillover receiver and a long-term spillover transmitter, with a shift in its long-term positioning in the EU system post-2016. The US stock market has experienced fluctuations between roles as a receiver and a transmitter, while the EU stock market has assumed a predominantly transmitting role with a diminishing trend. The USD index and the Euro index have consistently functioned as spillover transmitters since 2008, although the Euro index's role has demonstrated variability over time, lacking a clear positioning post-2016 (Shang and Hamori, 2021). Regarding industrial production, the US has primarily transmitted spillovers during 2008–2016, while the EU has primarily received spillovers during 2008–2019. Both the US and EU CPI indices have predominantly operated as spillover receivers.

4.1.4. Median dynamic net pairwise directional connectedness

In the subsequent section, we will embark on a detailed exploration of the dynamics of net pairwise directional connectedness (NPDC). This analysis aims to provide deeper insights into how commodity, stock, and currency markets, as well as macroeconomic indicators, interact within the US and EU. The study places particular emphasis on the concept of pairwise connectedness as a valuable metric for understanding how the impact of return shocks is transmitted across various variables. However, due to the complexity of both the US and EU systems, each comprising six variables, comprehensively interpreting the net pairwise connectedness across the entire dataset is a formidable undertaking. Consequently, we will narrow our focus to examine the pairwise connectedness related to crude oil and gold. To enhance our understanding of these interactions, we will employ a network topology approach.

The dynamic net pairwise spillover outcomes and the net pairwise spillover network findings for the US are visually presented in Fig. 6 and Fig. 7, respectively. Similar to the directional connectedness results, positive values signify entities that transmit shocks, whereas negative values indicate those that receive shocks. To elaborate, the green lines represent the comprehensive net pairwise directional connectedness, while the red lines depict the short-term connectedness dynamics, and the blue lines depict the longer-term connectedness dynamics. The analysis of pairwise connectedness provides the opportunity to scrutinize interactions between pairs of variables and trace their evolution over time.

When it comes to NPDCs concerning the WTI in the US network, we clearly see that there are significant shifts before and after the 2008 global financial crisis. For most parts, t the long-term net pairwise connectedness consistently shows that WTI dominates over the US CPI in the long run (Filis and Chatziantoniou, 2014). Moreover, we see that after 2008, WTI was constantly dominated by USD. Additionally, WTI was a short-term net receiver for the S&P 500 during the period of 2008–2015; however, its role transitioned to a short-term transmitter after the 2020 COVID-19 pandemic. Regarding the relations between WTI and US industrial production, we can observe that after 2015, WTI's transmitter role started to strengthen due to the rapid expansion of crude oil pipelines during 2010–2014 and the development of oil extraction technology.

Next, we focus on the linkage concerning gold. For most parts, gold acts as the short-term spillover receiver to WTI (Ding et al., 2021); nevertheless, gold tends to shift its role to short-term transmitter of shocks when there is geopolitical risk aversion. The net connectedness of gold experiences multiple sign changes. To elaborate, we observe that gold primarily dominates in the short term during the periods of 2001–2003, the year 2006, 2014–2015, and after 2022. Notably, we find that gold plays as the short-term spillover receiver from the other three indices (USDI, US_IP, and US_CPI) for most of the periods after 2008, while it acts as the transmitter to the S&P 500 during the period of

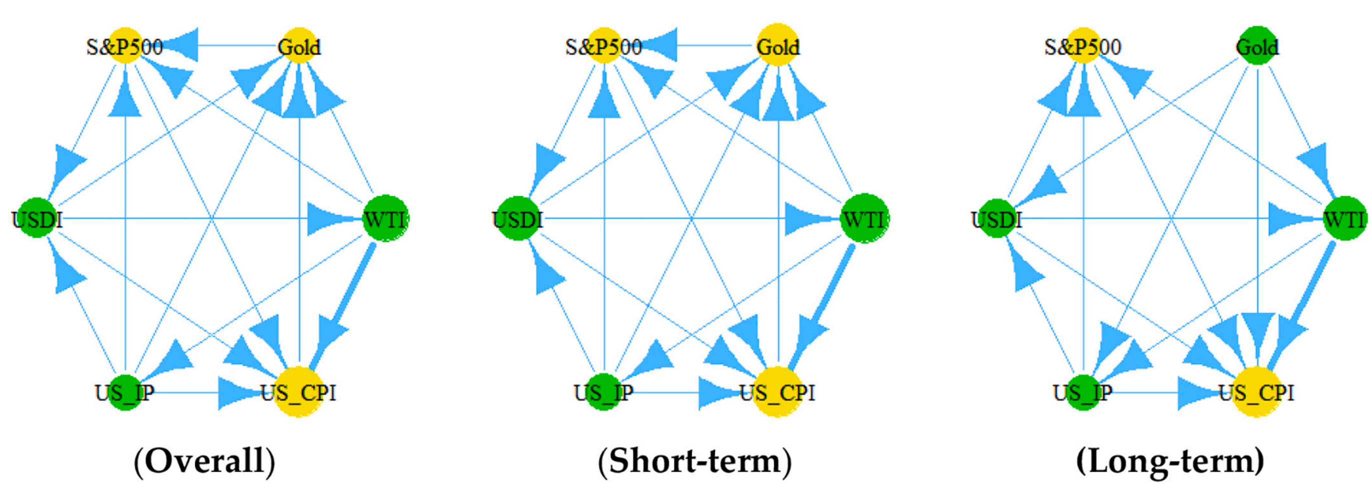
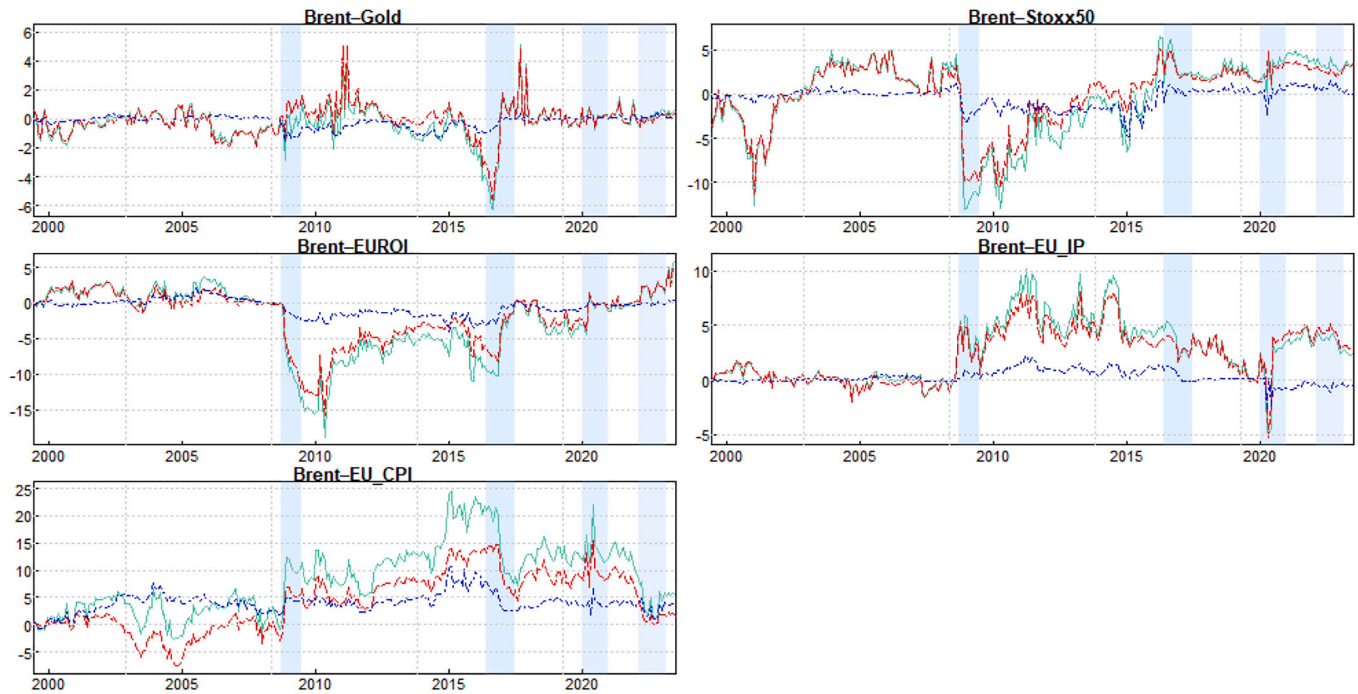
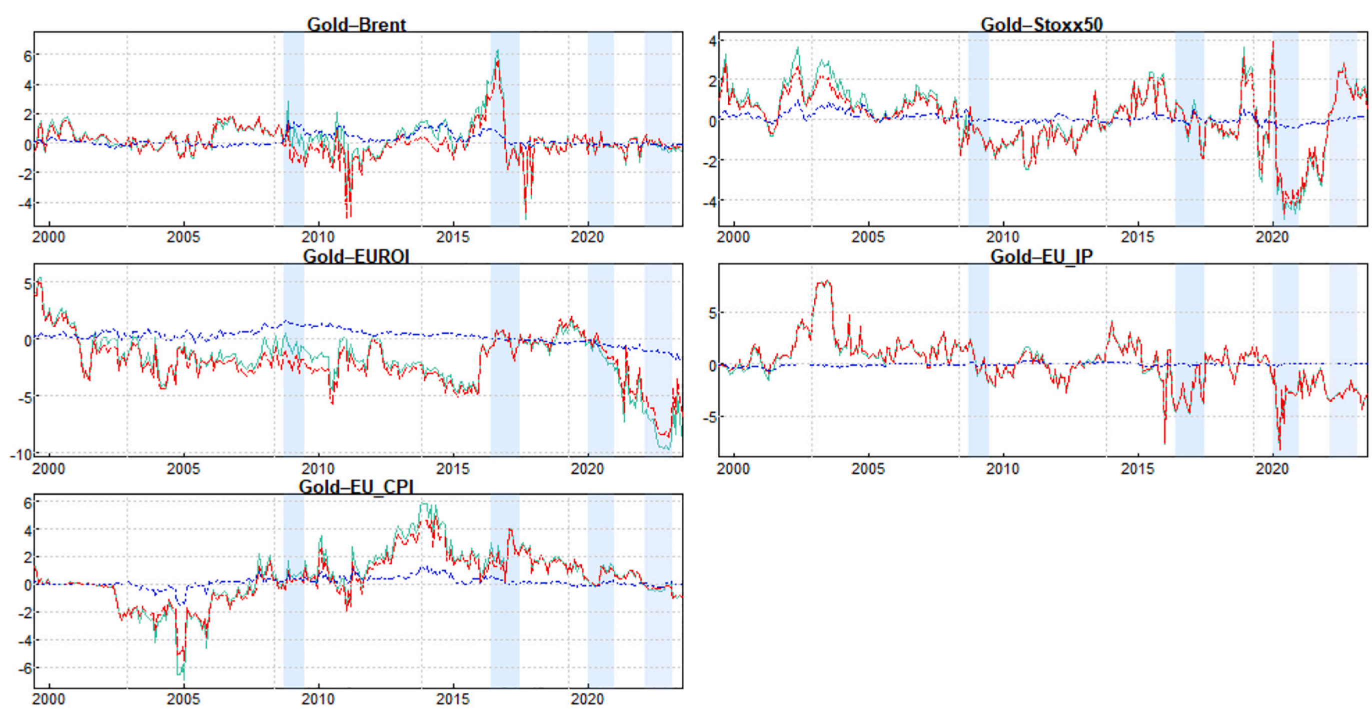


Fig. 7. Net Pairwise Spillovers Network for the US.
Notes: USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively. The nodes in green are the net transmitters within the network, whereas the nodes in yellow are the net receivers. The arrow direction points to the net receivers, and the links' thickness corresponds to all the net pairwise directional connection magnitudes.



(Brent)



(Gold)

Fig. 8. Net Pairwise Spillovers for the EU.
Notes: EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively. Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.

2008–2019 except for the Brexit period. Finally, combined with Fig. 7, which depicts the net pairwise spillover network for the US, we clearly see that for the overall, the short-term, and the long-term, the WTI, USD Index, and US Industrial Production Index are the spillover transmitters, while the S&P 500 and the US CPI act as the receivers. However, gold plays different roles in different time-frequency bands, i.e., acting as the receiver for the overall and short-term network and as the transmitter for the long-term network. The network results are consistent with the net value results in Table 2.

Likewise, the dynamic net pairwise spillover findings and the net pairwise spillover network outcomes for the EU are visually presented in Fig. 8 and Fig. 9, respectively.

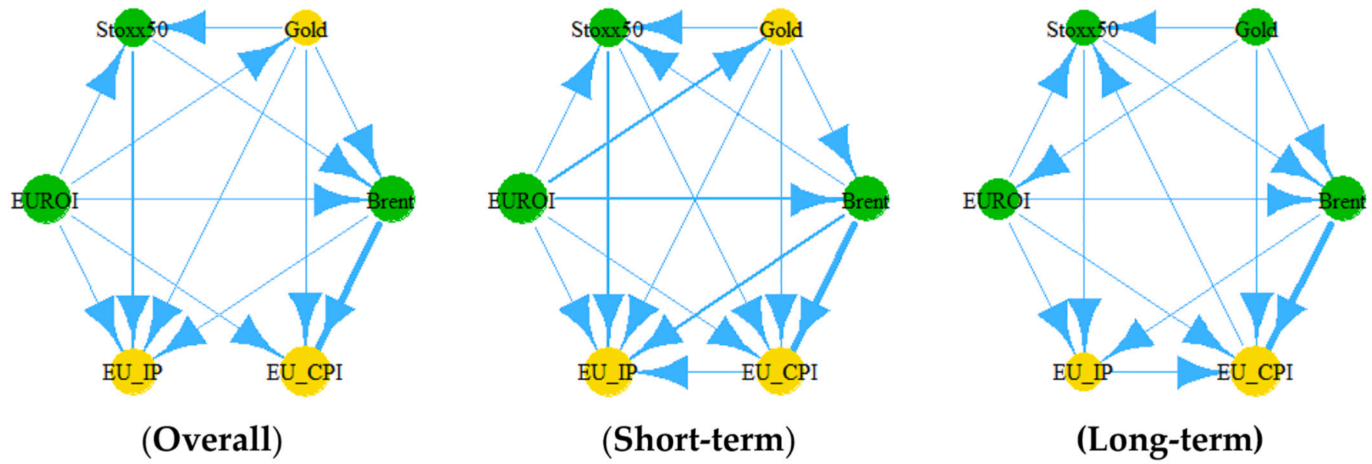


Fig. 9. Net Pairwise Spillovers Network for the EU.
Notes: EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively. The nodes in green are the net transmitters within the network, whereas the nodes in yellow are the net receivers. The arrow direction points to the net receivers, and the links' thickness corresponds to all the net pairwise directional connection magnitudes.

In the context of the NPDC relating to Brent in the EU network, noticeable shifts are apparent before and after the 2008 Global Financial Crisis. From 2008 onward, the short-term NPDC consistently highlights Brent's dominance over the EU CPI. Furthermore, the NPDC from Brent to the EU CPI peaked during the period of 2014–2016, aligning with the global crude oil oversupply, which led to a significant drop in crude oil prices. Notably, during the 2022 Russia-Ukraine conflict, the NPDC from Brent crude oil to the EU CPI saw a substantial decline, nearly approaching zero. This observation indicates that the upward trajectory of the EU CPI altered the dynamics of spillover reception, exerting a noteworthy influence on Brent crude oil. The ramifications of this conflict extended beyond the energy sector, affecting both gas and crude oil markets, as well as the food markets. Consequently, this multifaceted influence contributed to an upswing in the EU CPI during this period.

Furthermore, a noticeable trend emerges as we examine the period post-2008, wherein Brent crude oil was constantly dominated by the Euro index (Shang and Hamori, 2023). This dominance is discernible in the short-term NPDC between them. This trend, however, encounters an inflection point with the onset of the COVID-19 pandemic in 2020. The crisis appears to have reshaped their roles within this system. Subsequently, Brent crude oil assumes a heightened responsibility for explaining the shocks transmitted to the Euro index, particularly after the 2022 Russian invasion of Ukraine.

