Journal of Multinational Financial Management 79 (2025) 100921

Contents lists available at ScienceDirect

Journal of Multinational Financial Management

journal homepage: www.elsevier.com/locate/mulfin

Is connectedness between commodity volatility indices and G-7 stock market returns the same across return quantiles?

Waqas Hanif[a,b,c], Rim El Khoury[d], Sinda Hadhri[e,f,*]

[a] Rabat Business School, Université Internationale de Rabat, Rabat, Morocco
[b] CEFAGE - Center for Advanced Studies in Management and Economics, University of Algarve, Portugal
[c] Department of Management Sciences, COMSATS University Islamabad, Attock Campus, Pakistan
[d] Adnan Kassar School of Business, Lebanese American University, Lebanon
[e] UCLy (Lyon Catholic University), ESDES, Lyon, France
[f] UR CONFLUENCE: Sciences & Humanités (EA 1598), Lyon, France

ARTICLE INFO

JEL Classification:
C32
G01
G15

Keywords:
Spillover
G7 stock markets
oil
gold
quantile-based analysis

ABSTRACT

This study examines the connectedness and spillover effects among G7 stock markets, oil and gold volatilities from January 1, 2017, to June 16, 2022. By employing an in-quantile spillover approach, the study contributes to the existing literature by providing a comprehensive analysis of the linkages between these markets. The findings reveal that spillover effects are highly dynamic and vary significantly across different quantiles of the return distribution. During periods of market turbulence—such as the Covid-19 pandemic, trade tensions, and geopolitical conflicts—spillover intensity increases, indicating heightened market interdependence. The Japanese stock market and Gold volatility index (GVX) consistently act as net recipients of shocks, whereas the stock markets of Canada, France, Germany, Italy, the UK, and the USA serve as net transmitters. While long-term diversification opportunities appear limited, gold and oil exhibit effective hedging properties for short-term investors across various market conditions. From a policy perspective, these findings underscore the importance of monitoring market interdependencies, particularly during crisis periods. Policymakers should implement coordinated strategies to mitigate systemic risks in financial markets, especially in times of heightened uncertainty. Investors should consider short-term hedging strategies using gold and oil to minimize risk exposure during market downturns. Furthermore, financial regulators in G7 countries should enhance surveillance mechanisms to preempt excessive spillovers that may threaten financial stability.

1. Introduction

The speed of information transmission between financial markets has significantly increased due to financial liberalization and global market integration. This growing interconnectedness amplifies contagion effects, particularly during periods of financial distress (e.g., Ahmed et al., 2024; Serrano et al., 2024). Understanding how shocks propagate across markets is essential for informed investment decisions, effective portfolio risk management, and financial stability.

The G7 stock markets, representing some of the world's largest economies, are highly interdependent. However, their dynamic

---

[*] Corresponding author at: UCLy (Lyon Catholic University), ESDES, Lyon, France.
E-mail addresses: waqashanif085@gmail.com (W. Hanif), rimkhoury81@gmail.com (R. El Khoury), shadhri@univ-catholyon.fr (S. Hadhri).

https://doi.org/10.1016/j.mulfin.2025.100921
Received 26 December 2024; Received in revised form 25 July 2025; Accepted 29 July 2025

linkages with major commodities—specifically oil and gold volatilities—remain insufficiently investigated across varying market conditions and investment horizons. To address this gap, we employ a quantile-based connectedness framework combined with quantile coherence analysis, capturing asymmetric spillovers and time-frequency interdependencies across different quantiles of the conditional return distribution—corresponding to bearish (lower quantiles), normal (median), and bullish (upper quantiles) market states—as well as across short-, medium-, and long-term horizons.

This study seeks to answer the following central questions: How do spillover effects between G7 stock markets, oil, and gold volatilities evolve across different quantiles of the return distribution and over time? Which G7 markets act as net transmitters or receivers of return shocks, and how do these roles evolve over time and across quantiles? What are the implications of these dynamics for portfolio diversification, risk management, and financial stability? In doing so, we make several key contributions. First, while recent studies such as Tiwari et al. (2022) examine oil, gold, and stock market connectedness, they focus primarily on emerging economies and macroeconomic determinants of oil price movements. In contrast, we offer a financial-market-centered perspective, concentrating specifically on G7 stock markets and their linkages with oil and gold volatilities under varying market conditions and time horizons. Second, we extend the literature methodologically by integrating quantile connectedness with quantile coherence, capturing both distributional asymmetries and time-frequency interdependencies, which are crucial given the evidence of asymmetric spillovers in recent studies (Hao et al., 2024; Kyriazis et al., 2024; Ozcelebi et al., 2025). Third, we provide a crisis-specific lens by analyzing how global shocks—namely the COVID-19 pandemic and the Russia–Ukraine conflict—reshape risk transmission channels. Finally, by applying a rolling-window approach, we capture the evolving nature of risk transmission, providing valuable insights for investors and regulators concerned with systemic risk, portfolio diversification, and hedging strategies. Our inquiry contributes to key theoretical frameworks. We build on contagion theory, recognizing that shock transmission intensifies during market stress and exhibits asymmetries across the return distribution. We also relate to market microstructure theory, by considering how different investor types respond to volatility across horizons. Additionally, we contribute to portfolio choice theory, exploring the hedging roles of oil and gold under extreme conditions.

Given the increasing role of commodities, crude oil and gold have become central to financial market dynamics. Gold is widely regarded as a safe-haven asset (Baur and McDermott, 2010), offering downside risk protection during financial crises (Junttila et al., 2018). In contrast, oil markets are highly volatile and sensitive to macroeconomic shocks, geopolitical risks, and financial speculation, significantly affecting stock market returns (Elsayed et al., 2020; Fetais et al., 2024; Malik and Umar, 2019). The financialization of commodities, marked by increased institutional investor participation (Gorton and Rouwenhorst, 2006), has intensified linkages between commodities and financial assets, amplifying risk transmission and increasing financial market vulnerability to external shocks.

The G7 economies account for over 66 % of global wealth and stock market capitalization (Mensi et al., 2022). Yet, structural and policy differences among them lead to heterogeneous responses to financial disturbances. Recent extreme events, such as the COVID-19 pandemic and the Russia–Ukraine war, have introduced unprecedented uncertainty, reshaping global risk dynamics and emphasizing the need to assess market connectedness during turbulent periods. While geopolitical tensions heighten systemic instability, the pandemic delivered a severe economic shock that disrupted financial and commodity markets worldwide. During these crises, gold has demonstrated superior hedging effectiveness relative to oil, offering protection for both equity and commodity portfolios (Adekoya et al., 2021; Hsu and Tsai, 2025). This underscores the need to revisit traditional diversification strategies and explore how extreme events alter the hedging roles of key assets like oil and gold.

Prior research on G7 market spillovers has largely focused on aggregate information transmission, neglecting tail dependencies and market asymmetries. Shahzad et al. (2016) emphasized that bearish and bullish conditions significantly alter inter-asset relationships, while Beber and Brandt (2010) showed that markets react more strongly to negative information due to loss aversion. The faster transmission of negative shocks contributes to contagion, making it essential to study spillovers under varying conditions. Investment horizon also matters: Bredin et al. (2017) demonstrated that short-term investors, such as hedge funds, react quickly to volatility, whereas long-term investors, like pension funds, prioritize underlying trends. Basher and Sadorsky (2016) highlighted the need for distribution-specific strategies, and Tiwari et al. (2022) confirmed that relationships among oil, gold, and stock markets vary across both market conditions and time horizons. However, most existing models rely on mean-level spillovers, overlooking how shocks behave differently across the return distribution, especially in crises.

To fill these gaps, we examine spillover effects between G7 stock markets, oil, and gold volatilities across different return quantiles, market states, and time horizons, using data from January 1, 2017, to June 16, 2022. Our analysis is guided by three hypotheses. First, we expect spillover effects to be asymmetric across the return distribution, with stronger spillovers in the tails—during extreme bearish and bullish market conditions—than in the center (H1). Second, we hypothesize that the roles of G7 stock markets as net transmitters or receivers of return shocks evolve dynamically over time and across different quantiles, reflecting shifts in market interdependencies under varying stress levels (H2). Third, we expect gold and oil to serve as effective hedging instruments for G7 equity markets, particularly during periods of high volatility and financial crises, as revealed by time-frequency spillover dynamics (H3).

To test these hypotheses, we apply a quantile connectedness approach which captures nonlinear and tail-dependent spillovers (i.e., how shocks in the returns of oil or gold propagate to G7 stock markets under different market states). We complement this with quantile coherence analysis which assesses how interconnections evolve across multiple time horizons. By incorporating both the distributional and temporal dimensions, this study provides a richer understanding of cross-market risk transmission. Our findings offer important implications. For investors, they inform portfolio construction, risk management, and strategic asset allocation by highlighting asymmetries in return spillovers. For policymakers, the results suggest that the financialization of oil and gold strengthens feedback loops between commodities and financial systems, raising concerns for macroeconomic stability. By studying risk transmission through the lens of commodity price uncertainty, our results can guide financial regulation and crisis response coordination among G7 economies.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Sections 3 and 4 outline the methodology and data. Section 5 presents and discusses the empirical findings, and Section 6 concludes.

2. Literature review

2.1. Theoretical foundations of spillovers

Spillovers refer to the transmission of shocks from one financial market to others, manifesting in price or volatility changes. This phenomenon intensifies with the integration of global markets and the acceleration of information flows across economies. Several theories offer insights into spillover mechanisms, each highlighting different sources of cross-market interdependence.

The fundamentals-based theory suggests that spillovers stem from economic linkages. Shocks to corporate fundamentals—such as capital issuance, mergers, or acquisitions—can influence stock prices across interconnected economies (Hamao et al., 1990). When markets share similar economic structures, shocks in one economy affect others through real or financial channels. In contrast, the investor-induced hypothesis attributes spillovers to behavioral factors. Petmezas and Santamaria (2014) emphasize herding behavior, where uninformed investors imitate informed traders. This mimicking leads to correlated trading across markets as investors reallocate portfolios based on developments elsewhere. The contagion theory highlights the role of panic, market stress, and sentiment-driven reactions. According to Xiong (2001), rapid cross-market volatility arises from rising uncertainty and loss aversion. Kyle and Xiong (2001) explain that higher uncertainty increases investors' risk aversion, prompting synchronized sell-offs across markets. Finally, network theory views spillovers as the result of structural interdependencies. Stronger financial linkages between markets increase the likelihood of risk transmission. Factors such as trading volume surges, liquidity constraints, or changes in market regulation trigger spillovers (Calvo, 2004). The speed of information dissemination also shapes spillovers, as investors react to global developments by adjusting their exposures (Ederington and Lee, 1993; Harvey and Huang, 1991).

Therefore, spillovers constitute multifaceted phenomena caused by a range of factors, and comprehending the fundamental mechanisms behind them is essential for investors, policymakers, and analysts to manage risks and make informed decisions. Investigating the interconnection among different assets remains crucial for two key reasons. First, the performance of a portfolio depends on asset selection and composition (Baumöhl et al., 2018). Second, policymakers use such insights to shape effective policies (Ciner et al., 2013). Consequently, extensive studies continue to examine the various types of asset interconnections.

2.1.1. Spillovers between oil and stock markets

Crude oil is a key commodity that affects economies and financial markets worldwide. Fluctuations in oil prices impact corporate profits, inflation, and monetary policies, influencing both energy and non-energy firms. Thus, understanding oil-stock market interactions is crucial for investors and policymakers. Several theoretical models explain the relationship between oil prices and stock markets.

First, the cash flow hypothesis posits that oil price fluctuations influence firms' expected future cash flows and, consequently, stock valuations (Fisher, 1930; Williams, 1938). An increase in oil prices raises production costs, reduces profits, and leads to lower stock prices, particularly in energy-intensive sectors (Mohanty et al., 2011). Oil shocks directly impact companies' operating costs and compress cash flows, which in turn depress net income and stock performance (Aloui and Jammazi, 2009; Filis, 2010). Additionally, rising oil prices may indirectly affect stock valuations by pushing up inflation and interest rates, thereby increasing discount rates and the cost of capital.

Second, the macroeconomic hypothesis emphasizes the role of oil prices in shaping macro-financial conditions. Oil price hikes trigger inflationary pressures, prompting central banks to adopt tighter monetary policies and raise interest rates (Basher and Sadorsky, 2006). These restrictive policies increase borrowing costs, dampen investment, and reduce future earnings, ultimately leading to stock market declines.

Third, the market sentiment hypothesis suggests that investor psychology mediates the oil–stock nexus. In periods of optimism, investors favor equities, boosting stock prices. Conversely, during periods of pessimism or heightened uncertainty, investors shift capital toward perceived safe-haven assets such as gold and oil, which raises their prices but weakens equity markets (Kollias et al., 2013; Gkillas et al., 2019).

Finally, geopolitical risk channels play a critical role in oil-stock market dynamics. Events like armed conflicts, political instability, or natural disasters disrupt oil supply chains, often resulting in sharp oil price spikes (Hamilton, 2003). These supply shocks elevate operational costs and uncertainty, which negatively affect global equity markets (Morana, 2013).

Recently, the financialization of oil—driven by futures contracts, ETFs, and derivatives—strengthens its role as a financial asset rather than a pure (Mensi et al., 2017). Empirical studies show that oil-stock interactions intensify, particularly during crises. The Global Financial Crisis (2008–2009), oil market crashes (2008 & 2014), and COVID-19 pandemic amplify oil-market spillovers, challenging traditional diversification strategies (Dai and Zhu, 2022).

2.1.2. Spillovers between gold and stock markets

Gold and stocks exhibit contrasting investment characteristics: gold is a safe-haven asset, while stocks are growth-driven and riskier. However, their relationship is dynamic, influenced by economic conditions and investor behavior. Several theories can be utilized to explain gold-stock market interdependencies, including the flight to safety hypothesis, inflation hedge, currency fluctuations, and portfolio diversification.

The flight to safety hypothesis posits that during financial crises or periods of heightened uncertainty, investors shift capital from risky assets such as equities to safer alternatives like gold (Salisu et al., 2021). Gold's historical reputation as a store of value and hedge against turmoil reinforces its appeal during downturns. Empirical evidence from Baur and McDermott (2010) and Chkili (2016) confirms that gold prices typically rise during stock market declines, offering investors protection from losses. Moreover, gold is often viewed as a zero-beta asset, implying no systematic risk exposure to broader financial markets.

The inflation hedge theory further explains gold's role in financial markets. When inflation expectations rise, gold becomes more attractive as it preserves purchasing power and guards against currency depreciation. Higher expected inflation typically leads to declining stock valuations due to increased capital costs and lower profit margins. Thus, rising gold prices often precede or coincide with falling equity prices, reinforcing gold's function as an inflation hedge.

Currency dynamics also shape the gold-stock relationship. A weaker U.S. dollar tends to boost gold prices, as investors seek alternatives to depreciating fiat currencies. Simultaneously, a falling dollar may depress equity markets through increased import costs and reduced investor confidence. Conversely, a strong dollar usually leads to lower gold prices and improved stock performance. These inverse movements illustrate how currency fluctuations can jointly influence both asset classes.

The portfolio diversification theory offers another perspective, suggesting that investors spread their assets across classes like stocks and gold to reduce overall portfolio risk (Gilmore and McManus, 2002). Because gold and stocks often respond differently to macroeconomic shocks, their inclusion in a diversified portfolio enhances stability. Notably, gold and oil prices also display a positive correlation due to their shared sensitivity to inflation. Rising oil prices typically boost inflation expectations, increasing gold demand as a hedge (Narayan et al., 2010). Additionally, falling oil prices during downturns often trigger safe-haven flows into gold (Gao et al., 2021). The interdependence between oil, gold, and stock markets intensifies during crisis periods, underscoring the importance of examining their joint behavior under stress. Junttila et al. (2018) and Chen and Wang (2019) show that gold consistently mitigates stock market downturns, supporting its role in risk management strategies during financial instability.

In light of financialization, shifting market sentiment, and the rise of extreme events, dynamic models are needed to better understand cross-asset spillovers. This study responds to that need by applying quantile-based connectedness and quantile coherence methodologies. These tools allow for the identification of asymmetric and time-varying spillover effects across different market states and investment horizons, contributing a more granular and dynamic view of financial market interactions.

2.2. *Empirical evidence*

Earlier studies primarily explore spillover effects using traditional econometric frameworks such as the Vector Error Correction Model (VECM), multivariate GARCH-type models, and Vector Autoregressive (VAR) models. While these models yield important insights, they often fall short in capturing non-linear relationships and evolving inter-market dynamics. To address these limitations, Diebold and Yilmaz (2009) develop a spillover index based on forecast error variance decompositions within a VAR system. This framework is later extended by Diebold and Yilmaz (2012) to include dynamic directional spillovers, enabling a more granular understanding of transmission mechanisms. The Diebold-Yilmaz (DY) model gains popularity in measuring interconnectedness across financial markets, particularly in studies of volatility spillovers (Maghyereh et al., 2019). However, despite its strengths, this approach does not differentiate between short- and long-term spillover effects. Moreover, it lacks the capacity to capture asymmetric responses across different states of the return distribution—such as extreme bullish or bearish market conditions—especially during financial crises.