Additionally, Brent was a long-term and short-term net receiver for the Stoxx 50 during most of the period of 2008–2015; however, its role transitioned to a short-term transmitter after the 2016 Brexit referendum for both the overall, short-term, and long-term NPDC, indicating the weakened influence of the stock market in the EU after this event.

With respect to the dynamics between Brent and EU industrial production, an interesting pattern emerges. Post-2008, there is a discernible strengthening in Brent's role as a spillover transmitter to EU industrial production, both in the short-term and long-term context. However, the onset of the COVID-19 pandemic in 2020 appears to have induced a transitory shift in the relationship between these variables. This crisis additionally led to the transformation of Brent's traditional role as a long-term spillover transmitter, now assuming the role of a long-term receiver from EU industrial production.

Our focus now shifts to the dynamics surrounding gold. In general, the NPDC between gold and Brent displays a pattern of frequent changing dynamics within this network, with gold predominantly assuming a role as a long-term spillover transmitter. However, there are three distinct periods that warrant attention. Firstly, during the 2011–2012 Arab Spring, Brent temporarily acted as the short-term spillover transmitter to gold. The second one is during the 2016 Brexit referendum, which caused the gold to transform into the spillover transmitter, reaching a historically record due to its risk-hedge investment status and its close connections with the Euro index. The third period is in 2017, coinciding with robust global economic growth, declining oil inventories in major oil-consuming countries like the US, and decisions by the Organization of the Petroleum Exporting Countries (OPEC) to cut crude oil production.

For most parts, gold acts as the long-term spillover transmitter before 2016 and as the long-term receiver after 2016. Although there are some temporary shifts during 2016–2019, gold consistently plays as the short-term receiver from the Euro index, further enhanced during the 2022 Russia–Ukraine conflict.

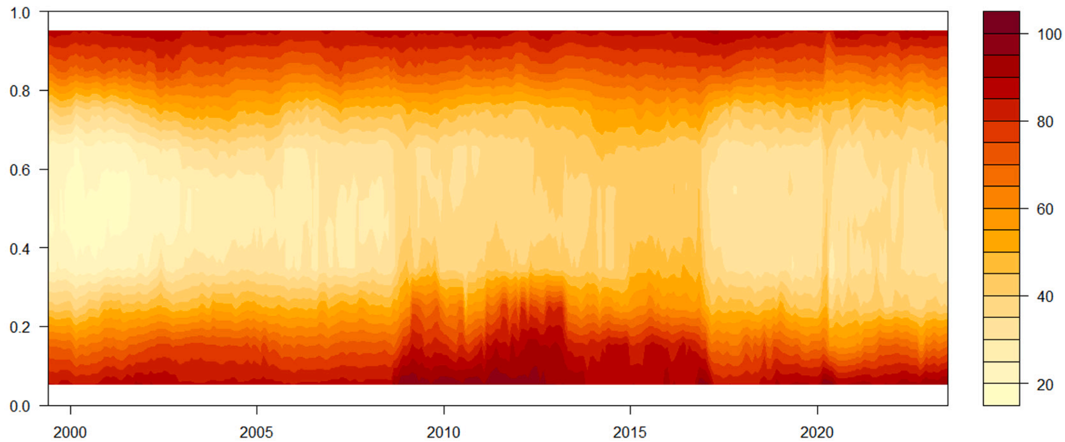
After 2011, the short-term net pairwise connectedness underscores the prominence of the gold over the EU CPI, reaching its historically highest zenith around 2013–2014, aligning with a period of gold price upswing. This upswing can be plausibly attributed to the escalation of risks and uncertainties induced by the Greek debt crisis and the first time of Russian-Ukrainian conflict, prompting a search for safe-haven assets, with gold being a notable choice.

The progression of NPDC between gold and EU industrial production, as well as the Stoxx 50, exhibits numerous transitions between their roles as receivers and transmitters. Notably, during the 2020–2021 COVID-19 pandemic, gold assumes the role of short-term spillover receivers from EU industrial production and the Stoxx 50, whereby these two indices are more volatile and influential to impose a risk propagation effect on gold. The short-term spillover transmitter role of gold in the stock market index strengthens during periods marked by conflicts or geopolitical risks.

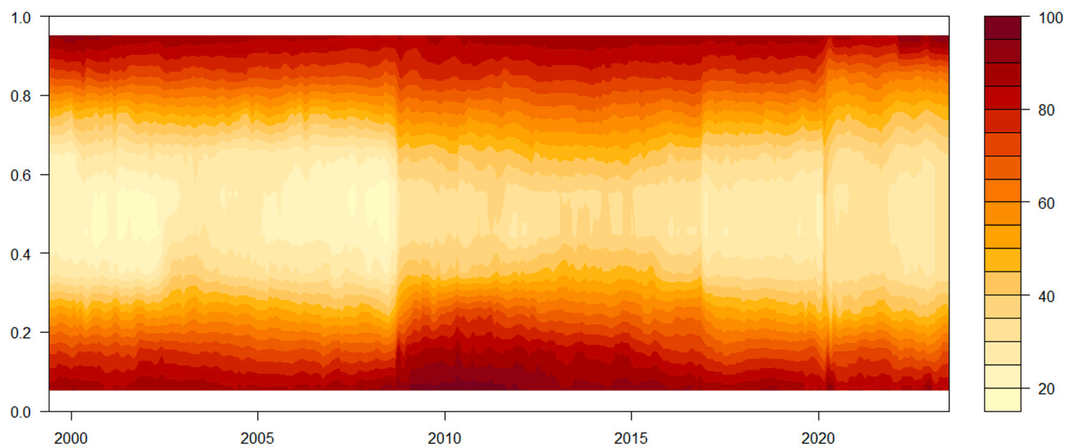
In conjunction with Fig. 9, which delineates the Net Pairwise Spillover Network for the EU, a discernible pattern emerges. It becomes evident that, in the context of overall, short-term, and long-term considerations, Brent, the Euro index, and the Stoxx50 consistently function as spillover transmitters. Conversely, the EU industrial production and the EU CPI assume roles as spillover receivers across the various frequency bands throughout the entire sample period. Notably, gold exhibits distinct roles in varying time-frequency bands: it serves as a receiver in the overall and short-term networks and transitions into the role of a transmitter in the long-term network. These network findings align harmoniously with the numerical results presented in Table 3.

4.2. Quantile dynamic connectedness analysis results

In this subsection, we redirect our attention to quartile dynamic connectedness analysis results. This perspective is broader than the



(**US**)



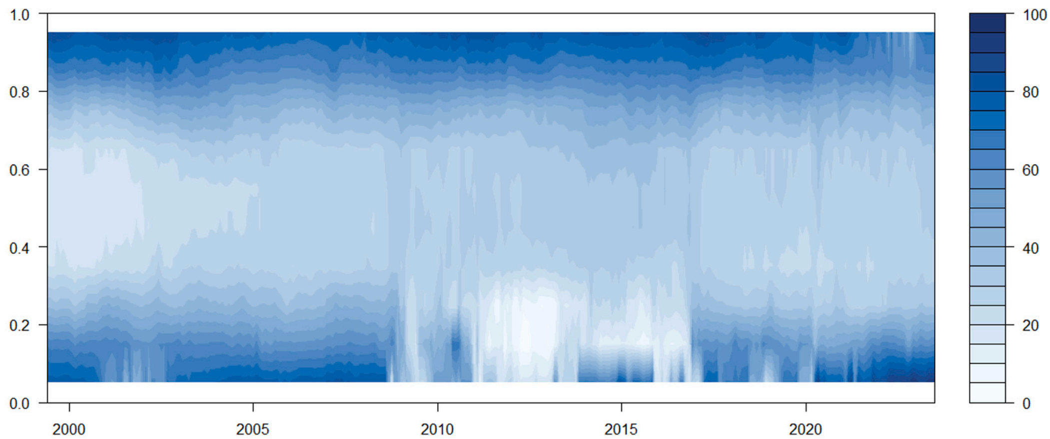
(**EU**)

Fig. 10. Overall dynamic total connectedness for the US and EU over time and quantiles.
Notes: Results are based on the quantile time-frequency connectedness.

previous one, as we had previously focused on the median quantile.

To illustrate the benefits of quantile frequency connectedness, we now turn our focus to the time-varying connectedness, depending on the specific quantile under consideration for the US, which is visually represented in Fig. 10. Except for the insights for normal market or economy conditions, we delve into the connectedness behavior in the extreme conditions of the market or economy: the lower quantiles, associated with negative returns, and the higher quantiles, linked to positive returns. We observe that the interconnectedness between market and macroeconomic indicators is more pronounced at these extreme quantiles depicted along the horizontal axis. This observation aligns with the findings of Chatziantoniou et al. (2021). The varying colors along the vertical axis in the dynamic connectedness plots serve as indicators of periods marked by heightened uncertainty across quantiles. These shaded regions typically correspond to times characterized by economic and financial crises, signifying an increase in system instability and turbulence. In our analysis, we can distinctly pinpoint periods of turbulence from 2008 to 2016, encompassing events like the 2008 Global Financial Crisis, the Arab Spring of 2011–2012, the global crude oil oversupply of 2014–2015, the 2016 Brexit Referendum, and the onset of the COVID-19 pandemic in 2020. Moreover, we observe elevated market risk from 2008 through 2016. Interestingly, we notice a degree of asymmetry in connectedness between the US at the lower and upper extreme quantiles. T This suggests that there are distinct patterns in the shock transmission between extremely positive returns and extremely negative returns. In contrast, the EU's connectedness, especially around the median quantile, appears rather symmetric. This implies that spillovers between highly positive returns and highly negative returns exhibit similar behavior. Furthermore, the overall TCI at the extreme lower quantiles is significantly higher than at the extreme higher quantiles, particularly during major international crises. This indicates that system risk or market uncertainty is notably higher during crisis periods than during phases of positive returns.

Fig. 11 shows how the short-term dynamic total connectedness has changed over time and in different quantiles. Particularly, the time-varying quantile connectedness exhibits asymmetricity. We observe an increase in short-term interconnectedness at the extreme higher quantiles, but a decrease at the extreme lower quantiles. This pattern is especially pronounced during the periods from 2008 to 2016 and reverses after the onset of the 2020 COVID-19 pandemic. Fig. 12 presents another intriguing perspective: the long-term dynamic total connectedness across time and quantiles. Here, we see that long-term interconnectedness only increases at the extreme lower quantiles during 2008–2016 and at the very beginning of 2020. This aligns with the idea



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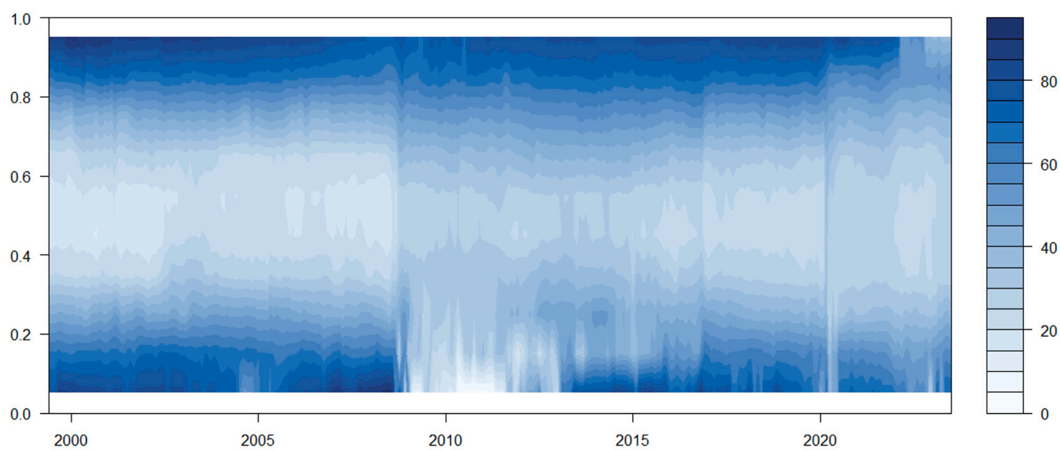


(**EU**)

Fig. 11. Short-term dynamic total connectedness for the US and EU over time and quantiles.
Notes: Results are based on the quantile time-frequency connectedness.

that during true crises, the overall TCI is primarily influenced by long-term connectedness. Major crises fundamentally change the interconnections, which is captured by the dynamics of long-term TCI. Interestingly, around 2023, the long-term TCI increases at both the extreme lower and higher quantiles.

A visual representation of the average TCI values over quantiles for the US and the EU is displayed in Fig. 13. What's particularly interesting is that the average total TCI across quantiles displays symmetry around the x-axis. However, this symmetry doesn't hold for short-term and long-term TCI. In both the US and the EU, short-term TCI is higher at the extreme upper quantiles, corresponding to periods of positive returns, while long-term TCI is higher at the extreme lower quantiles, corresponding to periods of negative returns. This observation highlights how the dynamics of interconnectedness vary depending on the investment horizon and market conditions.

It is worth noting that in the context of the US and EU systems, each comprising six variables, it becomes a formidable task to comprehensively interpret all the results breaking down the average extreme quantile connectedness, the extreme quantile dynamic total connectedness, the extreme quantile dynamic net total connectedness, the extreme quantile dynamic net pairwise directional connectedness, and the extreme quantile net pairwise directional connectedness network for both the US and the EU. As such, in this section, we primarily focus on elucidating the outcomes of the average extreme quantile connectedness, the extreme quantile dynamic total connectedness, and the extreme quantile net pairwise directional connectedness network. These results provide highly aggregated insights into extreme quantile connectedness. It's important to note that the results pertaining to the extreme quantile dynamic net total connectedness and the extreme quantile dynamic net pairwise directional connectedness can be found in Appendix A for reference.

4.2.1. Average extreme quantile connectedness

In this subsection, we present the average dynamic connectedness at extreme quantiles, such as the lower end 5% quantile and the upper end 95% quantile. The average extreme quantile results cover the whole sample period and do not account for the dynamic effects of specific events. These findings are summarized in Table 4 (5% quantile), Table 5 (95%) for the US, Table 6 (5% quantile), and Table 7 (95% quantile) for the EU, which include the time-domain values as well as the short-term and long-term connectedness values presented in parentheses.