Financial markets are inherently heterogeneous, involving a wide range of participants including high-frequency traders, long-term institutional investors, and retail actors. Consequently, spillover patterns may vary depending on investment horizons, trading behaviors, and market sentiment. Short-term investors react swiftly to market shocks, whereas long-term investors respond more gradually to macroeconomic developments. This heterogeneity necessitates a multi-scale framework that accounts for variations in spillovers across both time horizons and return quantiles.

Recent studies increasingly recognize that spillovers among stock, oil, and gold markets differ across market regimes and time frequencies. These differences underscore the limitations of one-size-fits-all econometric models and call for more adaptive, distribution-sensitive methods. In this context, the integration of quantile-based approaches and coherence analysis offers promising avenues for capturing nonlinear, time-varying spillover effects under diverse market conditions.

Commodities—particularly oil and gold—are of central importance to financial and macroeconomic systems. Oil, a critical input in production and transportation, is highly sensitive to geopolitical and macroeconomic shocks. It is often viewed as a strategic investment asset due to its link to global growth prospects (Mensi et al., 2021). In contrast, gold is widely perceived as a safe-haven asset, particularly during periods of heightened financial volatility (Baur and McDermott, 2010). These contrasting characteristics make oil and gold essential benchmarks for studying asset price co-movements.

The volatility dynamics of oil and gold exhibit marked differences during crises. For instance, during episodes of financial distress, investors tend to reallocate capital toward gold, reinforcing its hedging role. In contrast, oil volatility is often driven by changes in global demand, supply disruptions, and speculative trading behavior (Arouri et al., 2015). These distinct responses highlight the necessity of analyzing oil and gold in relation to equity markets under varying conditions. Given the breadth of research in this area, the following section offers an updated synthesis of empirical studies published since 2019.

2.2.1. *Spillovers between gold and stock markets*

Gold is historically regarded as a safe-haven asset, particularly during periods of stock market distress. However, its spillover effects with equity markets are complex, dynamic, and sensitive to economic conditions. While early studies confirm gold's ability to hedge against stock market downturns, recent research indicates that this relationship is asymmetric, time-dependent, and varies across investment horizons.

Empirical evidence consistently supports gold's role in mitigating stock market risk. For example, Hung and Vo (2021) show that gold serves as an effective hedge during negative stock price movements. Similarly, Chen and Wang (2019), using quantile GARCH models, find that gold helps mitigate downside risks in the U.S. stock market. Junttila et al. (2018) demonstrate that gold and oil function as hedging instruments, though their effectiveness shifts depending on prevailing economic conditions.

Furthermore, Maghyereh et al. (2019) apply time-frequency analysis to explore gold's relationship with Islamic financial securities. They find that gold acts as a robust hedge, particularly in the medium-to-long term. During the COVID-19 pandemic, Adekoya et al. (2021) show that gold plays a key role in mitigating risks in both stock and oil markets, reinforcing its function as a crisis-period hedge.

Despite this evidence, gold's behavior during extreme events remains debated. Some studies argue that its hedging power weakens under heightened uncertainty or extreme volatility. This highlights the importance of applying methods that can account for nonlinearity and asymmetry in gold's risk transmission.

Recent research adds more nuance to the gold-stock relationship. Ming et al. (2020), using wavelet coherence analysis, show that gold provides long-term hedging benefits but is less effective in the short run, particularly in the Chinese market. In contrast, Zhang et al. (2021) argue that gold is not a reliable hedge in China, suggesting that regional factors may influence gold's safe-haven function.

These conflicting results underscore the need for quantile-based and time-frequency methods to capture gold's dynamic risk-mitigation properties. Such models are well-suited to assess how gold's hedging capacity changes across different return distributions and investment horizons.

In addition to stock market interactions, gold plays a significant role within commodity markets. Mensi et al. (2021) examine spillovers between gold, gold mining stocks, oil, and silver using quantile regression-based connectedness models. They find strong co-movement between gold and gold mining stocks, while oil and silver show greater spillover intensity at extreme quantiles. Moreover, Mensi et al. (2021) explore the transmission of shocks from precious metals to equity markets in major commodity-exporting countries. Their results confirm that gold's spillovers are particularly pronounced in the short term, highlighting its relevance for short-horizon investors during volatile periods.

2.2.2. *Spillovers between oil and stock markets*

Crude oil plays a fundamental role in global economic activity, making its relationship with stock markets a central topic in financial research. Empirical evidence confirms that oil-stock spillovers are highly asymmetric and time-varying, with volatility transmission intensifying during crises. However, the direction and magnitude of these spillovers depend on market states, regional characteristics, and the broader economic environment.

Several early studies show that oil price fluctuations significantly affect stock markets. For example, Arouri et al. (2015) find that during downturns, investors prefer gold over oil, underscoring gold's stronger safe-haven role. Mensi et al. (2018) demonstrate that oil price shocks disproportionately affect BRICS stock markets. Naeem et al. (2020), using quantile coherence, reveal that oil serves as a hedging tool under extreme market conditions, with pronounced spillovers during high volatility periods. Tiwari et al. (2022) apply wavelet methods and find that oil spillovers shift in response to macroeconomic fundamentals and global risk. Sakurai and Kurosaki (2020) report that post-COVID-19, oil's influence on stock market volatility surges due to elevated uncertainty. Similarly, Umar et al. (2021) show that oil price shocks have a stronger effect on volatility in BRICS and GCC markets than in developed economies.

Beyond global trends, regional spillover patterns are also important. Enwereuzoh et al. (2021) examine African stock markets and find that oil-related spillovers persist across both short- and long-term horizons. Mensi et al. (2021) show significant oil-stock market spillovers in MENA countries across multiple frequencies. Wu et al. (2020) use wavelet techniques and confirm that crude oil drives equity market fluctuations globally, particularly over medium- and long-term investment horizons. Yu et al. (2020) highlight oil's central role in global markets by showing a strong interdependence between WTI oil prices and equity markets in the US and China. Bouri et al. (2021) find that oil volatility increases cross-market spillovers during financial downturns. Tian et al. (2022) further show that downside oil shocks generate stronger spillovers than upside shocks, with sector- and region-specific effects.

Recent research focuses on spillovers during crisis periods. Alshater et al. (2024) explore intraday spillovers between oil and European stock markets during COVID-19 and the Russia-Ukraine war, identifying sectors as either net transmitters or receivers. Hanif et al. (2024) analyze the world's major oil producers and consumers, showing that demand-driven oil shocks have significant effects in the US, Russia, and India, while risk-related shocks dominate in China and India at median quantiles. Their study also finds that market interconnectedness intensifies during extreme conditions such as the COVID-19 crisis and geopolitical conflicts, emphasizing the historical relevance of these events. Gubareva et al. (2025) take a novel approach by examining tail risk spillovers between oil, AI, clean tech, and traditional financial markets. They find that oil and the USD function as buffers against extreme spillovers from AI and green technologies, a conclusion supported by Elsayed et al. (2024). These findings reaffirm oil's enduring role in financial market dynamics and its relevance in modern hedging strategies—particularly within the context of growing digital finance and technological integration.

2.2.3. *Spillovers between oil, gold, and stock markets*

The interconnectedness between gold, oil, and stock markets is vital for understanding financial contagion, portfolio diversification, and risk transmission. Gold and oil differ in their spillover dynamics due to their distinct economic roles. Jiang et al. (2019) and Jiang and Ye (2022) confirm both function as hedges, but their effectiveness depends on market conditions and investment horizons. Recent research emphasizes these differentiated effects. Dai and Zhu (2022) highlight oil and gas spillovers in China and Belt and Road countries. Mensi et al. (2021) find asymmetric spillovers between crude oil, gold, and Chinese sectoral indices, identifying gold as a superior hedge in times of market turbulence. Wen et al. (2020) show negative spillovers dominate during crises. Akkoc and Civcir (2019) confirm gold's safe-haven properties using SVAR-DCC-GARCH, while Abdulkarim et al. (2020) demonstrate oil's influence on Islamic equity markets via wavelet and GARCH approaches.

Commodity-financial asset spillovers are particularly strong in high-frequency settings. Mensi et al. (2021) find that gold's short-term spillovers dominate, making it relevant for intraday traders. Mensi et al. (2023) extend this with oil futures and precious metals, offering broader insights into hedging. Uddin et al. (2020) show gold improves diversification for U.S. equity investors, while Lin et al. (2019) highlight unidirectional contagion from gold and oil to stocks using wavelet decomposition.

Advanced time-frequency methods offer additional insights. Hung and Vo (2021) use time-frequency analysis to examine commodity-stock co-movements. Tiwari et al. (2019) find long-run interdependence between oil and BRICS markets. Mensi et al. (2022) find that negative shocks from gold and oil disproportionately affect EU stock subsectors, with strong unidirectional spillovers. Mensi et al. (2022) use intraday data to show that gold plays a stronger diversification role than oil during COVID-19, albeit at a higher cost.

Recent work further explores spillovers during extreme events. Mensi et al., (2023) find G7 markets—except Japan—are net transmitters of volatility to gold and oil uncertainty indices, reinforcing gold's relative resilience. Mensi et al. (2024) use quantile-on-quantile regressions to examine MENA markets and find asymmetric dependence, with stocks more influential at lower quantiles.9

Complementing this, Mensi et al. (2024) analyze extreme quantile connectedness between WTI and Vietnamese sectors, showing oil is a net receiver in downturns and a contributor in upturns. El Khoury et al. (2025) find oil diversifies Indonesian sectors better than gold, especially during COVID-19. Mensi et al. (2024) reveal stronger return spillovers at extreme quantiles, with gold and oil as net recipients. Younis et al. (2025) extend this to oil, gold, Bitcoin, and GCC markets during the Russia-Ukraine and Israel-Palestine conflicts. They find gold offers better diversification in select regions, while oil remains a key risk driver. Harnphattananusorn (2024) shows that in Thailand, gold and stocks act as net shock transmitters, oil and FX as receivers. Mensi et al., (2021) explore MENA natural gas, oil, and gasoline markets, uncovering regional interdependencies. Similarly, Mensi et al. (2023) assess oil futures and precious metals' connectedness to financial assets, identifying key hedging insights. Despite extensive research, spillover dynamics between gold, oil, and G7 markets remain underexplored. Shahzad et al. (2020) compare gold and Bitcoin within G7 markets, confirming gold as a consistent hedge; Bitcoin only holds in Canada.

Building on this, Mensi et al. (2022) explore G7 market spillovers to global green bonds and oil. To fill the remaining gaps, our study examines extreme spillovers using quantile coherence and connectedness models to capture the frequency dynamics and asymmetries between oil, gold, and G7 stock markets.

3. Research methodology

3.1. Quantile connectedness approach

In order to explore the quantile connectedness between commodity volatilities, specifically OVX and GVX, and G7 countries, our study adopts the approach proposed by Ando et al. (2022)[1]. This approach builds upon the methodology suggested by Diebold and Yilmaz (2012), (2014). Traditional spillover models, such as Diebold and Yilmaz (2012), assume uniform transmission across the entire return distribution, which overlooks asymmetries under extreme market conditions. The quantile connectedness approach overcomes this limitation by capturing tail dependencies, allowing us to assess how risk spillovers differ under bullish, bearish, and normal market conditions. This method is particularly valuable in crisis analysis, as it helps uncover how systemic risk propagates in extreme scenarios—insights that standard methods fail to capture.

By utilizing this established framework, we aim to analyze the interconnectedness and transmission of shocks between these commodities and the G7 countries. This methodology provides a robust foundation for investigating the dynamics and dependencies within the complex relationship between commodity volatilities and the G7 economies. This approach considers the dependence of y_t on x_t within each quantile of the conditional distribution of the ratio y_t/x_t in quantile regression. This allows us to express the quantile vector autoregression, known as QVAR(q), as follows:

$$y_t = c(q) + \sum_{i=1}^{p} \phi_i(q) y_{t-i} + \varepsilon_t(q), \quad q\epsilon(0,1) \tag{1}$$

Where y_t and p are the $N\,x1$ vector of endogenous variables and the lag length, respectively. The mean vector $N \times 1$ is $c(q)$. The $N \times N$ $QVAR$ coefficient matrix is given as $\phi_i(q)$. The error term $\varepsilon_t(q)$ is variance–covariance matrix $N \times N$, $\sum(q)$. The $\widehat{\phi}_i$ and $\widehat{c}_i$ are estimated by assuming that the residuals follow the quantile constraint, $Q_q\left(\varepsilon_t(q)/y_{t-1},\ldots,y_{t-p}\right) = 0$. The population qth conditional quantile of response y is written as:

$$Q_q\left(y_t/y_{t-1},\ldots,y_{t-p}\right) = \widehat{c}(q) + \sum_{i=1}^{p} \widehat{\phi}_i(q) y_{t-i} \tag{2}$$

---

[1] A detail explanation is reported in Appendix-A(A1).

At many quantiles, we construct the quantile connectedness matrix. We can explain the infinite order vector moving average (MA) with $QVAR(\infty)$ from Eq. (1) as:

$$y_t = c\mu(q) + \sum_{i=1}^{\infty} \Psi_i(q)\varepsilon_{t-1}(q), \quad t = 1, \dots, T \tag{3}$$

At every quantile, y_t is the total of residuals $\varepsilon_t(q)$. To explain the generalized forecast error variance decompositions (GFEVD) at a forecast horizon H, our study adopts the method suggested by Koop et al. (1996) and Pesaran and Shin (1998). This methodology provides a framework for analyzing the decomposition of forecast error variances into the contributions from different variables or factors. By utilizing this approach, we aim to gain insights into the relative importance and contributions of various factors in explaining forecast errors at the specified forecast horizon H. The methodology employed in this study has been extensively utilized in the literature, offering a comprehensive and robust approach to comprehend the origins of forecast uncertainty and their corresponding implications.

$$\widetilde{C}_{ij}^{g}(H) = \frac{\sum q_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Psi_h(q) \sum(q) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Psi_h(q) \sum \tau \Psi_h(q' e_i)\right)}, \tag{4}$$

In Eq. (4), $\widetilde{C}_{ij}^{g}(H)$ signifies the *jth* variable contribution to *ith* variable variance of forecast error at the horizon H_t. The e_i is a 0 vector with 1 on the *ith* position. In the decomposition matrix, each element is normalized as:

$$\widetilde{C}_{ij}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum\limits_{j=1}^{k} \Theta_{ij}^{g}(H)}, \text{with} \sum_{j=1}^{k} \widetilde{C}_{ij}^{g} = 1 and \sum_{ij=1}^{k} \widetilde{C}_{ij}^{g}(H) = k \tag{5}$$

The total connectedness index (TCI) at qth quantile is given as:

$$TCI(q) = \frac{\sum\limits_{i=1}^{k} \sum\limits_{j=1, i\neq j}^{k} \widetilde{C}_{ij}^{g}(q)}{\sum\limits_{i=1}^{k} \sum\limits_{j=1}^{k} \widetilde{C}_{ij}^{g}(q)} \times 100 \tag{6}$$

The " $TO_{i\to j}$" spillover Index is:

$$TO_{i\to j} \quad (q) = \frac{\sum\limits_{j=1, i\neq j}^{k} \widetilde{C}_{ji}^{g}(q)}{\sum\limits_{j=1}^{k} \widetilde{C}_{ji}^{g}(q)} \times 100 \tag{7}$$

Similarly, the The " $FROM_{i\leftarrow j}$" spillover Index is:

$$FROM_{i\leftarrow j} \quad (q) = \frac{\sum\limits_{j=1, i\neq j}^{k} \widetilde{C}_{ij}^{g}(q)}{\sum\limits_{j=1}^{k} \widetilde{C}_{ij}^{g}(q)} \times 100 \tag{8}$$

At last, the NET spillover Index is:

$$NET_i(q) = TO_{i\to j} \ (q) - FROM_{i\leftarrow j}(q) \tag{9}$$

The positive values of $NET_i \ (q)$ indicate the net transmission from other markets, whereas the negative values $NET_i \ (q)$ indicate the net receiver from other markets.

3.2. Quantile coherence approach

In our study, we adopt Baruník and Kley (2019) [2] methodology to investigate the dependence on assets at different frequencies, including short, medium, and long frequencies at various quantiles, specifically the 5th, 50th, and 95th quantiles.