Focusing on Table 4, we can see that WTI has a respective impact of 16.32%, 16.20%, 14.90%, 16.26%, and 18.75% on the gold, S&P 500, USD Index, US Industrial Production Index, and US CPI. Gold, the US

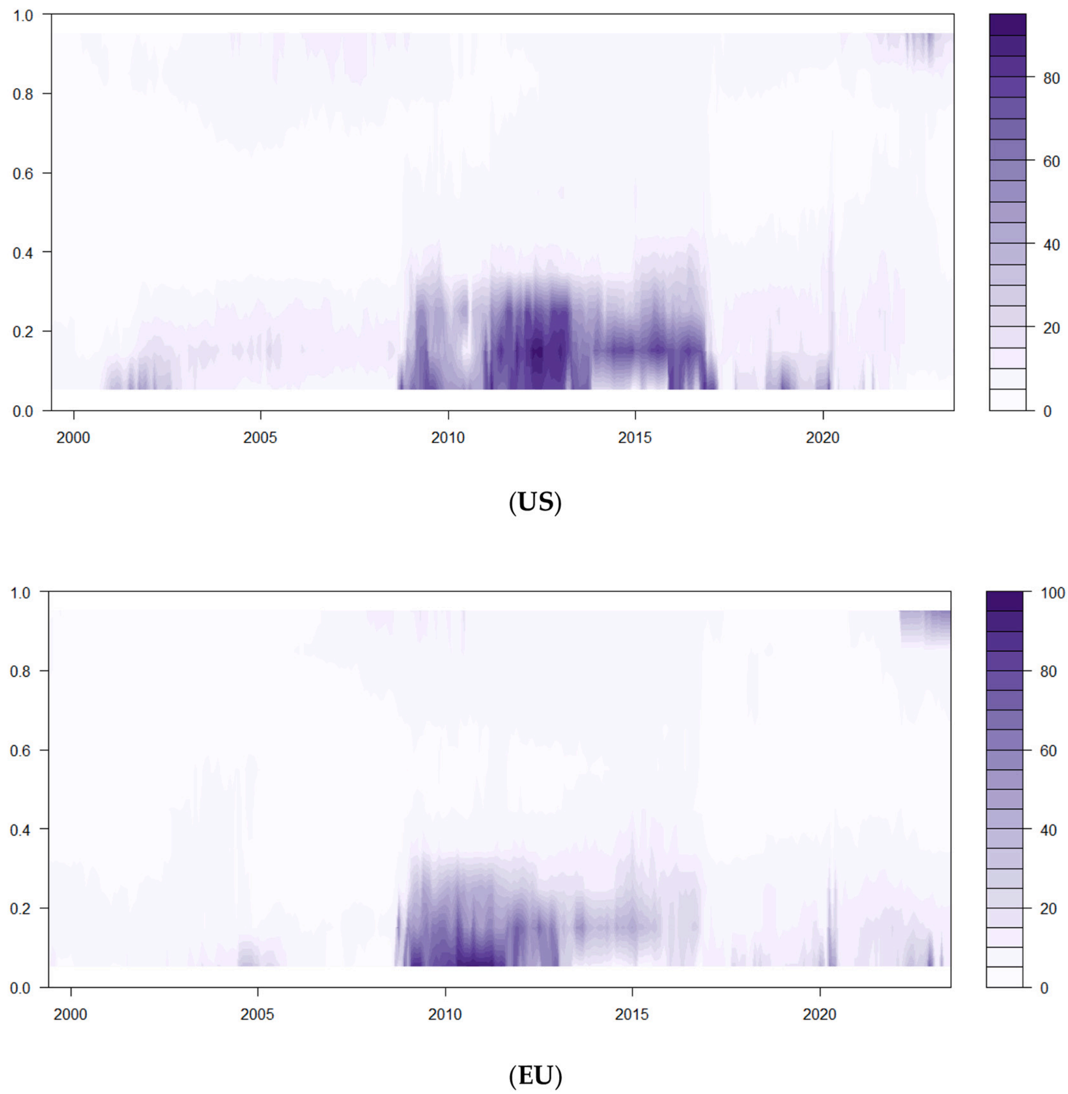
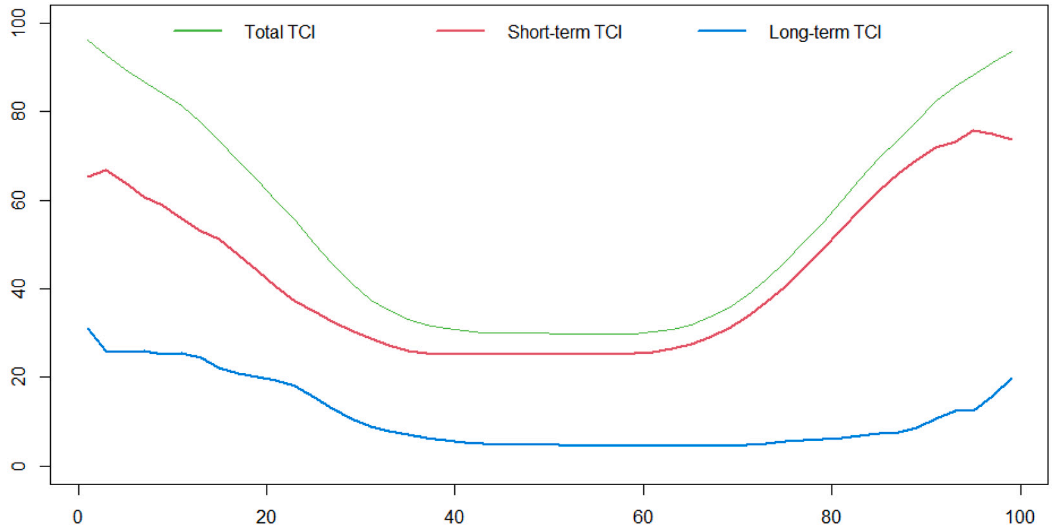


Fig. 12. Long-term dynamic total connectedness for the US and EU over time and quantiles.
Notes: Results are based on the quantile time-frequency connectedness.

Industrial Production Index, and the US CPI receive the most spillover from the WTI at the extreme lower quantile, indicating that when these series are negative returns, i.e., when the economy or the market is in a downturn situation, gold, US industrial production, and the US CPI receive the most spillover of shocks from the WTI in this system. These influences can be disintegrated into spillovers occurring in the short and long terms. The WTI, which impacts the US CPI the most, is responsible for 11.42% of short-term spillovers and 7.33% of long-term spillovers. In total, WTI influences the other variables by up to 82.44% and is influenced by other variables to the extent of 75.75%, indicating that it is a net transmitter of shocks with a net transmission of 6.69%. It is both a short-term and long-term transmitter of shocks, with short-term net spillovers of 6.69% and long-term net spillovers of 0.92%. However, in the 5% extreme lower quantile context, US industrial production stands out as the highest overall net transmitter of shocks among all the series, whereas the US CPI comes in as the highest short-term net transmitter of spillovers at 7.02%, and gold acts as the highest long-term net transmitter at 3.83%. On the other hand, the USD index acts as the biggest receiver of spillovers, either overall or short-term, while the US CPI is the biggest receiver for the long term. The S&P 500 and the USD index are both influenced by US industrial production, most during the economy or the market downturn. Leaving aside the macroeconomic indices, gold and the S&P 500 are most influenced by the WTI (Liu et al., 2021b; Smales, 2021), while the USD index is most influenced by the S&P 500.

Next, let us focus on Table 5. We can see that in the 95% extreme higher quantile context, S&P 500, the US Industrial Production Index, and the US CPI receive the most spillover from the WTI at the extreme higher quantile, indicating that when these series are positive returns, i.e., when the economy or the market is in an upturn condition, S&P 500, US industrial production, and the US CPI are influenced by WTI most in this system. These influences can be disintegrated into spillovers occurring in the short and long terms. The WTI, which impacts the US CPI the most, is responsible for 15.84% of short-term spillovers and 3.10% of long-term spillovers, and in turn, it is impacted by the US CPI the most. In total, WTI is a net transmitter of shocks with a net transmission of 5.86%, with short-term net spillovers of 5.32% and long-term net spillovers of 0.54%. However, although WTI stands out as the highest overall net transmitter of shocks among all the series, the US CPI comes in as the highest short-term net transmitter of spillovers at 8.06%, and the S&P 500 acts as the highest long-term net transmitter at 5.45%. On the other hand, the S&P 500 acts as the biggest receiver of short-term spillovers, while the US CPI is the biggest receiver for the long term. During an economic upturn, the gold and USD indexes are both heavily influenced by the US CPI. Leaving aside the macroeconomic indices, gold, the S&P 500, and the USD Index are both influenced by the WTI the



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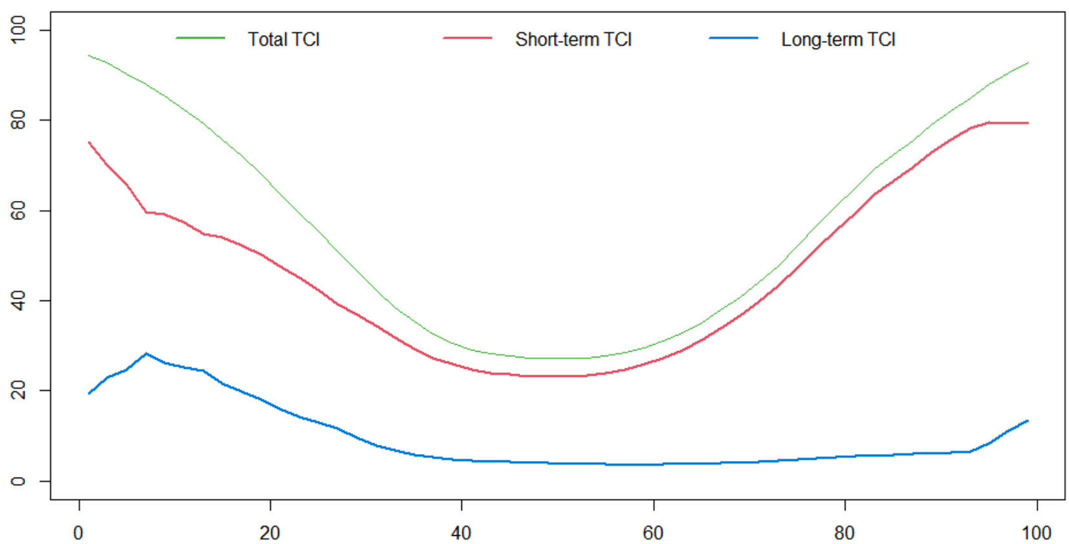


(EU)

Fig. 13. Averaged short-term, long-term, and overall dynamic total connectedness over quantiles for the US and EU.
Notes: Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.

most, while the USD Index tends to be impacted equally by the WTI, gold, and the S&P 500.

In summary concerning the US results, in the 5% extreme lower quantile context, WTI's influence ranges from 14.90% on the USD Index to 18.75% on the US CPI, with gold, the US Industrial Production Index, and the US CPI being the most affected during downturns, receiving the highest spillover effects at the lower quantile. When there is an economic downslide, US industrial production stands out as the highest overall net transmitter of shocks, while the US CPI and gold are prominent as short-term and long-term net transmitters. The USD index is the primary receiver of short-term spillovers, while the US CPI is the biggest receiver for the long term. In the 95% extreme higher quantile context, the S&P 500, US Industrial Production Index, and US CPI are most affected by the WTI during economic upturns. Short-term and long-term spillovers are again evident, with WTI having the highest impact on the US CPI in the short term. The US CPI emerges as the highest short-term net transmitter of spillovers, while the S&P 500 takes the lead in long-term net transmission during an economic soaring or bullish market. Short-term spillovers are most pronounced in the S&P 500, while the US CPI is the primary receiver for the long term.

Focusing on Table 6 for the 5% quantile dynamic connectedness results of the EU, we can see that Stoxx 50, the Euro index, the EU Industrial Production Index, and the EU CPI receive the most spillover from the Brent at the extreme lower quantiles, indicating that when these series are negative returns, i.e., when the economy or the market is in a bearish situation, Stoxx 50, the Euro index, EU industrial production, and the EU CPI receive the most spillover of shocks from the Brent in this system. These influences can be disintegrated into spillovers occurring in the short and long terms. The Brent, which impacts the EU CPI the most, is responsible for 11.80% of short-term spillovers and 6.25% of long-term spillovers, and in turn, it is impacted by the EU CPI the most. In total, Brent is a net transmitter of shocks with a net transmission of 10.59%, with short-term net spillovers of 6.97% and long-term net spillovers of 3.62%. However, in the 5% extreme lower quantile context, although Brent stands out as the highest overall and short-term net transmitter of shocks among all the series, the Euro index comes in as the highest long-term net transmitter of spillovers at 5.02%. On the other hand, EU industrial production acts as the biggest receiver of spillovers, either overall or long-term, while gold is the biggest receiver in the short term. Gold is influenced by the Euro index the most during

Table 4
Average 5% Quantile Dynamic Connectedness for the US.

	WTI	Gold	S&P500	USDI	US_IP	US_CPI	FROM
WTI	24.25	13.82	15.89	12.16	16.58	17.30	75.75
	(17.17, 7.07)	(9.03, 4.79)	(10.38, 5.51)	(8.57, 3.59)	(10.51, 6.07)	(11.76, 5.54)	(50.25, 25.50)
Gold	16.32	25.76	15.16	11.50	15.29	15.97	74.24
	(12.17, 4.16)	(21.22, 4.53)	(11.16, 4.00)	(8.68, 2.82)	(10.41, 4.88)	(12.03, 3.93)	(54.46, 19.78)
S&P500	16.20	14.12	23.84	13.12	17.61	15.11	76.16
	(10.59, 5.61)	(9.26, 4.86)	(17.62, 6.23)	(9.22, 3.90)	(10.93, 6.68)	(10.04, 5.07)	(50.04, 26.12)
USDI	14.90	13.16	15.25	25.02	16.85	14.82	74.98
	(11.46, 3.44)	(10.3, 2.86)	(11.68, 3.57)	(20.87, 4.15)	(12.29, 4.55)	(11.50, 3.31)	(57.24, 17.74)
US_IP	16.26	13.76	15.85	13.73	25.58	14.82	74.42
	(10.38, 5.88)	(8.5, 5.26)	(10.29, 5.56)	(9.53, 4.20)	(17.09, 8.49)	(9.29, 5.53)	(47.99, 26.42)
US_CPI	18.75	14.59	15.70	12.52	16.22	22.21	77.79
	(11.42, 7.33)	(8.75, 5.84)	(9.49, 6.21)	(8.43, 4.09)	(9.52, 6.70)	(14.73, 7.48)	(47.61, 30.18)
TO	82.44	69.45	77.85	63.04	82.55	78.01	
	(56.02, 26.42)	(45.84, 23.61)	(53, 24.85)	(44.44, 18.60)	(53.67, 28.88)	(54.63, 23.38)	**TCI**
Net	6.69	−4.79	1.69	−11.94	8.13	0.22	**75.56**
	(5.77, 0.92)	(−8.62, 3.83)	(2.96, −1.27)	(−12.80, 0.86)	(5.68, 2.45)	(7.02, −6.80)	**(51.27, 24.29)**

Notes: Average Extreme Quantile Dynamic Connectedness for the US at 5% Quantile based on a 100-month rolling-window QVAR. The values enclosed within the first and second sets of parentheses () signify the connectedness measures corresponding to short-term and long-term frequencies, respectively. The ij-th item of the upper-left 6 × 6 submatrix offers the ij-th pairwise directional connectedness, i.e., the percentage of the 12-month-ahead forecast error variance of variable i due to shocks from variable j. The rightmost ("FROM") column displays total directional connectedness, i.e., row sums ("from all others to i"). The bottom ("TO") row presents total directional connectedness, i.e., column sums ("to all others from j"). The difference in total directional connectivity is shown in the bottom-most ("NET") row (TO–FROM). Total connectedness (mean "from" connectedness, or equivalently, mean "to" connectedness) is the bottom-right element (in boldface). USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively.

Table 5
Average 95% Quantile Dynamic Connectedness for the US.

	WTI	Gold	S&P500	USDI	US_IP	US_CPI	FROM
WTI	25.73	14.69	15.10	12.71	14.21	17.56	74.27
	(23.4, 2.32)	(13.11, 1.57)	(13.68, 1.42)	(11.25, 1.46)	(12.85, 1.37)	(15.87, 1.69)	(66.76, 7.51)
Gold	15.09	29.40	14.31	11.83	12.60	16.77	70.60
	(13.81, 1.29)	(26.67, 2.73)	(13.11, 1.2)	(10.61, 1.22)	(11.26, 1.34)	(15.37, 1.4)	(64.16, 6.44)
S&P500	16.36	13.95	29.40	12.58	13.26	14.45	70.60
	(15.86, 0.50)	(13.49, 0.46)	(28.36, 1.03)	(12.19, 0.39)	(12.91, 0.36)	(13.99, 0.46)	(68.44, 2.17)
USDI	13.60	13.54	13.33	29.93	14.35	15.24	70.07
	(12.35, 1.25)	(11.91, 1.64)	(12.04, 1.29)	(26.87, 3.06)	(13.18, 1.17)	(13.48, 1.76)	(62.96, 7.12)
US_IP	16.13	13.52	14.75	14.96	26.45	14.19	73.55
	(14.23, 1.90)	(11.76, 1.76)	(13, 1.75)	(13.06, 1.89)	(23.61, 2.85)	(12.44, 1.75)	(64.49, 9.05)
US_CPI	18.94	16.47	13.92	13.33	11.99	25.35	74.65
	(15.84, 3.10)	(13.59, 2.87)	(11.96, 1.96)	(11.44, 1.90)	(10.27, 1.72)	(21.38, 3.97)	(63.10, 11.55)
TO	80.13	72.17	71.42	65.40	66.42	78.21	
	(72.09, 8.04)	(63.86, 8.31)	(63.79, 7.62)	(58.55, 6.86)	(60.47, 5.95)	(71.16, 7.05)	**TCI**
Net	5.86	1.57	0.81	−4.67	−7.13	3.56	**72.29**
	(5.32, 0.54)	(−0.30, 1.87)	(−4.64, 5.45)	(−4.41, −0.26)	(−4.03, −3.10)	(8.06, −4.50)	**(64.99, 7.31)**

Notes: Average Extreme Quantile Dynamic Connectedness for the US at 95% Quantile based on a 100-month rolling-window QVAR. The values enclosed within the first and second sets of parentheses () signify the connectedness measures corresponding to short-term and long-term frequencies, respectively. The ij-th item of the upper-left 6 × 6 submatrix offers the ij-th pairwise directional connectedness, i.e., the percentage of the 12-month-ahead forecast error variance of variable i due to shocks from variable j. The rightmost ("FROM") column displays total directional connectedness, i.e., row sums ("from all others to i"). The bottom ("TO") row presents total directional connectedness, i.e., column sums ("to all others from j"). The difference in total directional connectivity is shown in the bottom-most ("NET") row (TO–FROM). Total connectedness (mean "from" connectedness, or equivalently, mean "to" connectedness) is the bottom-right element (in boldface). USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively.

Table 6
Average 5% Quantile Dynamic Connectedness for the EU.

	Brent	Gold	Stoxx50	EUROI	EU_IP	EU_CPI	FROM
Brent	24.93	13.29	15.64	15.75	14.10	16.29	75.07
	(17.83, 7.10)	(9.31, 3.98)	(10.97, 4.67)	(10.78, 4.97)	(10.33, 3.77)	(11.88, 4.41)	(53.27, 21.80)
Gold	15.98	24.99	14.56	17.77	12.79	13.91	75.01
	(12.21, 3.77)	(21.44, 3.55)	(11.23, 3.33)	(14.02, 3.75)	(10.39, 2.40)	(11.4, 2.51)	(59.26, 15.75)
Stoxx50	17.97	13.22	24.41	15.27	15.01	14.12	75.59
	(12.61, 5.35)	(9.45, 3.77)	(17.85, 6.57)	(10.73, 4.54)	(11.23, 3.78)	(9.99, 4.13)	(54.01, 21.57)
EUROI	16.14	16.04	14.18	25.15	13.87	14.61	74.85
	(11.84, 4.30)	(12.70, 3.34)	(10.71, 3.47)	(20.44, 4.72)	(11.08, 2.79)	(11.52, 3.09)	(57.85, 16.99)
EU _IP	17.51	13.28	16.10	14.42	24.31	14.37	75.69
	(11.77, 5.75)	(9.30, 3.98)	(11.09, 5.01)	(10.09, 4.34)	(18.90, 5.41)	(10.20, 4.18)	(52.45, 23.24)
EU_CPI	18.06	14.24	14.26	14.73	14.18	24.53	75.47
	(11.80, 6.25)	(9.96, 4.28)	(9.62, 4.64)	(10.31, 4.42)	(10.04, 4.14)	(17.59, 6.94)	(51.74, 23.73)
TO	85.66	70.07	74.74	77.94	69.96	73.30	
	(60.24, 25.43)	(50.73, 19.35)	(53.62, 21.12)	(55.93, 22.01)	(53.08, 16.88)	(54.99, 18.31)	**TCI**
Net	10.59	−4.94	−0.85	3.10	−5.73	−2.17	**75.28**
	(6.97, 3.62)	(−8.53, 3.59)	(−0.39, −0.45)	(−1.92, 5.02)	(0.63, −6.36)	(3.25, −5.42)	**(54.76, 20.52)**

Notes: Average Extreme Quantile Dynamic Connectedness for the EU at 5% Quantile based on a 100-month rolling-window QVAR. The values enclosed within the first and second sets of parentheses () signify the connectedness measures corresponding to short-term and long-term frequencies, respectively. The ij-th item of the upper-left 6 × 6 submatrix offers the ij-th pairwise directional connectedness, i.e., the percentage of the 12-month-ahead forecast error variance of variable i due to shocks from variable j. The rightmost ("FROM") column displays total directional connectedness, i.e., row sums ("from all others to i"). The bottom ("TO") row presents total directional connectedness, i.e., column sums ("to all others from j"). The difference in total directional connectivity is shown in the bottom-most ("NET") row (TO–FROM). Total connectedness (mean "from" connectedness, or equivalently, mean "to" connectedness) is the bottom-right element (in boldface). EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively.

Table 7
Average 95% Quantile Dynamic Connectedness for the EU.

	Brent	Gold	Stoxx50	EUROI	EU_IP	EU_CPI	FROM
Brent	24.47	14.92	14.74	14.75	14.06	17.06	75.53
	(22.38, 2.09)	(13.48, 1.44)	(13.47, 1.27)	(13.64, 1.11)	(12.89, 1.16)	(15.30, 1.76)	(68.78, 6.75)
Gold	14.47	27.86	13.11	17.26	12.52	14.79	72.14
	(13.13, 1.34)	(25.14, 2.71)	(11.92, 1.18)	(15.67, 1.59)	(11.33, 1.19)	(13.24, 1.55)	(65.3, 6.85)
Stoxx50	15.65	15.20	25.10	14.03	14.25	15.77	74.90
	(14.82, 0.83)	(14.41, 0.79)	(24.08, 1.02)	(13.54, 0.49)	(13.63, 0.62)	(14.39, 1.38)	(70.79, 4.11)
EUROI	14.46	17.69	12.69	27.72	12.85	14.59	72.28
	(13.25, 1.20)	(15.58, 2.12)	(11.54, 1.15)	(25.12, 2.61)	(11.65, 1.21)	(12.98, 1.60)	(65.00, 7.28)
EU _IP	15.69	14.16	14.39	13.34	27.96	14.45	72.04
	(14.72, 0.97)	(13.14, 1.03)	(13.39, 1.00)	(12.49, 0.86)	(26.43, 1.53)	(13.06, 1.39)	(66.79, 5.24)
EU_CPI	17.51	15.05	13.45	14.07	12.49	27.42	72.58
	(14.35, 3.15)	(12.72, 2.33)	(11.51, 1.94)	(12.31, 1.76)	(10.52, 1.98)	(22.00, 5.42)	(61.41, 11.17)
TO	77.77	77.03	68.38	73.45	66.18	76.66	
	(70.27, 7.49)	(69.33, 7.71)	(61.84, 6.54)	(67.66, 5.80)	(60.02, 6.16)	(68.97, 7.69)	**TCI**
Net	2.24	4.89	−6.52	1.18	−5.86	4.08	**73.25**
	(1.49, 0.75)	(4.03, 0.86)	(−8.96, 2.43)	(2.66, −1.48)	(−6.78, 0.92)	(7.56, −3.48)	**(66.35, 6.90)**

Notes: Average Extreme Quantile Dynamic Connectedness for the EU at 95% Quantile based on a 100-month rolling-window QVAR. The values enclosed within the first and second sets of parentheses () signify the connectedness measures corresponding to short-term and long-term frequencies, respectively. The ij-th item of the upper-left 6 × 6 submatrix offers the ij-th pairwise directional connectedness, i.e., the percentage of the 12-month-ahead forecast error variance of variable i due to shocks from variable j. The rightmost ("FROM") column displays total directional connectedness, i.e., row sums ("from all others to i"). The bottom ("TO") row presents total directional connectedness, i.e., column sums ("to all others from j"). The difference in total directional connectivity is shown in the bottom-most ("NET") row (TO–FROM). Total connectedness (mean "from" connectedness, or equivalently, mean "to" connectedness) is the bottom-right element (in boldface). EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively.

the economy or market downturn.

Now, let's turn our attention to Table 7. In the context of the 95% extreme higher quantile, two prominent variables, the EU Industrial Production Index and the EU CPI, emerge as the primary recipients of spillover effects from Brent. This implies that when these variables exhibit positive returns, indicating an economic upturn or favorable market conditions, they are most influenced by Brent in the EU system. These influences can be further dissected into short-term and long-term spillovers. Brent, having the most substantial impact on the EU CPI, is accountable for 14.35% of short-term spillovers and 3.15% of long-term spillovers. In return, it is also significantly influenced by the EU CPI. Overall, Brent functions as a net transmitter of shocks with a net transmission rate of 2.24%. This comprises short-term net spillovers of 1.49% and long-term net spillovers of 0.75%. On the contrary, in the 95% extreme upper quantile context, gold takes the lead as the most substantial overall net transmitter of shocks among all the variables. During this context, the EU CPI emerges as the highest short-term net transmitter of spillovers at 7.56%, while Stoxx 50 plays the role of the most significant long-term net transmitter at 2.43%. However, in terms of receiving spillovers, Stoxx 50 acts as the most significant recipient of both overall and short-term spillovers, while the EU CPI takes on the role of the most substantial long-term receiver.

In summary, concerning the EU results, in the 5% extreme lower quantile context, Brent has the most substantial influence on Stoxx 50, the Euro index, EU industrial production, and the EU CPI during bearish market conditions. Brent serves as a net transmitter of shocks, with an overall net transmission of 10.59%, comprising short-term net spillovers of 6.97% and long-term net spillovers of 3.62%. However, in the 5% extreme lower quantile context, the Euro index emerges as the highest long-term net transmitter of spillovers (Zhu et al., 2023), while EU industrial production is the primary overall and long-term receiver, and gold is the primary receiver for the short term. Gold is most influenced by the Euro index during market downturns. Turning to Table 7, in the 95% extreme higher quantile context, the EU Industrial Production Index and the EU CPI are most affected by Brent when the economy is in an upturn condition. However, gold stands out as the highest overall net transmitter of shocks, while the EU CPI is the highest short-term net transmitter, and Stoxx 50 leads in long-term net transmission. Stoxx 50 is the primary receiver of overall and short-term spillovers, while the EU CPI is the primary receiver for the long term.

In summary for this subsection, the total connectedness for the extreme quantiles (5% and 95% quantiles) reaches approximately 75% at the extreme lower quantiles and 73% at the extreme upper quantiles for both the US and the EU. This indicates that TCIs are more significant at the extreme quantiles, suggesting higher uncertainties across these extreme quantiles. These fluctuations may signify periods of booming markets, economic growth, and financial crises, especially when compared to the median quantiles. Fig. 13 reinforces these findings by illustrating the symmetry of the overall TCI while also highlighting that TCIs at extreme quantiles are higher than those at the median quantiles (Yousaf et al., 2022). Notably, the short-term TCIs at 5% extreme quantiles are lower than those at 95% extreme quantiles, whereas the long-term TCIs at 5% extreme quantiles are higher than those at 95% extreme quantiles, both for the US and the EU, suggesting that risks or uncertainties are processed more quickly and exert short-term influence during the bullish market or booming economic than during the bearish market, in contrast, risks or uncertainties concerning the structural shifts are more pronounced and exert long-term influence during the bearish market or economy crisis than during the bullish market. For both the 5% extreme lower quantile and the 95% extreme upper quantile, TCIs are primarily influenced by short-term spillovers in both the US and the EU.

Comparing the average extreme quantiles connectedness results between the US and EU, the similarities are listed as follows:

- The highest pairwise connectedness is both found between the crude oil and CPI for the 5% quantiles.
- Either industrial production or the CPI are both influenced by crude oil the most at the 5% and 95% quantiles.
- The crude oil in either the US or the EU influences the stock market, the currency index, the industrial production index, and the CPI more than the influences from gold at 5% quantiles.
- The crude oil in either the US or the EU influences the stock market, industrial production index, and CPI more than the influences from gold at 95% quantiles.
- In terms of the Net median connectedness, only crude oil is the constant 5% and 95% quantile spillover transmitters across various time horizons, encompassing overall, short-term, and long-term connectedness.
- Gold in both the US and the EU serves as the net receiver of 5% quantile spillovers in terms of overall and short-term connectedness; however, it is the net transmitter of spillovers in the context of long-term connectedness, indicating that gold mainly exerts prolonged influence in the long run during a bearish market or downslide economic downslide.
- Generally, most of the Net connectedness at the 5% quantile is shaped by a combination of an opposing directional short-term and long-term spillover.

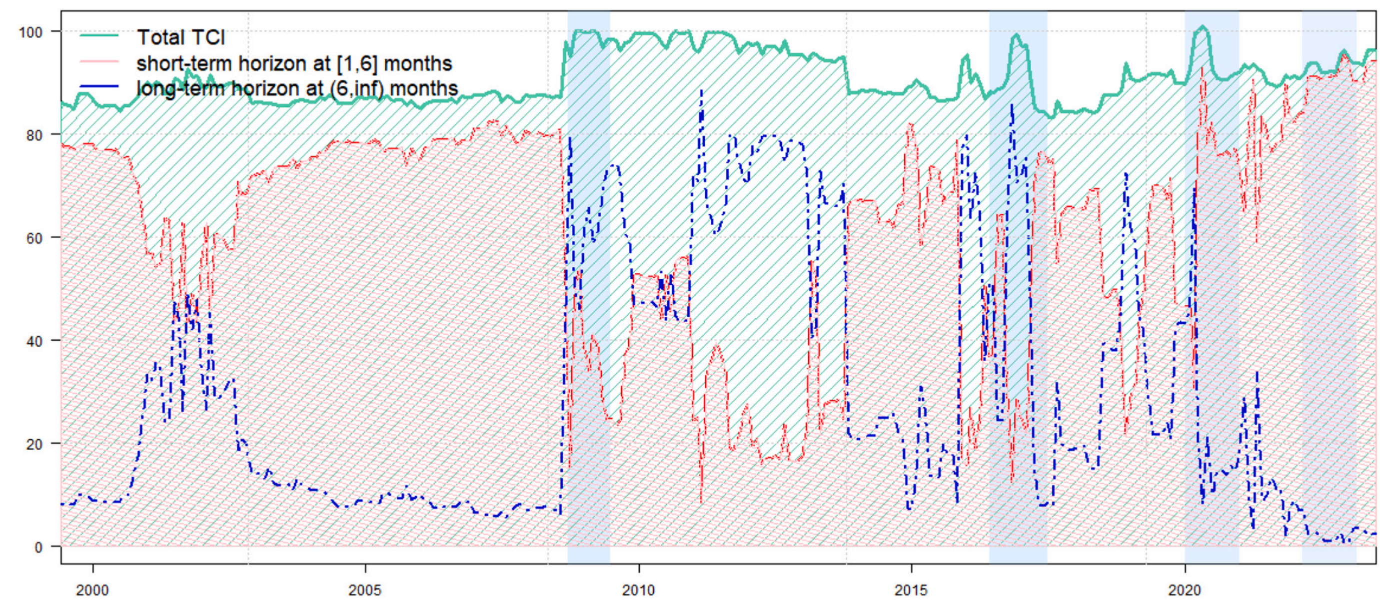
Subsequently, the differences are listed as follows:

- The highest pairwise connectedness at the 95% quantiles is from WTI to US CPI for the US system and from gold to the Euro index for the EU system.
- The WTI contributes more to the US_CPI than the Brent contributes to the EU_CPI at 95% quantile, indicating that the US CPI receives more spillover from crude oil returns than it does in the EU.
- The Brent contributes more to the EU industrial production than the WTI contributes to the US_IP at 5% quantile, indicating that there is a possibility that during the downslide economic condition, industrial production in the EU is more reliant on crude oil and more sensitive to changes in crude oil prices.
- The S&P 500 and the USD index receive the largest spillover from US industrial production at the 5% extreme quantiles, while the Stoxx 50 and the Euro index receive the largest spillover from Brent crude oil, implying that during economic downturns, the US stock market and currency index are mostly influenced by industrial activity, whereas the EU stock market is mostly influenced by crude oil prices.
- The S&P 500 receives the largest spillover from the WTI at the 95% extreme quantiles, while the Stoxx 50 receives the largest spillover from the EU industrial production, implying that during economic upturns, the US stock market is mostly influenced by the WTI crude oil prices, whereas the EU stock market is mostly influenced by the industrial production.
- The USD index is highly influenced by the US CPI, while the pairwise connectedness from gold to the Euro index is at the 95% extreme quantiles.
- The USD index is highly impacted by WTI crude oil prices, while the Euro index is highly impacted by gold at the 95% quantile, indicating that at a bullish market or booming economy, the Euro index is more sensitive to the changes in gold prices. One plausible rationale behind this phenomenon lies in the behavior of the EU, notably the United Kingdom (UK), which holds the distinction of being the world's second-largest gold exporting nation according to the leading gold exporting countries ranking in 2022. During periods of economic upturns, the demand from investors for safe-haven assets tends to be less pronounced compared to economic crises. Consequently, this diminished demand exerts downward pressure on the price of gold. The repercussions of this decline manifest in several ways: a reduction in the foreign trade revenues of the EU, given that a significant portion of its foreign exchange earnings is derived from gold exports; a depreciation of the euro; and a subsequent decline in the currency index.