Standard time-frequency approaches, such as wavelet coherence and Fourier spectral analysis, focus solely on frequency dependencies and assume constant relationships across quantiles, which may not hold in turbulent markets. Quantile coherence extends these frameworks by capturing both time-frequency dependencies and distributional asymmetries, allowing us to analyze how spillovers evolve across different time scales and risk conditions. This dual perspective is particularly useful in detecting financial contagion patterns, as it provides a more refined crisis-contingent view of financial linkages compared to traditional spectral methods.

---

[2] Appendix-A(A2) for details.

Baruník and Kley (2019) approach is widely recognized and enables a detailed examination of asset dependence, offering valuable insights for risk management and portfolio construction. The two stationary processes $(X_{i,j1})$, $(Y_{i,j2})$ dependemce define the relation as:

$$\widehat{\mathfrak{R}}^{j1,j2}(\omega;\tau_1,\tau_2) := \frac{\mathfrak{f}^{j1,\quad j2}(\omega:\tau_1,\tau_2)}{(\mathfrak{f}^{j1,\quad j2}(\omega:\tau_1,\tau_2)\mathfrak{f}^{j1,\quad j2}(\omega:\tau_1,\tau_2))1\big/2} \tag{10}$$

Where quantile cross-spectral density is $\mathfrak{f}^{j1,j2}$ for every $\tau \in [0,1]$ and $j \in \{1,\ldots,d\}$. The quantile spectral densities of the processes $(X_{i,j1})$, $(Y_{i,j2})$ are $\mathfrak{f}^{j1,j1}$ and $\mathfrak{f}^{j2,j2}$ which are calculated from the Fourier transform of the matrix of quantile cross-covariance kernels $\Gamma_k(\tau_1, \tau_2):\quad=\quad\Upsilon_k^{j1j2}\quad(\tau_1,\tau_2)j1j2 = 1,\ldots,d))$

where

$$\Upsilon_k^{j1j2}(\tau_1,\tau_2) := Cov(I\Big\{X_{t+kj1}\quad\leq\quad q_{j1}(\tau_1)\Big\},\quad I\Big\{X_{t+j2}\quad\leq\quad q_{j2}(\tau_2)\Big\}) \tag{11}$$

For $j \in \{1,\ldots,d\}$,$k \in Z$, $\tau_1,\tau_2 \in [0,1]$ and $I\{A\}$ is the indicator function of event A. For continuous cases, this measure corresponds to the difference in the copula of $X_{t+k,j1}$,$X_{t,j2}$ and the independent copula. We estimate the coefficients of cross-sectional dependence only when $j_1 \neq j_2$. The matrix of quantile cross-spectral density kernels matrix is written as:

$$\mathscr{F}(\omega,\tau_1,\tau_2) : (f^{j1,\quad j2}(\omega;\tau_1,\tau_2))_{j1j2=1,\ldots,d} \tag{12}$$

where

$$\mathfrak{f}^{j1,\quad j2}(\omega;\tau_1,\tau_2) := (2\pi)^{-1}\sum_{k=-\infty}^{\infty}\Upsilon_k^{j1j2}(\tau_1,\tau_2)e^{-ik\omega} \tag{13}$$

In line with the study conducted by Baruník and Kley (2019), we employ the concept of smooth quantile cross-periodograms to calculate the quantile coherence. We compute the quantile coherence matrix at the 5th, 50th, and 95th quantiles. These quantiles represent combinations of the left, medium, and right tails of the distributions, enabling us to capture various aspects of the dependence structure.

Furthermore, we consider three frequencies in our study: short-term, medium-term, and long-term. The short-term frequency corresponds to a time window of 5 days, the medium-term frequency corresponds to 22 days, and the long-term frequency corresponds to 250 days. By examining dependence at different frequencies, we aim to uncover how the coherence or dependence between assets varies across different time scales.

By employing these methodologies, we can gain insights into the dynamics of asset dependence at different quantiles of the return distribution and frequencies, providing a comprehensive understanding of the risk profiles and co-movements of the assets under consideration.

4. Data and preliminary analysis

We base our analysis on the G7 stock markets' daily closing spot prices, which include Canada, France, Germany, Italy, Japan, the UK, and the US. In this study, we use the CBOE Crude Oil Volatility Index (OVX) and the CBOE Gold Volatility Index (GVX) as proxies for oil and gold market volatilities, respectively. Table 1 defines all variables. Our investigation primarily focuses on the Covid-19 pandemic and the Russian 2022 conflict, comparing them to the pre-Covid era. The sample period runs from January 1, 2017, to June 16, 2022, covering the Covid-19 period beginning on March 11, 2020, and the Russia–Ukraine war period beginning on February 24, 2022. By doing this, we evaluate how volatile G7 stock markets, oil prices, and gold prices are related throughout these particular time periods without taking into account the impact of previous crises like the oil crisis of 2014–2016, the European debt crisis of 2011, and the global financial crisis of 2007–2008. Stock returns are computed as the continuously compounded daily returns, measured

Table 1
Variables definition.

Variable	Description	Source
Canada	Daily return of the Canadian stock market index (S&P/TSX Composite Index)	Refinitiv Datastream
France	Daily return of the French stock market index (CAC 40)	Refinitiv Datastream
Germany	Daily return of the German stock market index (DAX)	Refinitiv Datastream
Italy	Daily return of the Italian stock market index (FTSE MIB)	Refinitiv Datastream
Japan	Daily return of the Japanese stock market index (Nikkei 225)	Refinitiv Datastream
UK	Daily return of the UK stock market index (FTSE 100)	Refinitiv Datastream
US	Daily return of the US stock market index (S&P 500)	Refinitiv Datastream
OVX	Oil Volatility Index: measures market-implied volatility of crude oil prices (based on WTI futures)	CBOE
GVX	Gold Volatility Index: measures market-implied volatility of gold prices (based on gold futures)	CBOE

Note: This table summarizes the variables used in the analysis. Stock market indices represent daily total returns for major economies and are sourced from Refinitiv Datastream. Volatility indices (OVX and GVX) measure the market-implied volatility of crude oil and gold futures prices, respectively, and are obtained from the CBOE.

using the natural logarithm of the ratio of consecutive closing prices: $\ln(P_t/P_{t-1})$, where P_t and P_{t-1} represent the closing prices on days t and t − 1, respectively.

Table 2 displays summary statistics on the daily returns of the G7 stock markets, as well as the daily OVX and GVX. For stock returns, the mean represents the average daily percentage change in stock prices, while the standard deviation captures return volatility, measuring the typical fluctuation around the mean. For OVX and GVX, the mean values reflect the average level of implied volatility in the oil and gold markets, respectively, over the sample period. The standard deviation of OVX and GVX measures the dispersion of implied volatility values over time. Except for the UK, all series show positive average daily returns. The average daily return over the sample period ranges from −0.001 % for the UK to 0.035 % for the US. Compared to the gold market, the oil market exhibits a higher average volatility of 0.034 %, whereas gold's average volatility is only 0.012 %. All G7 countries display high unconditional volatilities, as indicated by the standard deviation of their stock returns. The volatility indices for oil (OVX) and gold (GVX) are even more pronounced, with standard deviations of 5.150 and 4.657, respectively. These statistics align with the price movements of stock and commodity markets observed during the sample period, which includes several episodes of turmoil. All of the G7 countries' skewness coefficients are negative, which denotes a left-skewed distribution. The kurtosis coefficients suggest non-normal distributions for all return series. By examining the results of the Jarque-Bera (JB) test, the non-normality is identified. The ADF and KPSS tests disprove the null hypothesis that all series are non-stationary. Furthermore, the results of the Ljung-Box Q (10) test also show that all series have significant autocorrelation in lags 1–10, rejecting the null hypothesis.

Fig. 1 depicts the dynamics of OVX, GVX, and G7 stock prices. The graph shows a decline in all G7 stocks during the Covid-19 outbreak in China in late 2019. This decline, which coincides with the pandemic, is attributed to investor and regulator uncertainty, which causes the stock markets to decline (Mazur et al., 2021; Zaremba et al., 2021). The subsequent increase in stock prices indicates a recovery of the stock markets from the adverse effects of the pandemic. Meanwhile, OVX and GVX exhibit an upward trend throughout the sample period, with notable surges in early 2020 and 2022, coinciding with the pandemic and the Russian–Ukrainian war. These notable events introduce disruptions and heighten uncertainty regarding the future supply and demand dynamics of energy commodities, particularly oil (e.g., Niu et al., 2022). As a consequence, oil prices experience increased volatility. On the other hand, factors such as inflation, a weak U.S. dollar, geopolitical risks, and the inherent inelasticity of supply and demand for gold in response to price changes, arising from global instability, all play a role influencing the volatility of gold markets (Beckmann and Czudaj, 2013; Gkillas et al., 2020; Li et al., 2023; Reboredo, 2013).