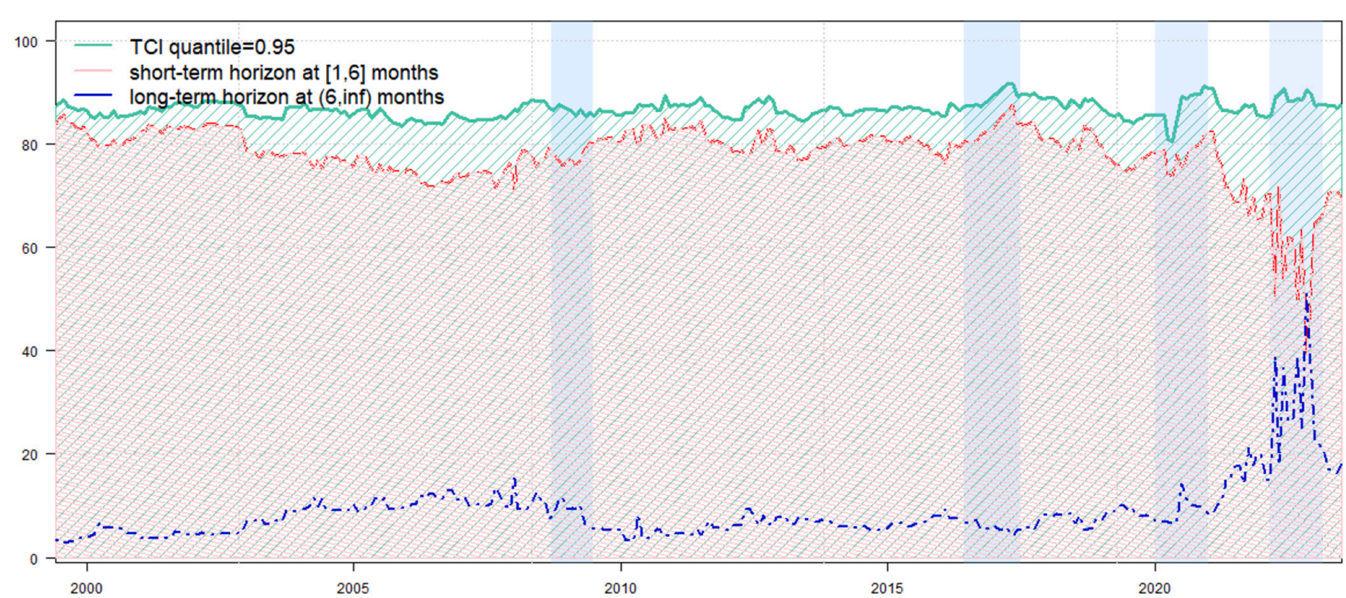
- In terms of the Net connectedness, in the US, the industrial production index acts as the transmitter of 5% quantile spillovers across the overall, short-term, and long-term timeframes. In contrast, in the EU, the Stoxx 50 acts as the receiver of 5% quantile spillovers across the overall, short-term, and long-term timeframes.
- In the US, the USD index exhibits the lowest TO connectedness over both the 5% and 95% quantiles, indicating that it has the least impact within the network. Conversely, in the context of the 5% quantile connectedness, US industrial production, and in the context of the 95% quantile connectedness, WTI, display the highest TO quantile connectedness. This confirms their most influential status in distinct market conditions or economic contexts.
- In the EU, Brent demonstrates the highest TO quantile connectedness over both the 5% and 95% quantiles, reinforcing the image of Brent's predominant influence in the EU system.

4.2.2. *Extreme quantile dynamic Total connectedness*

Here, we will proceed with the interpretation of the extreme quantiles of short-term, long-term, and total dynamic connectedness, as displayed in Fig. 14. Overall, we see 5% quantile total spillovers start increasing

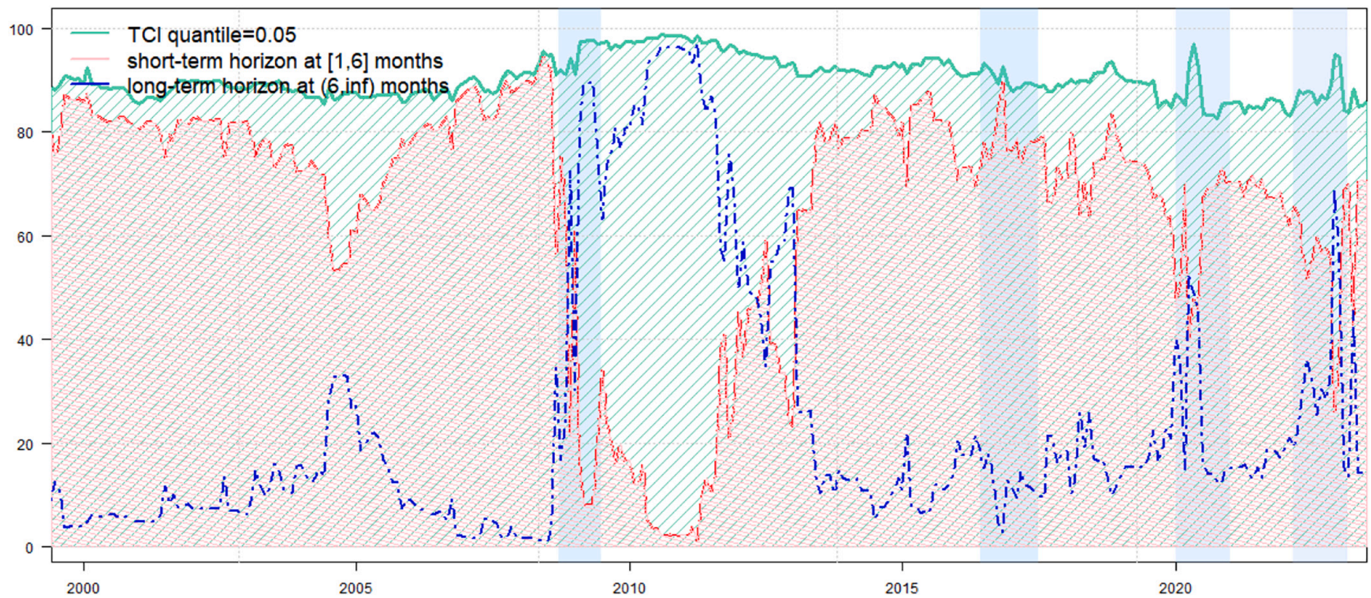


(US at 5% quantile)

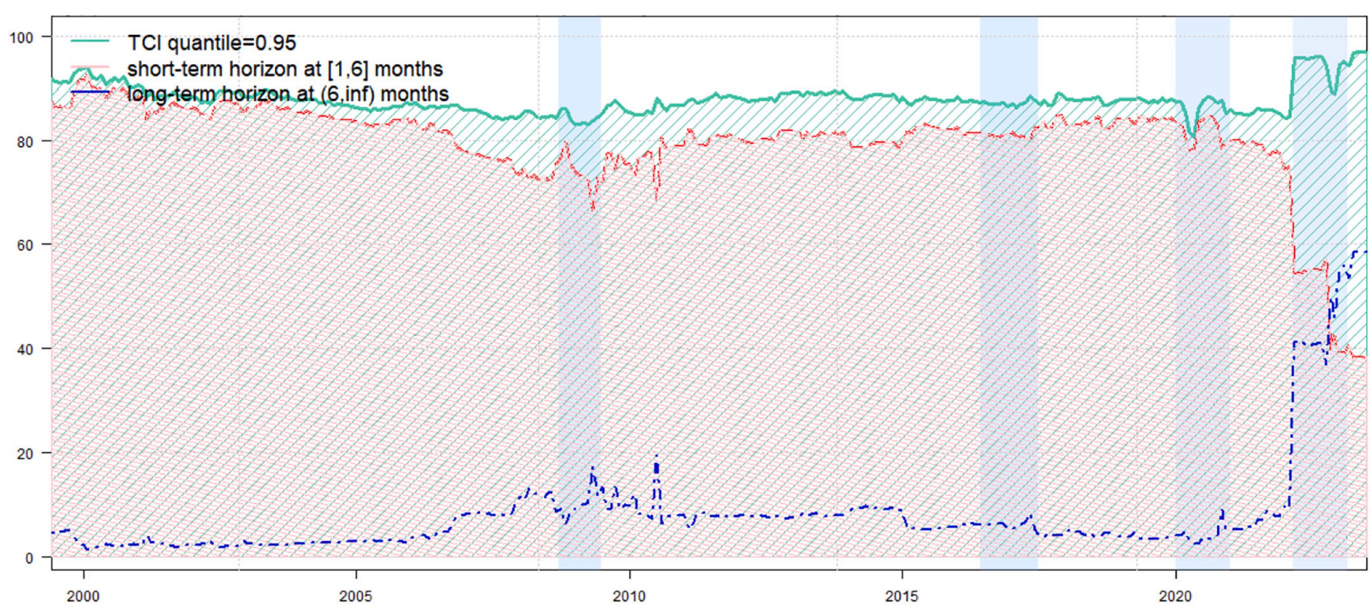


(US at 95% quantile)

Fig. 14. Extreme Quantile Dynamic Total Spillovers for the US and EU.
Notes: Results are based on the quantile time-frequency connectedness. Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.



(EU at 5% quantile)



(EU at 95% quantile)

Fig. 14. (*continued*).

substantially from 2008 GFC within the US system until 2014. The peak in 2011 can be attributed to the 2011 US debt ceiling crisis. A sudden rise was observed both in 2016 and 2020 (Benlagha and Omari, 2022), corresponding to the 2016 US presidential election and the COVID-19 pandemic, which caused a transitory risk upswing within the US system. Afterward, we see that 5% short-term TCI starts to increase, especially after stepping into 2022 and reaching an unprecedented level for the first time after the 2023 US banking crisis. In turn, the long-term TCI decreased after 2021. Concerning the 95% quantile total spillover, mainly contributed by short-term connectedness, the most volatile period is during 2022, which corresponds to the Russia-Ukrainian conflict.

Concerning the EU extreme quantiles short-term, long-term, and overall TCI results, we see 5% quantile total spillovers start increasing substantially from 2008 GFC within the EU's system until 2014. Two subsequent thrusts were observed in 2020 and 2022, corresponding to COVID-19 and the 2022 Russian invasion of Ukraine, which caused a transitory risk upswing within the US system. Another observation is that the 5% short-term TCI and long-term TCI are highly symmetric by slicing the 50% quantile. Overall, the 5% quantile TCI is mainly contributed by short-term connectedness, while there are three inverse patterns that long-term connectedness contributed to the overall TCI most: the first happened during 2008–2013, including the GFC and the

Greek debt crisis; the second happened at the beginning of the 2020 COVID-19 pandemic outbreak; and the third time happened at the Russian invasion of Ukraine in 2022. Concerning the 95% quantile total spillover, mainly contributed by short-term connectedness, the most volatile period is during 2022, which corresponds to the Russia-Ukrainian conflict, and the second volatile period is during 2008–2011, which corresponds to the European debt crisis. The extreme quantile dynamic total connectedness is characterized by convergence and symmetry when there are crises or geopolitical risks.

The extreme quantile dynamic total connectedness is characterized by the continuing convergence and divergence of the short-term and long-term spillover. Notably, the connectedness in both the lower and upper extreme quantiles is much higher, suggesting that the markets are more sensitive to both extreme negative and positive information shocks. When comparing different frequency bands, it becomes evident that the total TCI is predominantly contributed by the short-term spillover at both the 5% and 95% quantiles, implying that the risk spillovers are primarily driven by short-term shocks and the risk propagation or information transmission time is comparably rapid. However, during times of crises or heightened geopolitical risks, the reverse pattern (mainly contributed by the long-term spillover) dominates the 5% quantile results, corroborating the speculation put forth by JP Morgan, which emphasizes the likelihood of commodities being subjected to an extended period of geopolitical tensions and rising risk premiums. By contrast, the 95% quantile results are relatively moderate and stable.

4.2.3. Extreme quantile net pairwise directional connectedness network

Next, we see the net pairwise directional connectedness network results for the US and EU, which are illustrated in Fig. 15 and Fig. 16, respectively.

As Fig. 15 shows, WTI and the US industrial production index are the net directional spillover transmitters for both the overall 5% quantile, short-term, and the long-term 5% quantile, i.e., the extreme lower quantiles. Gold and the USD index are 5% quantile short-term spillover receivers while acting as 5% quantile long-term transmitters, indicating that when great crises happen, gold and the USD index tend to be transmitters in the long run, verifying that gold and the US dollar are likely to be the safe-haven equities during crises or market turmoil (Triki and Maatoug, 2021). The S&P 500 and US CPI tend to be 5% quantile short-term transmitters (Du and He, 2015) and long-term receivers, indicating that during a downslide or bearish market, the S&P 500 and US CPI are more likely to exert spillover effects on other variables in the short run, while in the long run, they receive spillover shocks from other indices. These results might provide some insights for investors and policymakers. Longer-term connectedness is often related to structural transformations or significant events, indicating fundamental shifts in investor expectations or systemic risk in the long run. This kind of connectedness reflects the slow adaptation of markets and macroeconomic to changing conditions. In contrast, shorter-term connectedness reflects the rapid processing of information and immediate responses to sudden shocks and events. It captures the more market-sensitive or market-expectations-driven reactions of financial and economic systems. Similarly, WTI is the solely consistent net directional spillover transmitter, while the USD index and the US industrial production index are consistently net directional spillover receivers for both the overall 95% quantile, the short-term 95% quantile, and the long-term 95%

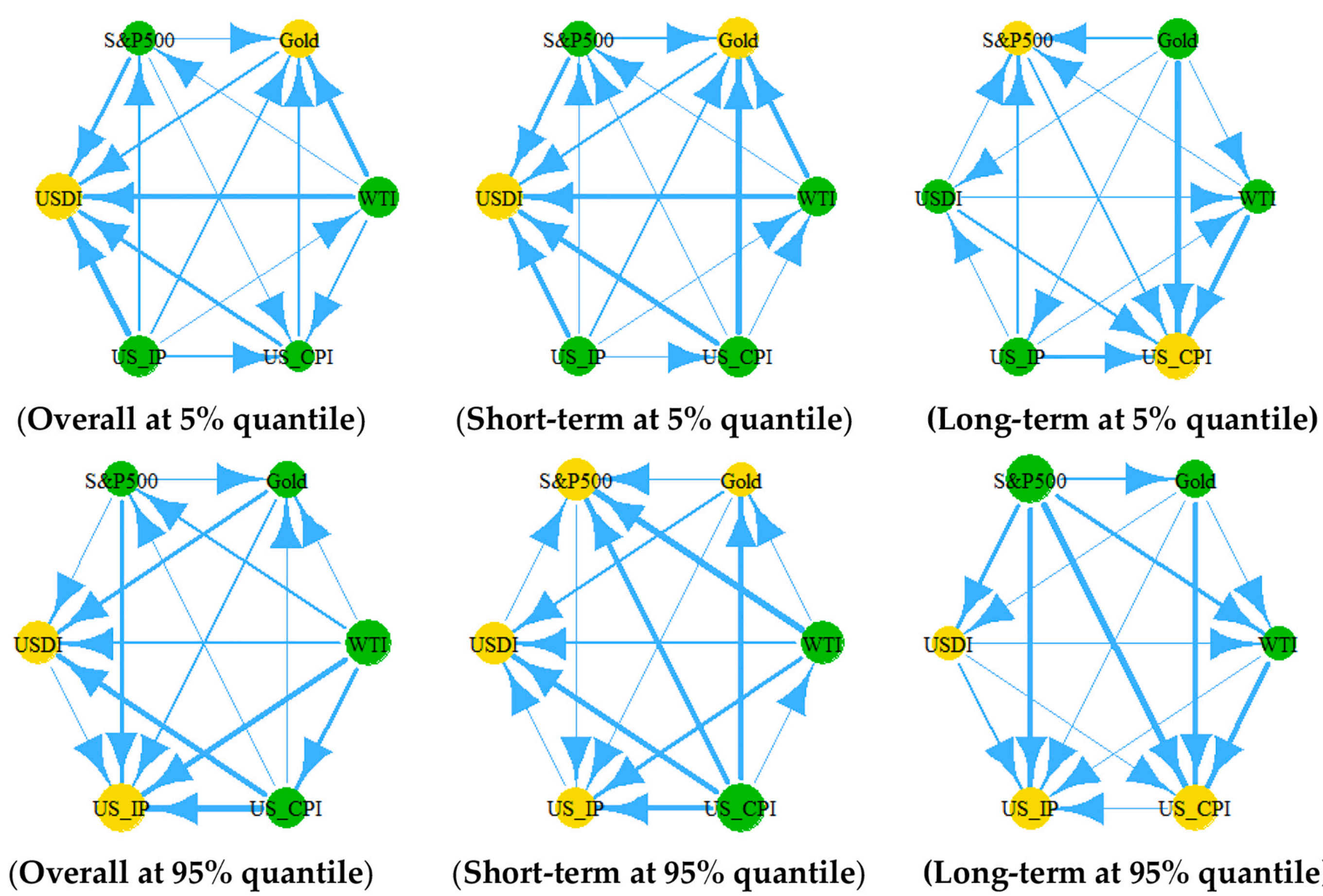


Fig. 15. Extreme Quantile Net Pairwise Spillovers Network for the US.
Notes: USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively. The nodes in green are the net transmitters within the network, whereas the nodes in yellow are the net receivers. The arrow direction points to the net receivers, and the links' thickness corresponds to all the net pairwise directional connection magnitudes.

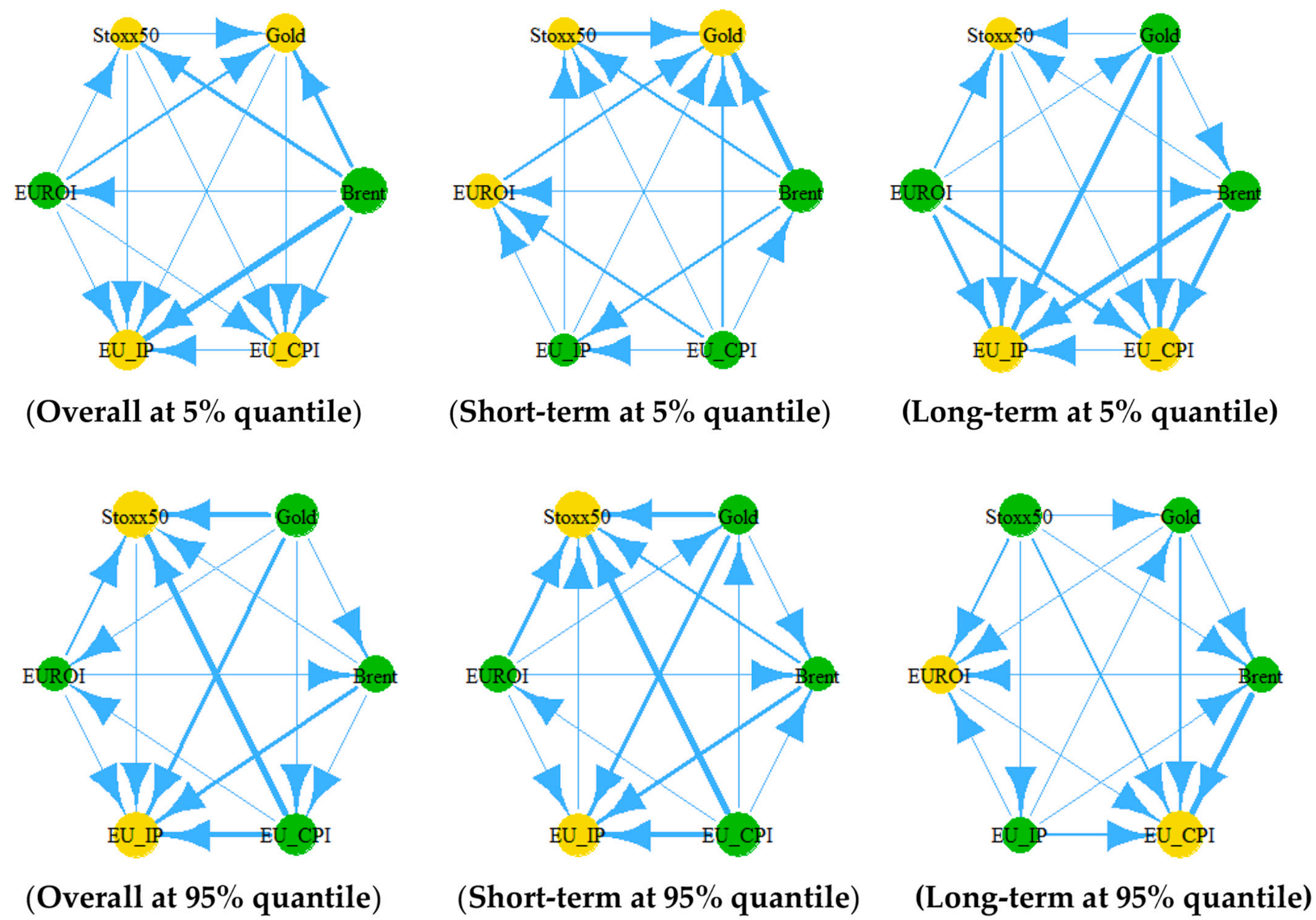


Fig. 16. Extreme Quantile Net Pairwise Spillovers Network for the EU.
Notes: EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively. The nodes in green are the net transmitters within the network, whereas the nodes in yellow are the net receivers. The arrow direction points to the net receivers, and the links' thickness corresponds to all the net pairwise directional connection magnitudes.

quantile, i.e., the extreme upper quantiles. This indicates that in bullish market or economic upturns, the USD index and industrial production are more likely to be influenced by other factors in the US system. The S&P 500 and gold are 95% quantile short-term spillover receivers and long-term transmitters, indicating that they are influenced by short-term shocks when immediate expectation changes occur due to frequent fluctuations or events in this system; however, they exert spillover effects on other indices when there are structural changes in the long run. On the other hand, the US CPI is the 95% quantile short-term transmitter and long-term receiver, indicating that the US CPI acts as the short-term transmitter, reacting to immediate expectation changes due to relatively frequent fluctuations in this system, while acting as the long-term receiver, responding to structural changes in the long run.

By analogy, we see the net pairwise directional connectedness network results for the EU. As Fig. 16 shows, Brent is the net directional spillover transmitter, while the Stoxx 50 is the net directional spillover receiver for both the overall 5% quantile, the short-term quantile, and the long-term 5% quantile, i.e., the extreme lower quantiles. Gold and the Euro index are 5% quantile short-term spillover receivers while acting as 5% quantile long-term transmitters (Zhu et al., 2023), indicating that when great crises happen, gold and the Euro index tend to be transmitters in the long run, verifying that gold and the Euro index are effective risk hedges during crises or market turmoil. On the other hand, the EU industrial production index and EU CPI are 5% quantile short-term spillover transmitters while playing the role of long-term spillover receivers. These results indicate that during a downslide economy and market condition, the EU industrial production and the CPI are responsible for other indices' shocks in the short run, while the Euro index and gold exert spillover effects on other indices in the long run. These results might provide some insights for investors and policymakers. When structural changes happen, investors and policymakers should pay attention to these long-term transmitters for monitoring the long-term system risk reaction. On the other hand, when frequent volatility or events only change market expectations, investors and policymakers should enact policies and strategies concerning EU industrial production activity and CPI.

Similarly, Brent and gold are the consistent net directional spillover transmitters for both the overall 95% quantile, the short-term, and the long-term 95% quantile, i.e., the extreme upper quantiles. This indicates that in bullish markets or economic upturns, Brent and gold are more likely to consistently impact other indices in the EU system. The Stoxx 50 and EU industrial production are 95% quantile short-term spillover receivers and long-term transmitters, indicating that they are influenced by short-term shocks when there are fluctuations or events that could impact the short-term expectation for the market and economy in the EU system; however, they exert spillover effects on other indices when there are structural changes in the long run. On the other hand, the EU CPI and the Euro index are the 95% quantile short-term transmitter and long-term receiver, indicating that they are more powerful and influential in reacting to short-term expectation changes due to relatively frequent fluctuations in this system while receiving more influence from other indices and responding to structural changes in the long term.

5. Conclusions

This investigation utilizes a spectrum of commodities, comprising crude oil and gold prices, along with stock market indices, industrial production indices, and consumer price indices from both the United States (US) and the European Union (EU). Additionally, a pioneering measurement for assessing interconnectedness, namely the quantile frequency connectedness approach (as previously developed by Ando et al., 2018; Chatziantoniou et al., 2021; Baruník and Křehlík, 2018), is utilized. The quantile time-frequency connectedness provides a robust framework for scrutinizing time-varying connectedness and spillover transmission dynamics across diverse time-frequency bands and a range of quantiles.

This study encompasses two primary objectives. The first objective involves an in-depth analysis of the quantile time-frequency dynamic connectedness, with a specific focus on spillover effects within various markets and economic indicators, including the commodity market, stock market, currency index, industrial production index, and consumer price index, and to identify different effects of two major commodities, i.e., crude oil and gold, on others. The second objective centers on a comparative assessment of quantile time-frequency dynamic spillover patterns and network transmission roles of these variables within two distinct systems: the US and the EU.

This study presents several noteworthy contributions. Firstly, it is the first time for the application of a quantile time-frequency connectedness approach in the US and EU to investigate the time-varying connectedness and spillover transmission dynamics across commodities (e.g., crude oil and gold prices), stock market indices, currency indices, industrial production indices, and CPI over diverse time-frequency bands and at a range of quantiles. Another novelty lies in that it's the first time to compare the difference between crude oil and gold, particularly in their relationship with an encompassing set of key indices, such as stock markets, currency indices, industrial production indices, and consumer price indices, across diverse time-frequency bands and under varying market conditions. Significantly, it is also the first time to evaluate the spillover transmission mechanism within these markets and macroeconomic indicators across different time-frequency bands and over different quantiles for the US and EU.

The main findings are as follows:

Firstly, our analysis reveals that the level of systemic risk exhibited heterogeneity, varying over time and across quantiles (Yang et al., 2021), and dynamic total connectedness was more significant at the extremes. The TCI at the median quantile is relatively low, with short-term spillover contributing more significantly than long-term spillover for both the US and EU, while TCI at extreme quantiles (5% and 95%) is significantly higher (Liu et al., 2021a), indicating greater uncertainty during extreme market conditions. Our analysis has revealed that short-term and long-term dynamic total connectedness metrics do not consistently exhibit concurrent movements; on the contrary, they can exhibit divergence, depending on distinct economic and financial events or geopolitical risks that exert varying influences on the short-term and long-term dynamics. The dynamics of short-term and long-term total connectedness at the median quantile display similar trends over time. However, the dynamics of total connectedness at the extreme quantiles are characterized by highly reversal symmetry and the continuing convergence and divergence of the short-term and long-term spillover.

Secondly, the results emphasize that crude oil consistently serves as the primary net transmitter of both short-term and long-term shocks in the US and EU networks across various quantiles (median, extreme lower 5%, and extreme upper 95%), underscoring that crude oil is a major source of shocks within this network. Specifically, in both the US and EU, crude oil mainly transmits shocks to the CPI, followed by the industrial production index and the stock market, while the transmission mechanisms with the currency index depend on the quantiles and time-frequency bands. On the contrary, the scenario concerning gold is different both in time-frequency bands and the different quantiles. Gold acts as the net transmitter of long-term shocks in the US and EU networks across different quantiles (median, extreme lower 5%, and extreme upper 95%) while playing as the net receiver of short-term shocks at the median and extreme lower (5%) quantiles. At the extreme upper (95%) quantile, gold acts as the net receiver of short-term shocks within the US network, whereas it serves as the net transmitter of short-term shocks within the EU network, mainly impacting Euro index and EU industrial production.

Thirdly, through the dynamic total connectedness heatmaps over time and quantiles, the connectedness appears to be rather asymmetric for the US compared to the lower and upper extreme quantiles, indicating that spillovers between bullish and bearish markets behave differently and are comparably symmetric for the EU. The overall TCI at the extreme lower quantiles is considerably higher than the extreme higher quantiles, especially during the international great crisis. This would indicate that system risk or market uncertainty during crisis periods is higher than during booming economies or bullish markets. Moreover, during great crises or recessions, the long-term TCIs are significantly darker in the lower extreme quantiles than the short-term TCIs. It is worth noting that after 2022, the US' short-term TCI is getting darker in the extreme lower quantile, whereas the EU's short-term TCI is getting lighter in the extreme lower quantile. Analyzing the average total connectedness over quantiles and frequencies, it's evident that in both the US and the EU, the averaged overall TCIs exhibit a symmetric pattern. However, the averaged short-term and long-term TCIs in both regions show an asymmetric trend. The averaged short-term TCIs are higher at the upper end, and the averaged long-term TCIs are higher at the lower end. This observation suggests that during bullish markets or economic upturns, risks and uncertainties are processed more quickly and have a stronger short-term impact. However, during bearish markets or economic downturns, risks related to structural shifts become more prominent and exert a longer-term influence than during bullish periods.

Fourthly, let us discuss the transmitters and receivers.

- In the 5% extreme lower quantile context, US industrial production stands out as the largest overall net transmitter of shocks, whereas the US CPI comes in as the largest short-term net transmitter and gold as the largest long-term net transmitter; although Brent stands out as the highest overall and short-term net transmitter of shocks, the Euro index acts as the highest long-term net transmitter. In the 95% extreme upper quantile context, although WTI stands out as the largest overall net transmitter of shocks, the US CPI comes in as the largest short-term net transmitter, and S&P 500 acts as the largest long-term net transmitter; gold stands out as the largest overall net transmitter of shocks, while the EU CPI is the largest short-term net transmitter, and Stoxx 50 is the largest long-term net transmitter. These results identify the respective sources of market uncertainties or system risks within different markets or economic conditions, as well as with different influences in the short run or in the long run for the US and the EU, respectively.
- In the 5% extreme lower quantile context, the USD index stands out as the largest overall and short-term net receiver of shocks, whereas the US CPI comes in as the largest short-term net receiver; the EU industrial production index stands out as the largest overall and long-term net receiver of shocks; and gold acts as the highest short-term net receiver. In the 95% extreme upper quantile context, the US industrial production index stands out as the largest overall net receiver of shocks, the S&P 500 comes in as the largest short-term net receiver, and the US CPI acts as the largest long-term net receiver; the Stoxx 50 stands out as the largest overall and short-term net receiver of shocks, while the EU CPI is the largest short-term net receiver. These results identify which indicator is most vulnerable to the uncertainties or risks originating from different markets or economic conditions, as well as with different affected intervals (in the short run or the long run) for the US and the EU, respectively.

The study reveals both similarities and disparities when compared to previous literature. Notably, we find that dynamic total connectedness between markets and macroeconomic indicators is more pronounced at extreme quantiles (5% and 95% quantiles). This aligns with the findings of Ando et al. (2018), Chatziantoniou et al. (2021), Chatziantoniou et al. (2022), and Zhu et al. (2023), which also demonstrate higher TCI connectedness in extreme quantiles compared to the median quantile. Moreover, we highlight that the dynamic total connectedness under extreme market conditions is primarily driven by short-term spillovers within the systems. In contrast to the tail-dependence results of Ando et al. (2018) and Liu et al. (2021b), where the 95% extreme quantile connectedness was higher than the 5% extreme quantile connectedness during the 2008 global financial crisis, our study shows that the 5% extreme quantile connectedness of financial macroeconomic system risk is higher than the 95% extreme quantile connectedness during the 2008 global financial crisis, for both the US and the EU. Additionally, we observe that long-term TCI surpasses short-term TCI at the 5% extreme quantile during the periods of the 2008 financial crisis and the 2020 COVID-19 pandemic, indicating a structural change during these extreme events. This finding is consistent with Triki and Maatoug (2021), which showed that the SP500 correlates less with gold during peaceful periods and more during extreme geopolitical events. Our results suggest that pairwise connectedness between SP500 and gold is indeed larger during extreme quantiles (extreme market conditions) than during the median quantile (normal market conditions). Furthermore, we demonstrate that the pairwise connectedness between SP500 and gold in the 5% quantile is higher than in the 95% quantile, indicating that during bearish market conditions, the connectedness between them is higher than during bullish markets. In the 95% quantile, gold acts as the spillover transmitter to the Stoxx within the EU system, implying that gold transmits shocks to the stock market during bullish market conditions. This insight can aid policymakers, investors, and portfolio managers in identifying spillover transmitters during different market conditions, as these transmitters help identify potential root sources of systematic risk. Conversely, the SP500 consistently acts as the spillover transmitter within the US system, indicating regional differences in the sources of systematic risk between the US and the EU.