The dynamics of returns in the G7 stock markets, as well as OVX and GVX, are illustrated in Fig. 2, and a similar trend to Fig. 1 is observed. There is a significant decline in stock returns across the analyzed countries in early 2020, which is attributed to the outbreak of the pandemic in March 2020. During this period, the volatilities of the oil and gold markets also increase, with oil volatility reaching peaks of more than 50. The volatility in the gold market is more pronounced throughout the entire sample period, with the highest peaks occurring between 2019 and 2020.

Fig. 3 presents the results of pairwise correlations between the G7 stock returns and oil and gold volatilities. The highest correlation coefficients are observed between France and Germany (0.944), France and Italy (0.893), and Germany and Italy (0.884). These results are not surprising considering the geographic proximity and economic interdependence between these countries. The correlation coefficients between the other G7 countries range from 0.267 (between Canada and Japan) to 0.884 (between France and the UK), indicating relatively high pairwise correlations for most pairs. On the other side, the correlations between the G7 stock markets and OVX and GVX exhibit negative correlations with moderate coefficients ranging from −0.433 (for the pair Canada–OVX) to −0.154 (for Japan–OVX). These findings can be understood as increased volatility in oil and gold prices leading to uncertainty in macroeconomic outcomes during normal periods and supply/demand disruptions during crisis periods. However, these negative coefficients are moderate, suggesting moderate linkages between the G7 stock markets and OVX and GVX.

Table 2
Summary of descriptive statistics.

	Mean (%)	Std.Dev	Skewness	Kurtosis	J.B	Q(10)	Q2(10)	ADF	KPSS
Canada	0.018	1.220	−2.022	33.263	66777.390***	75.664***	1065.528***	−10.081***	0.044
France	0.014	1.304	−0.939	14.931	13471.919***	17.125***	297.960***	−11.31***	0.088
Germany	0.009	1.328	−0.658	15.153	13763.457***	15.848***	214.336***	−11.037***	0.107
Italy	0.008	1.459	−2.043	26.564	42960.256***	22.029***	126.906***	−10.607***	0.102
Japan	0.014	1.146	−0.107	5.722	1952.624***	7.833	360.674***	−11.287***	0.168
UK	−0.001	1.200	−1.174	17.867	19317.595***	22.003***	355.193***	−10.777***	0.049
US	0.035	1.233	−1.055	18.541	20714.517***	150.003***	1300.637***	−9.9778***	0.099
OVX	0.034	5.150	2.412	22.082	30385.457***	29.269***	117.146***	−11.287***	0.022
GVX	0.012	4.657	0.598	4.395	1235.961***	45.752***	180.546***	−11.567***	0.053

Note: This table presents summary statistics for the daily return series of all variables defined in Table 1 over the period from January 2017 to June 2022. Reported metrics include the mean (%), standard deviation, skewness, kurtosis, and the Jarque-Bera (J.B.) test for normality. Q(10) and $Q^2(10)$ represent the Ljung-Box test statistics for autocorrelation in returns and squared returns, respectively. ADF refers to the Augmented Dickey-Fuller test (Dickey and Fuller, 1979) for unit roots, and KPSS denotes the Kwiatkowski–Phillips–Schmidt–Shin (1992) stationarity test. *** indicates statistical significance at the 1 % level.

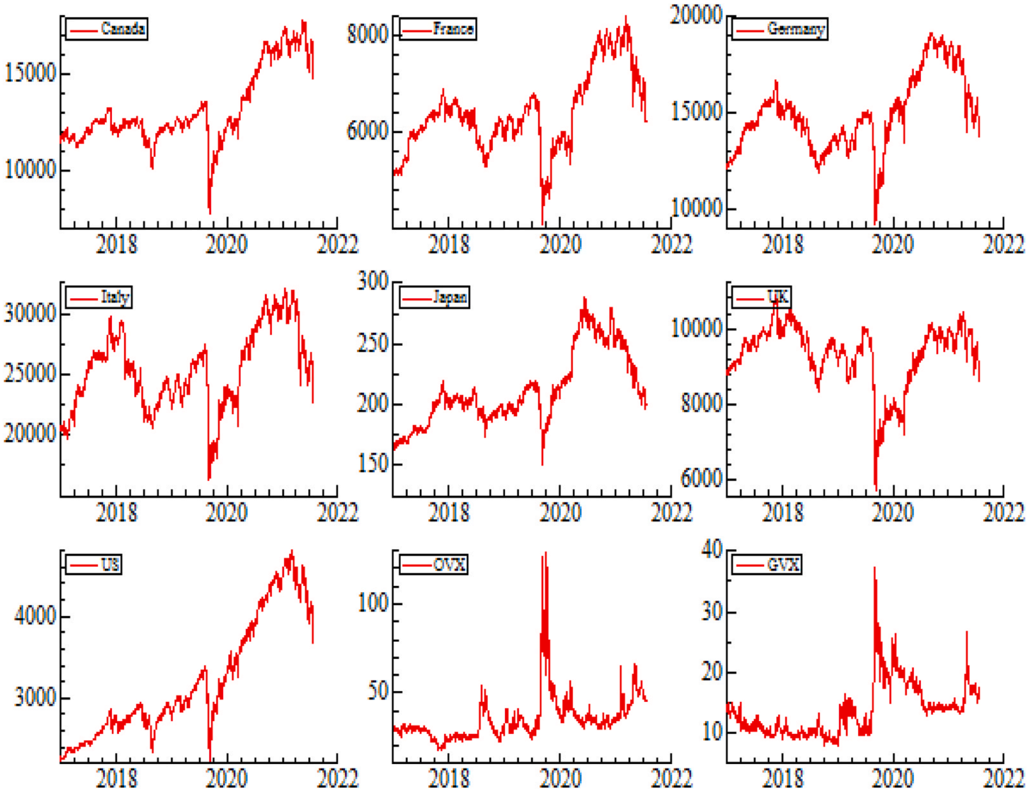


Fig. 1. Dynamics of G-7 stock prices and oil and gold volatilities. Note. This figure displays the levels of G7 stock market indices along with oil and gold volatilities over the period from January 1, 2017 to June 16, 2022. See Table 1 for definitions of all variables. The figure illustrates the general trends and structural shifts in market values.

5. Empirical findings and discussion

We present the results of our investigation on both average and time-varying quantile-based connectivity in this section. First, we summarize the findings of the static pairwise connectivity study, which examines the interconnectedness of the OVX, GVX, and G7 stock markets across quantiles. This approach contributes to our understanding of the interconnection and movement of these markets. Second, to understand the dynamic spillover between markets, we analyze the dynamic evolution of the Total Connectedness Index (TCI) through time for the medium, high, and low quantiles. Third, we illustrate the results of the time-varying net spillover of the markets and variables to elucidate individual contributions within the connectedness system. We, specifically, discuss the results of the net pairwise spillover before and during the Covid-19 period and during the Russian-Ukraine war, highlighting many notable differences. Finally, we interpret the results of the short-, medium-, and long-term quantile coherence matrices, which capture the level of coherence among the seven stock markets, oil volatility, and gold volatility over different time horizons. This analysis provides us with a comprehensive understanding of the coherence levels between these markets across various time intervals.

5.1. Static quantile-based pairwise spillovers between G7 stock returns, OVX and GVX

The results of the size and direction of information spillovers and connectivity at lower, medium, and upper quantiles appear in Table 3, Panels A, B, and C, respectively. Panel A shows the return spillover dynamics under bearish market conditions ($q = 0.05$). Own-share spillovers—capturing the proportion of forecast error variance explained by each variable's own shocks—range from 12.87 % for Japan to 14.13 % for the United States. These findings align with previous research, which highlights cross-country differences in the degree of financial (co)integration among G7 stock markets (Donadelli and Paradiso, 2014; Ghorbel et al., 2022; Gong and Kim, 2018; Tahai et al., 2004). The OVX (16.26 %) and GVX (15.54 %) also show high own-share values, but only GVX is statistically significant ($p = 0.01$), suggesting that gold volatility retains some degree of autonomous variation, even in turbulent periods. In contrast, the OVX's own-share is not statistically significant ($p = 0.78$), indicating that oil volatility is largely shaped by external equity market dynamics during downturns. These results reinforce the notion that international spillovers play a critical role in asset price movements, as previous studies suggest that 70–80 % of equity market returns are attributable to international factors (Fang et al., 2021).