The empirical results of this study offer several implications for policymakers and investors:

Overall, as Chatziantoniou et al. (2023) point out, it's crucial to distinguish between short-term and long-term connectedness mechanisms across various economic indicators and markets, as long-term connectedness closely correlates with structural shifts occurring over extended time periods, potentially manifesting fundamental alterations in investor expectations that have lasting implications for systemic risk. In contrast, short-term connectedness is attributed to rapid information assimilation, capturing the immediate market and macroeconomic responses to abrupt shocks and significant events. The observed response pattern holds significance for investors and policymakers. For investors, understanding short-term interconnectedness is essential for quickly responding to market shocks and adjusting portfolios. Long-term interconnectedness helps identify structural changes in markets, allowing for informed, forward-looking investment decisions. Policymakers can benefit from recognizing short-term interconnectedness to assess immediate repercussions and formulate timely responses. Long-term interconnectedness aids in evaluating financial system stability and informs policies addressing structural changes and long-term risks.

More specifically, it is essential for investors to acknowledge the dynamic nature of the relationships among crude oil prices, gold prices, stock market indices, currency indices, industrial production activity, and the Consumer Price Index (CPI), especially in diverse market conditions and time intervals, particularly during extreme market scenarios. Effective policies and strategies should be devised to facilitate market recovery after such events. Policymakers and regulators must closely monitor the repercussions of extreme market shocks, especially in times of financial stress. Particular attention should be given to inflation and stock market fluctuations, along with industrial production activity, as higher oil prices and currency appreciation can impact production costs and the balance of payments, subsequently influencing the CPI and stock markets. Given that systemic risks predominantly propagate in the short term, policymakers should prioritize short-term policies concerning short-term transmitters for effective risk containment. Simultaneously, a thorough exploration of long-term policies regarding long-term transmitters during extreme market conditions is warranted. In the analysis of financial markets and connectedness, spillover transmitters play a pivotal role by influencing the behavior or conditions of other markets through the transmission of shocks, risks, or changes. These transmitters act as catalysts for change and are considered sources of impact. Conversely, spillover receivers receive the impact or effects from other variables and reflect the consequences or responses to external factors. The identification of spillover transmitters is critical for policymakers, investors, and portfolio managers, as it aids in pinpointing potential root sources of systematic risk. This understanding empowers policymakers to design targeted interventions, enables investors to strategically position themselves based on interconnected movements, and allows risk managers to proactively develop strategies for mitigating adverse shocks. Investors should pay close attention to the dynamics of spillovers between markets, discerning between net contributors and net receivers of shocks. Net receivers of spillover tend to facilitate diversification in portfolios and investments. Given the evidence demonstrating that crude oil serves as a net transmitter of shocks for both the U.S. and EU, policymakers should contemplate developing preventive policies against fluctuations in crude oil prices. During extreme market conditions, central banks or policymakers should consider implementing appropriate monetary policies and countermeasures to mitigate heightened CPI in the long run. For the EU system, during economic downturns or bearish markets, policymakers or the central bank should consider interventions in the foreign exchange market to mitigate euro fluctuations. Conversely, during economic upturns or bullish markets, gold may be considered an alternative by policymakers or investors to regulate risks and uncertainty propagation.

Notwithstanding these discoveries, our future research will need to address several issues. Firstly, this paper employs return data for quantile time-frequency connectedness analysis in the commodity-financial-macroeconomic systems of the US and EU. However, there's a necessity to extend this analysis to include volatility for a comprehensive measurement of systematic risk. Secondly, although we present the results of connectedness, we haven't yet applied these findings to portfolio risk management. Consequently, our future research will involve exploring the application of these results to developing effective risk management strategies.

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CRediT authorship contribution statement

Jin Shang: Data curation, Investigation, Writing – original draft. **Shigeyuki Hamori:** Conceptualization, Funding acquisition, Project administration, Writing – review & editing.

Declaration of competing interest

The authors declare no conflicts of interest.

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Appendix A

We show the extreme quantile dynamic net total connectedness results for the US and the EU in Fig. A1 and Fig. A2, respectively. the extreme quantile dynamic net pairwise directional connectedness

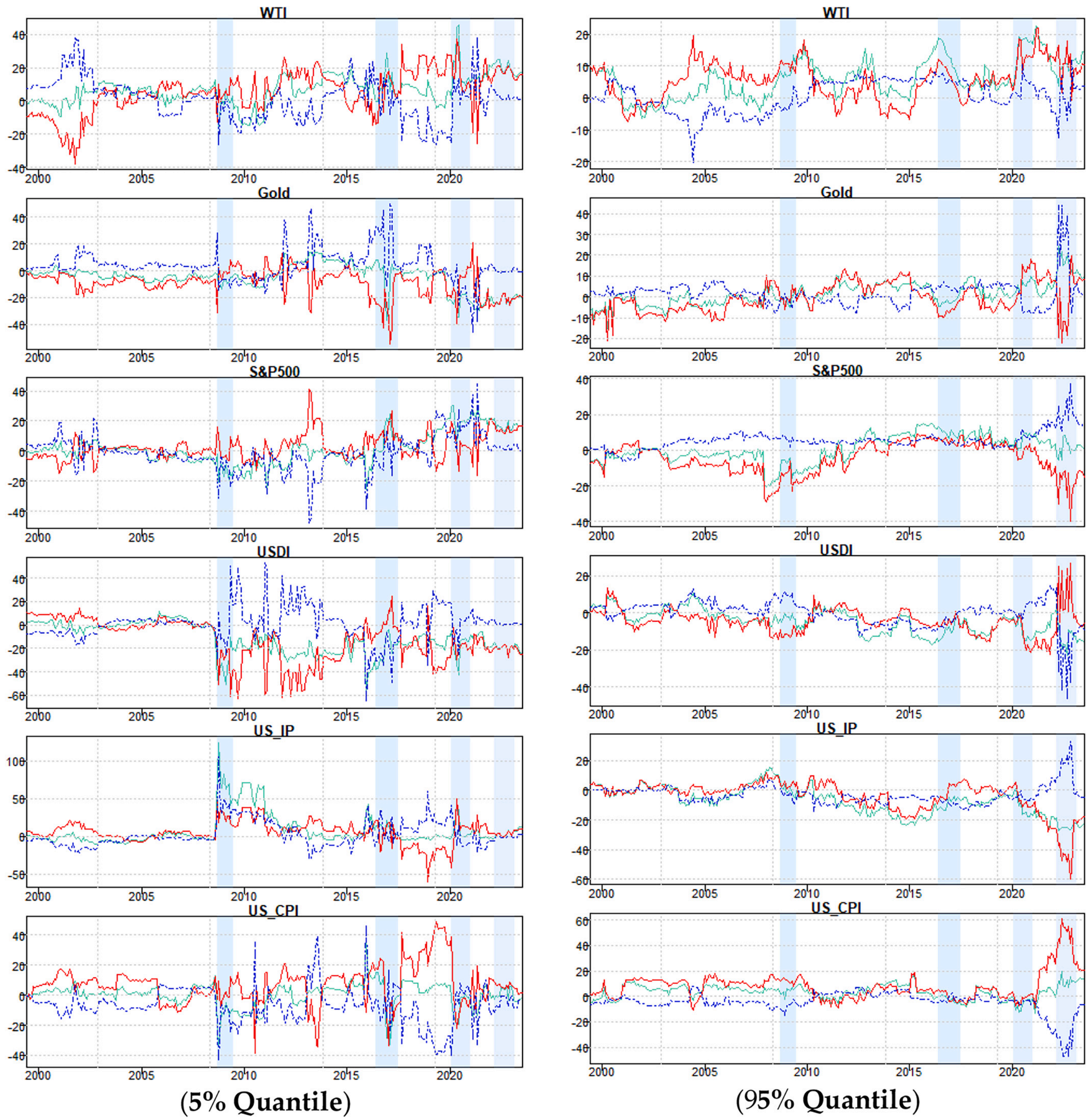

Fig. A1. Extreme Quantile Dynamic Net Total Connectedness for the US.
Notes: USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively. Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.

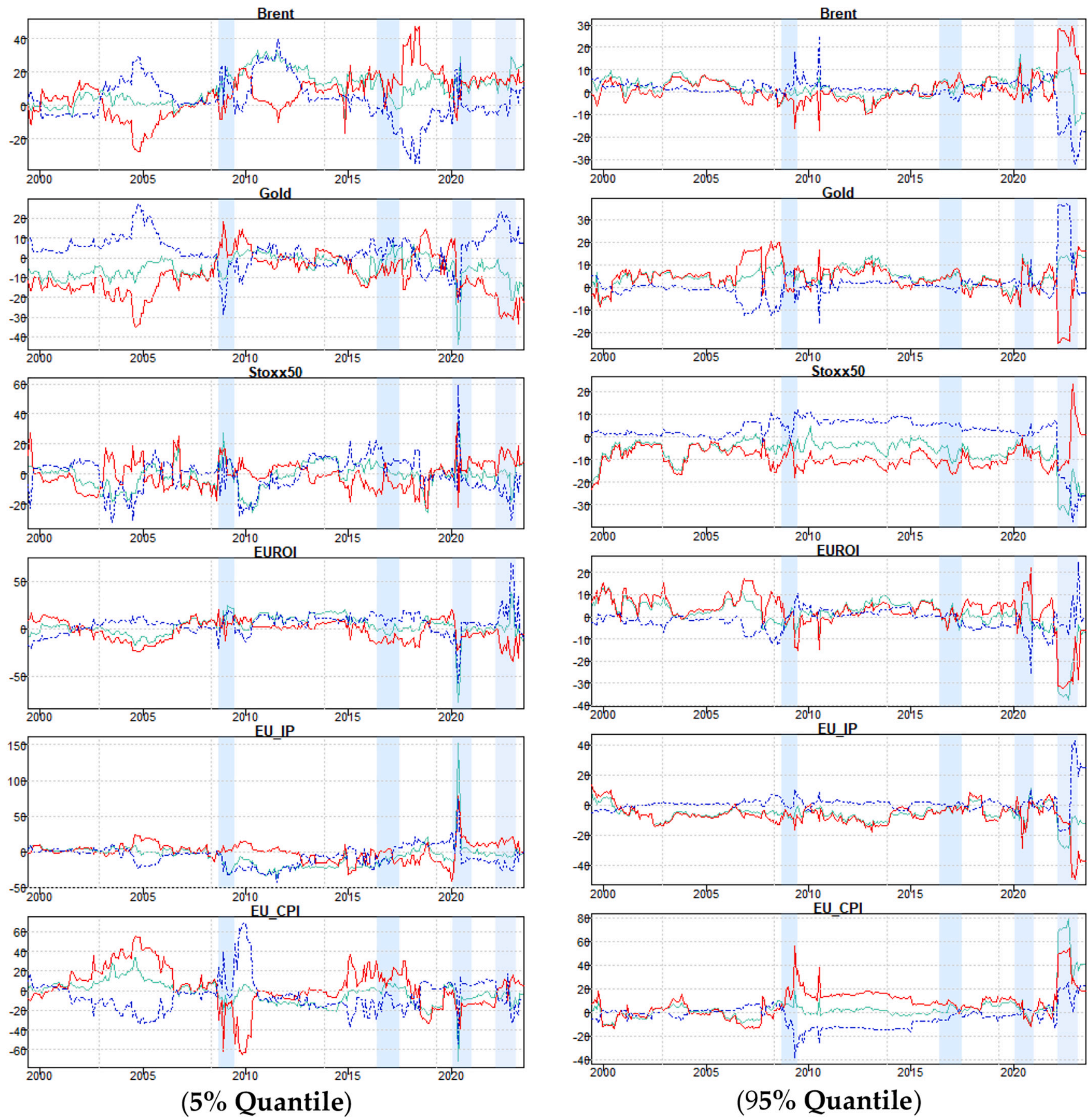

Fig. A2. Extreme Quantile Dynamic Net Total Connectedness for the EU.
Notes: EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively. Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.

Next, we show the extreme quantile dynamic net pairwise directional connectedness results for the US and the EU in Fig. A3 and Fig. A4, respectively.

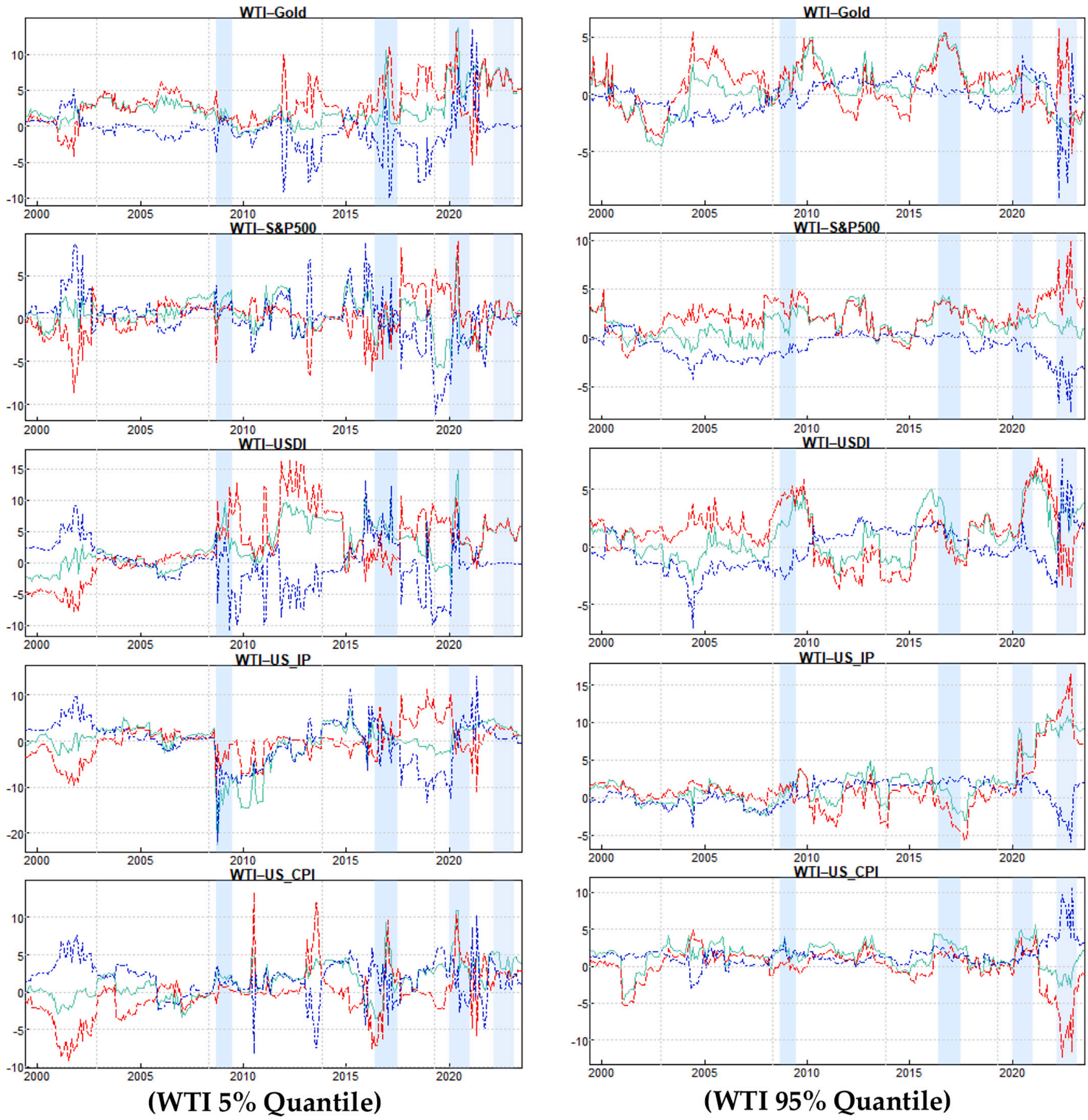

Fig. A3. Extreme Quantile Dynamic Net Pairwise Directional Connectedness for the US.
Notes: USDI, US_IP, and US_CPI denote the US dollar index, the industrial production of the US, and the consumer price index of the US, respectively. Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.

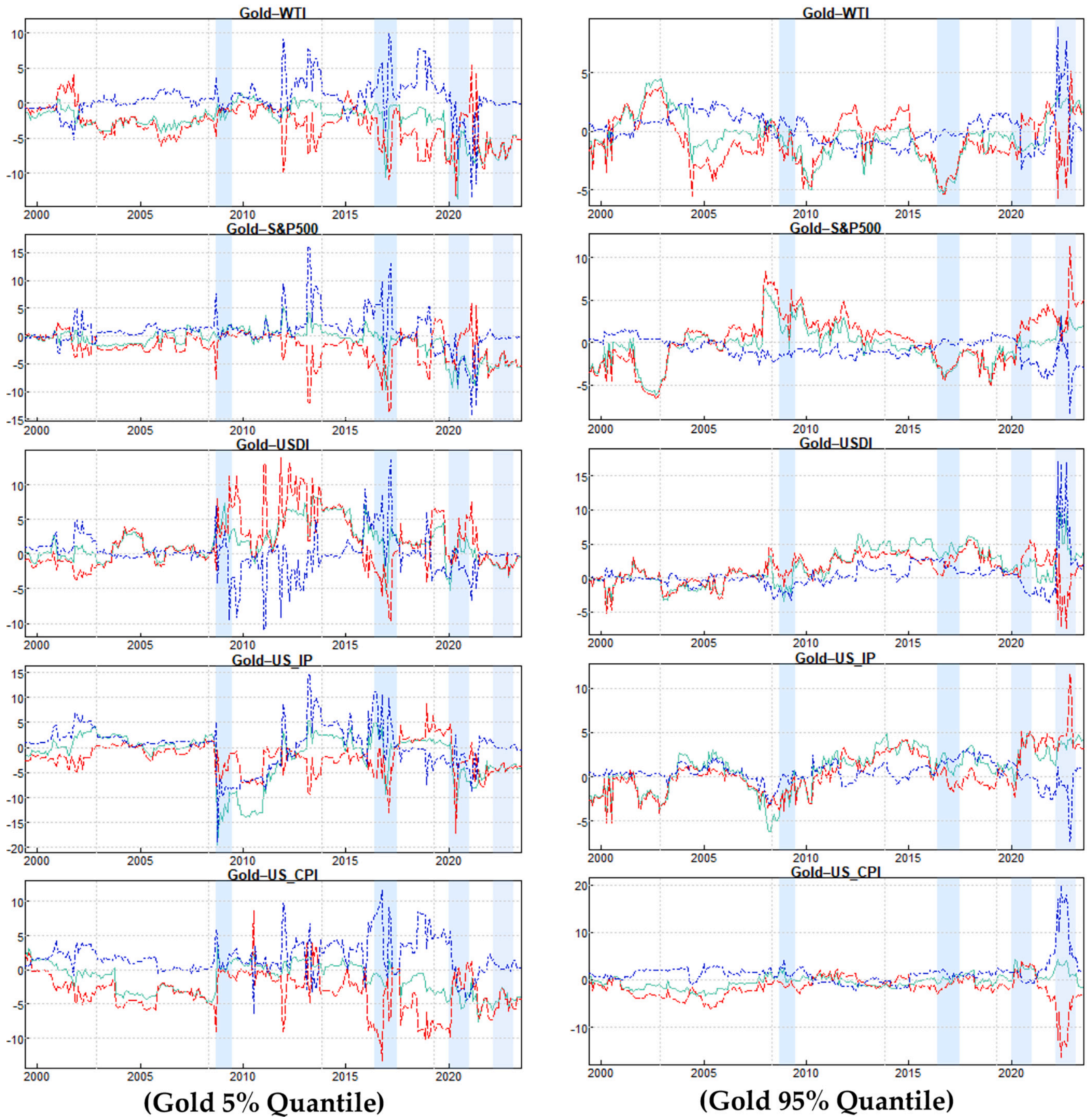

Fig. A3. (*continued*).

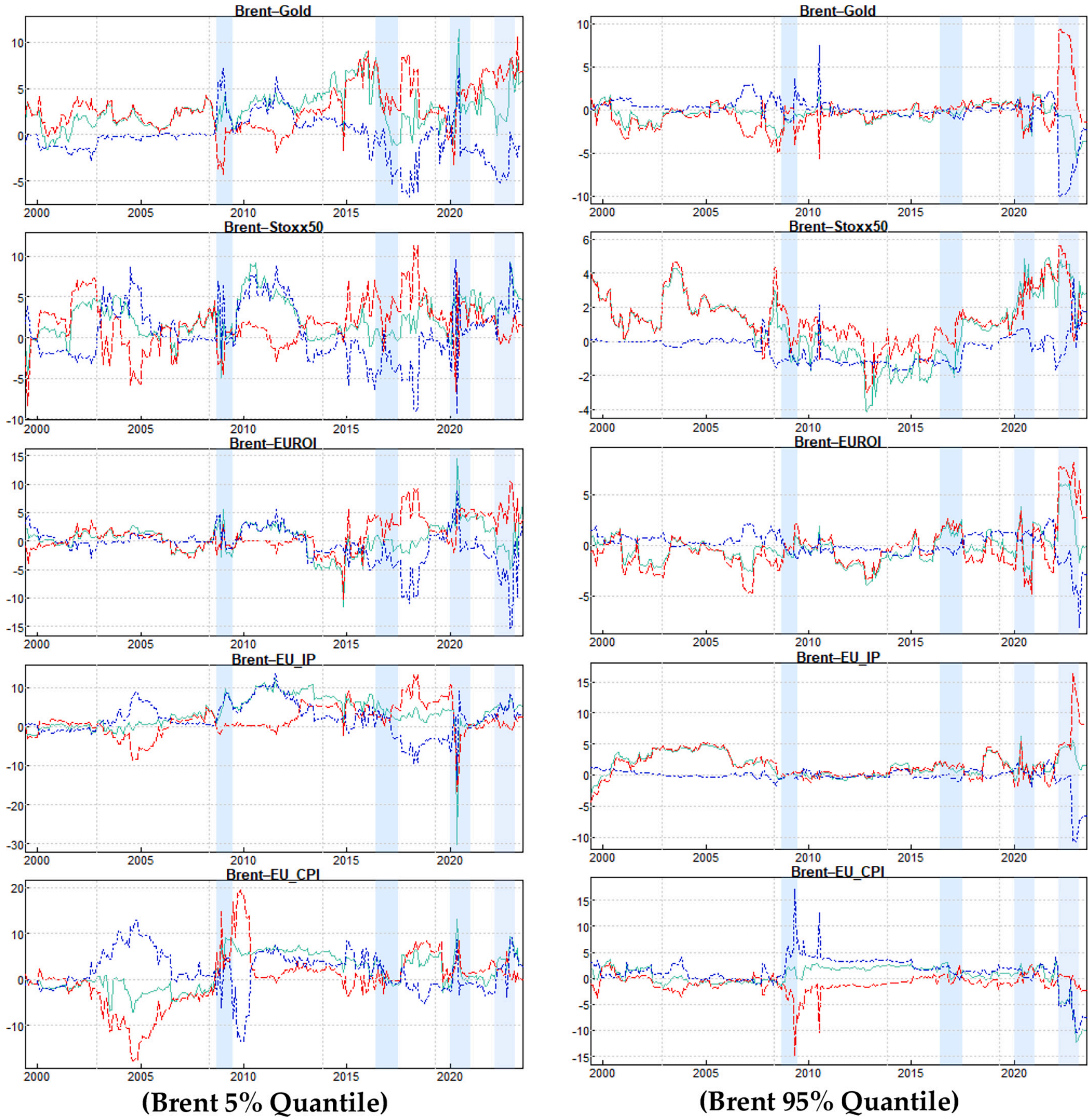

Fig. A4. Extreme Quantile Dynamic Net Pairwise Directional Connectedness for the EU.
Notes: EUROI, EU_IP, and EU_CPI denote the Euro index, the industrial production of the EU, and the consumer price index of the EU, respectively. Green, red, and the blue lines correspond to the overall, the short-term, and the long-term dynamics.

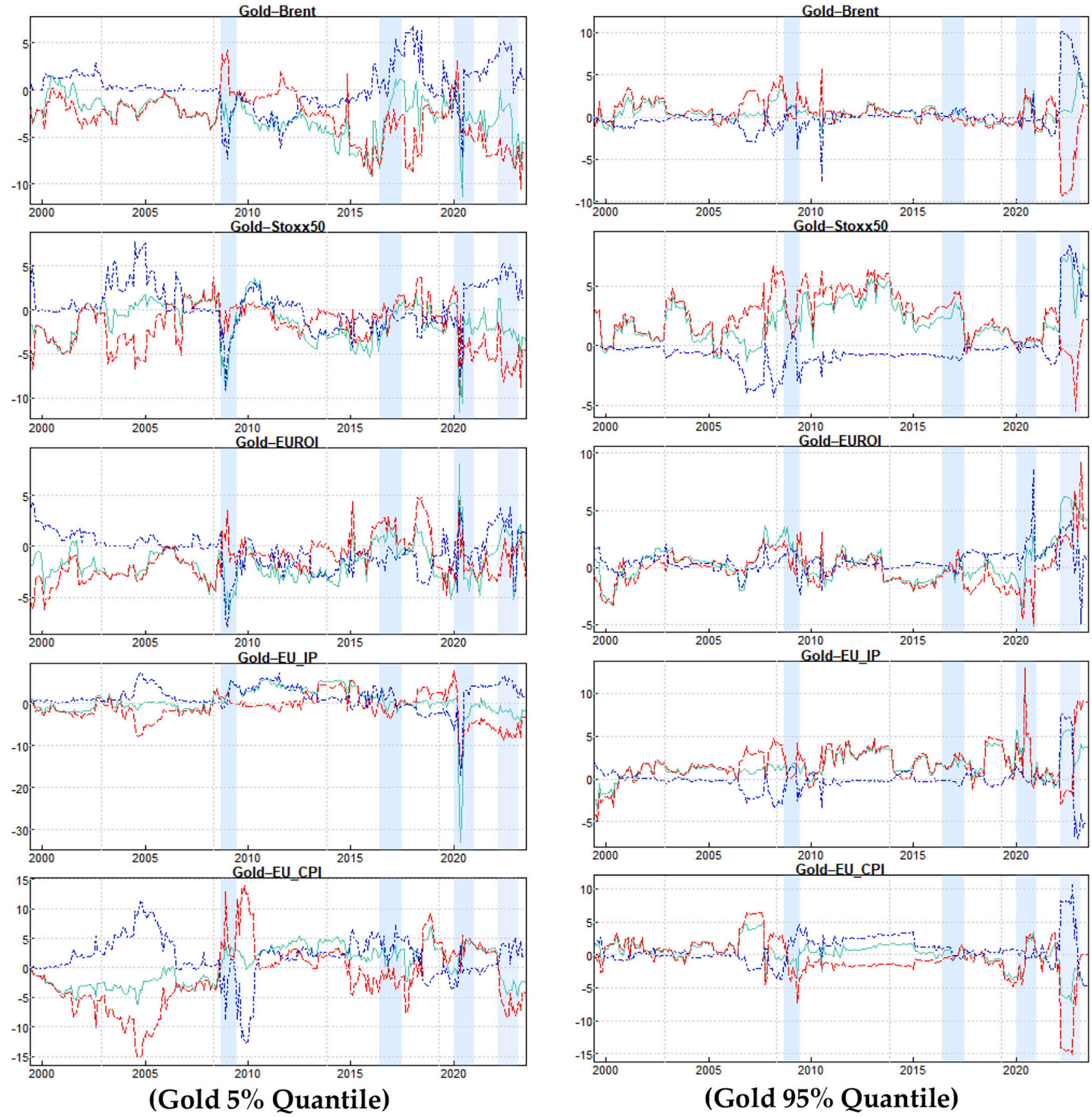

Fig. A4. (*continued*).

Appendix B

This study employs the quantile time-varying frequency connectedness approach as introduced by Chatziantoniou et al. (2022), enabling us to explore interdependencies across various quantiles and time-frequencies. This approach combines the quantile connectedness framework proposed by Chatziantoniou et al. (2021) with the time-frequency connectedness methodology introduced by Baruník and Křehlík (2018)

Assuming a quantile vector autoregression model, $QVAR(p)$, expressed by the following:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) y_{t-j} + u_t(\tau) \tag{1}$$

where y_t and y_{t-j} are $N \times 1$ dimensional endogenous variable vectors, and τ denotes the quantile, p represents the lag order of this model, $\mu(\tau)$ represents the conditional mean vector, Φ_j denotes the $N \times N$ dimensional model coefficient vectors, and u_t denotes the $N \times 1$ dimensional error vectors with the $N \times N$ dimensional error variance-covariance matrix represented by $\Sigma(\tau)$.

Transforming the $QVAR(p)$ to its quantile vector moving average expression, $QVMA(\infty)$ utilizing Wold's theorem:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) y_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=1}^{\infty} \Psi_i(\tau) u_{t-i}. \quad (2)$$

Importing the generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998), the share of the forecast error variance of variable i due to shocks from variable j can be expressed as follows:

$$\theta_{ij}(H) = \frac{(\Sigma(\tau))_{jj}^{-1} \Sigma_{h=0}^{H} \left((\Psi_h(\tau)\Sigma(\tau))_{ij} \right)^2}{\Sigma_{h=0}^{H} (\Psi_h(\tau)\Sigma(\tau)\Psi_h'(\tau))_{ii}}. \quad (3)$$

The normalization of $\theta_{ij}(H)$ can be expressed as follows:

$$\widetilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\Sigma_{k=1}^{N} \theta_{ij}(H)}. \quad (4)$$

The frequency response formula is:

$$\Psi_h : \Psi\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h, \quad (5)$$

where $i = \sqrt{-1}$ and ω is the frequency.

The Fourier transformation on the $QVMA(\infty)$ at $h = 1, 2, \ldots, H$ horizons could be expressed as follows:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E\left(x_t x_{t-h}'\right) e^{-i\omega h} = \Psi\left(e^{-i\omega h}\right) \Sigma_t \Psi'\left(e^{+i\omega h}\right). \quad (6)$$

The time-frequency GFEVD is denoted as formula (7), and its normalization expression could be denoted as formula (8):

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1} \Sigma_{h=0}^{\infty} \left((\Psi(\tau)(e^{-i\omega h})\Sigma(\tau))_{ij} \right)^2}{\Sigma_{h=0}^{\infty} (\Psi(\tau)(e^{-i\omega h})\Sigma(\tau)\Psi(\tau)(e^{i\omega h}))_{ii}} \quad (7)$$

$$\widetilde{\theta}_{ij}(\omega) \equiv \frac{\theta_{ij}(\omega)}{\Sigma_{k=1}^{N} \theta_{ij}(\omega)}, \quad (8)$$

where $\widetilde{\theta}_{ij}(\omega)$ represents the share of the ith variable's spectrum at a specific frequency ω, attributable to the shocks originating from the jth variable.

To compute connectedness over the short and long time-frequency, we assume a specific frequency range represented by $d = (a, b) : a, b \in (-\pi, \pi)$, $a < b$. The time-frequency GFEVD across the frequency band d is then defined as follows:

$$\widetilde{\theta}_{ij}(d) = \int_a^b \widetilde{\theta}_{ij}(\omega) d\omega \quad (9)$$

Subsequently, one can calculate the details of the frequency connectedness in a specific time-frequency band d,

$$NPDC_{ij}(d) = \widetilde{\theta}_{ij}(d) - \widetilde{\theta}_{ji}(d) \quad (10)$$

$$TO_i(d) = \Sigma_{i=1, i \neq j}^{N} \widetilde{\theta}_{ji}(d), \quad (11)$$

$$FROM_i(d) = \Sigma_{i=1, i \neq j}^{N} \widetilde{\theta}_{ij}(d), \quad (12)$$

$$NET_i(d) = TO_i(d) - FROM_i(d), \quad (13)$$

$$TCI_i(d) = N^{-1} \Sigma_{i=1}^{N} TO_i(d) = N^{-1} \Sigma_{i=1}^{N} FROM_i(d). \quad (14)$$

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107473.

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