Importantly, several statistically significant spillover effects emerge across markets. Among the G7 stock indices, Germany to

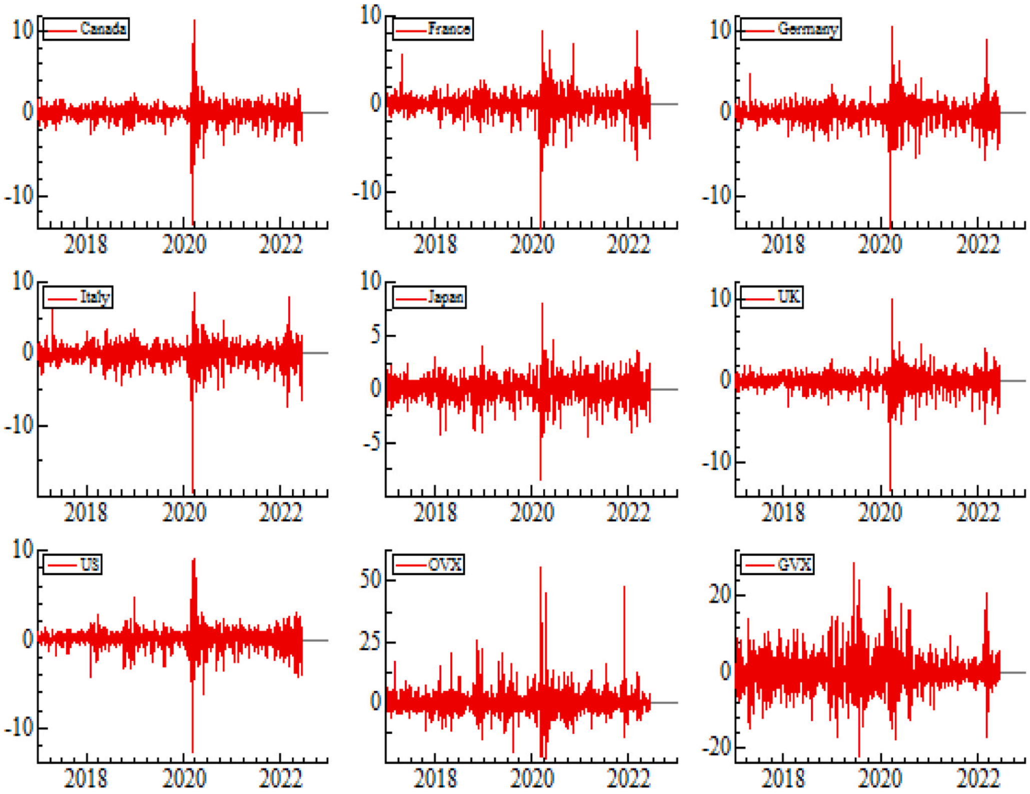
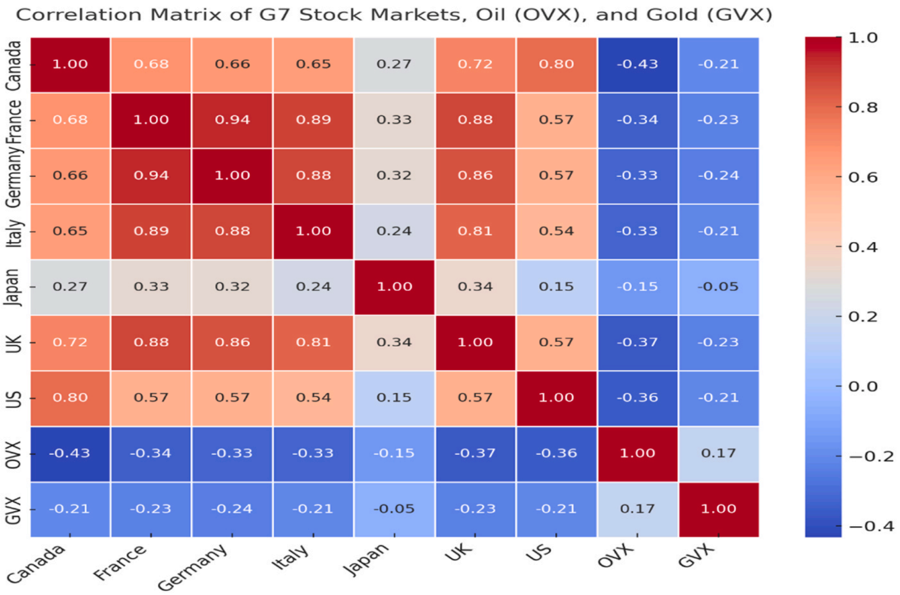


Fig. 2. Returns of G-7 stock prices, oil and gold volatilities. Note: This figure shows time-series plots of daily returns for G7 stock markets, oil volatility index (OVX), and gold volatility index (GVX) from January 1, 2017 to June 16, 2022. See Table 1 for definitions of all variables.


Correlation Matrix of G7 Stock Markets, Oil (OVX), and Gold (GVX)

	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX
Canada	1.00	0.68	0.66	0.65	0.27	0.72	0.80	-0.43	-0.21
France	0.68	1.00	0.94	0.89	0.33	0.88	0.57	-0.34	-0.23
Germany	0.66	0.94	1.00	0.88	0.32	0.86	0.57	-0.33	-0.24
Italy	0.65	0.89	0.88	1.00	0.24	0.81	0.54	-0.33	-0.21
Japan	0.27	0.33	0.32	0.24	1.00	0.34	0.15	-0.15	-0.05
UK	0.72	0.88	0.86	0.81	0.34	1.00	0.57	-0.37	-0.23
US	0.80	0.57	0.57	0.54	0.15	0.57	1.00	-0.36	-0.21
OVX	-0.43	-0.34	-0.33	-0.33	-0.15	-0.37	-0.36	1.00	0.17
GVX	-0.21	-0.23	-0.24	-0.21	-0.05	-0.23	-0.21	0.17	1.00

Fig. 3. Pairwise correlation between G-7 stocks markets, oil and gold volatilities. Note: The figure shows the correlation matrix illustrating the relationships between variables. See Table 1 for definitions of all variables. Positive correlations are shown in blue, while negative correlations are in red, with intensity representing the strength of the correlation.

Table 3
Return spillovers based on the quantile VAR.

Panel A. Lower Quantile (q=0.05).

	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	From
Canada	14.05	11.64	**11.75**	11.27	10.34	**11.73**	12.41	8.02	8.80	85.95
	(0.18)	(0.12)	(0.05)	(1.00)	(1.00)	(0.08)	(0.47)	(1.00)	(1.00)	
France	11.67	13.30	12.59	**11.84**	9.98	12.16	11.44	8.36	8.66	86.70
	(0.32)	(0.73)	(0.27)	(0.09)	(1.00)	(0.78)	(0.26)	(1.00)	(1.00)	
Germany	11.47	12.58	13.29	11.90	10.17	11.81	11.42	8.53	8.82	86.71
	(0.45)	(1.00)	(0.21)	(0.62)	(1.00)	(1.00)	(0.13)	(1.00)	(1.00)	
Italy	11.49	**12.49**	**12.53**	**13.21**	10.09	11.72	11.43	8.41	8.64	86.79
	(0.41)	(0.00)	(0.07)	(0.00)	(1.00)	(0.47)	(1.00)	(1.00)	(1.00)	
Japan	11.52	11.40	11.50	11.05	**12.87**	11.33	**11.86**	9.08	9.39	87.13
	(0.33)	(1.00)	(0.71)	(0.11)	(0.00)	(0.78)	(0.00)	(1.00)	(1.00)	
UK	11.81	12.32	12.22	**11.63**	10.18	13.58	11.51	8.27	8.48	86.42
	(0.32)	(0.36)	(1.00)	(0.03)	(1.00)	(0.78)	(0.91)	(1.00)	(1.00)	
US	12.34	11.79	11.71	**11.19**	10.15	11.44	**14.13**	8.48	8.77	85.87
	(0.31)	(0.87)	(0.37)	(0.07)	(1.00)	(0.81)	(0.00)	(1.00)	(1.00)	
OVX	10.06	10.46	10.72	10.45	10.23	10.50	10.34	16.26	10.99	83.74
	(0.95)	(0.98)	(1.00)	(0.90)	(0.83)	(1.00)	(1.00)	(0.82)	(0.45)	
GVX	10.65	10.44	10.59	10.47	10.66	10.63	10.66	10.35	**15.54**	84.46
	(0.53)	(1.00)	(1.00)	(1.00)	(0.44)	(0.59)	(1.00)	(1.00)	(0.01)	
To	91.02	93.12	93.61	89.79	81.79	91.33	91.06	69.51	72.55	773.77
Inc.Own	105.07	106.42	106.90	103.01	94.65	104.90	105.19	85.77	88.09	Total connectedness index
Net	5.07	6.42	6.90	3.01	−5.35	4.90	5.19	−14.23	−11.91	**85.97 %**

Panel B. Median Quantile (q=0.50).

	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	From
Canada	32.21	11.27	10.42	9.48	2.47	11.16	15.99	4.72	2.29	67.79
	(0.36)	(0.16)	(0.76)	(1.00)	(1.00)	(0.41)	(0.52)	(1.00)	(1.00)	
France	9.36	24.19	18.98	16.48	2.01	15.64	8.46	2.80	2.09	75.81
	(1.00)	(0.81)	(1.00)	(0.89)	(1.00)	(0.60)	(1.00)	(1.00)	(1.00)	
Germany	8.96	19.63	25.20	16.32	1.82	14.64	8.77	2.51	2.14	74.80
	(1.00)	(1.00)	(0.96)	(0.20)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
Italy	8.76	**18.23**	**17.64**	27.21	1.42	14.02	7.63	2.73	2.35	72.79
	(1.00)	(0.01)	(0.00)	(0.46)	(1.00)	(0.81)	(1.00)	(1.00)	(1.00)	
Japan	8.80	9.24	8.72	7.35	37.80	7.38	**14.41**	3.24	3.07	62.20
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.00)	(1.00)	(1.00)	
UK	10.39	17.13	15.58	13.85	2.03	**27.16**	8.76	3.07	2.03	72.84
	(0.78)	(1.00)	(1.00)	(1.00)	(1.00)	(0.02)	(1.00)	(1.00)	(1.00)	
US	17.34	10.24	9.82	8.42	2.05	8.51	**36.57**	3.99	3.06	63.43
	(0.61)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.00)	(1.00)	(1.00)	
OVX	8.13	5.51	4.85	5.16	1.64	5.46	6.42	59.66	3.17	40.34
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.55)	(1.00)	
GVX	4.22	4.73	4.65	4.02	1.65	4.01	5.00	3.33	**68.41**	31.59
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.00)	
To	75.96	95.97	90.65	81.08	15.10	80.81	75.42	26.39	20.21	561.59
Inc.Own	108.16	120.16	115.85	108.29	52.90	107.97	112.00	86.05	88.61	Total connectedness index
Net	8.16	20.16	15.85	8.29	−47.10	7.97	12.00	−13.95	−11.39	**62.40 %**

Panel C. Upper Quantile (q=0.95).

	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	From
Canada	14.07	11.77	11.45	11.12	9.79	11.17	11.61	9.37	9.64	85.93
	(0.28)	(0.25)	(0.18)	(0.98)	(1.00)	(0.54)	(0.87)	(1.00)	(1.00)	
France	11.31	13.26	12.22	**11.89**	9.21	11.87	10.60	10.05	9.61	86.74
	(0.17)	(0.46)	(0.54)	(0.01)	(1.00)	(0.19)	(0.47)	(0.99)	(1.00)	
Germany	11.03	12.22	13.09	11.85	9.54	11.44	10.69	10.15	10.01	86.91
	(0.46)	(0.96)	(0.46)	(0.17)	(1.00)	(0.83)	(0.37)	(1.00)	(1.00)	
Italy	11.06	**12.12**	11.81	**13.34**	9.68	11.39	10.55	10.16	9.89	86.66
	(0.45)	(0.00)	(0.20)	(0.00)	(1.00)	(0.79)	(1.00)	(0.99)	(1.00)	
Japan	10.98	10.91	10.76	10.70	**13.52**	10.68	**10.92**	10.78	10.76	86.48
	(0.43)	(1.00)	(0.57)	(0.56)	(0.06)	(0.94)	(0.00)	(0.54)	(0.83)	
UK	11.27	11.98	11.51	11.67	9.54	13.22	10.72	10.35	9.74	86.78
	(0.42)	(0.73)	(0.99)	(0.53)	(1.00)	(0.91)	(0.18)	(0.66)	(1.00)	
US	12.46	11.28	11.31	11.05	9.56	11.09	**14.42**	9.40	9.43	85.58
	(0.21)	(0.98)	(0.33)	(0.29)	(1.00)	(0.90)	(0.00)	(1.00)	(1.00)	
OVX	10.28	9.98	10.06	9.87	10.63	9.93	9.74	17.21	12.29	82.79
	(0.71)	(1.00)	(1.00)	(1.00)	(0.73)	(1.00)	(1.00)	(0.35)	(0.37)	
GVX	10.36	9.79	9.93	9.86	10.74	9.91	10.00	12.80	16.61	83.39
	(0.68)	(1.00)	(1.00)	(1.00)	(0.68)	(1.00)	(1.00)	(0.95)	(0.22)	

(*continued on next page*)

Table 3 (*continued*)

Panel C. Upper Quantile (q=0.95).

	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	From
To	88.74	90.04	89.06	88.00	78.68	87.48	84.83	83.05	81.37	771.25
Inc.Own	102.81	103.29	102.15	101.34	92.19	100.70	99.25	100.26	97.99	Total connectedness index
Net	2.81	3.29	2.15	1.34	−7.81	0.70	−0.75	0.26	−2.01	**85.69 %**

Note: This table reports the results of the Generalized Forecast Error Variance Decomposition (GFEVD) derived from the Quantile Vector Autoregression (QVAR) model across different quantiles. See Table 1 for definitions of all variables. Each entry indicates the percentage of the H = 10-step-ahead forecast error variance of one variable (row) explained by shocks from another variable (column), using a lag length of 1. The "From" column shows the total spillovers received by each market from all others, while the "To" row reflects the spillovers each market transmits to others. "Inc. Own" includes own-variable variance shares. The "Net" row indicates whether a market is a net transmitter (positive value) or receiver (negative value) of shocks. The analysis utilizes daily return data for the G7 stock markets, the oil volatility index (OVX), and the gold volatility index (GVX) over the period from January 2017 to June 2022. Panels A, B, and C correspond to bearish, normal, and bullish market conditions, respectively, as represented by the 5th, 50th, and 95th conditional quantiles. To assess the statistical significance of each spillover coefficient, the analysis follows recent studies on connectedness (Antonakakis, Chatziantoniou, and Gabauer, 2020; Chatziantoniou and Gabauer, 2021; Gabauer, Chatziantoniou, and Stenfors, 2023) and computes empirical p-values based on 1000 Monte Carlo simulations under the null hypothesis of no dynamic connectedness, using a block permutation approach. Bolded estimates indicate statistical significance at the 10 % level, with p-values reported in parentheses.

Canada (11.75 %, $p = 0.05$), France to Italy (12.49 %, $p = 0.00$), Germany to Italy (12.53 %, $p = 0.06$), US to Japan (11.86 %, $p = 0.00$), UK to Canada (11.73 %, $p = 0.08$), and Italy to France (11.84 %, $p = 0.09$), to UK (11.63 %, $p = 0.07$) and to US (11.19 %, $p = 0.09$) all represent significant return transmission pathways under bearish conditions. These figures suggest a dense network of cross-market linkages, particularly among European economies and between the US and Japan. The spillover effects among the remaining G7 markets remain relatively moderate (Liow, 2015). Interestingly, while OVX and GVX exhibit moderate spillover effects on G7 stock markets—ranging from 8.02 % to 9.39 %—none of these are statistically significant. In contrast, the spillovers from G7 markets to OVX and GVX—ranging from 10.06 % to 10.72 % for OVX and 10.44–10.66 % for GVX—are generally larger, with GVX's own variance share (15.54 %) being the only statistically significant own-share among the commodity indices ($p = 0.01$). The Total Connectedness Index (TCI) for this regime stands at 85.97 %, indicating a high degree of systemic interconnectedness under downside risk conditions. Germany emerges as the strongest net transmitter (net = 6.90 %), while OVX and GVX act as the most pronounced net recipients of shocks (net = –14.23 % and –11.91 %, respectively), along with Japan (–5.35 %), suggesting their vulnerability to global equity market stress. These findings offer empirical support for Hypothesis 1 (H1), which posits that spillovers intensify under extreme market conditions, as seen here with the elevated TCI and numerous statistically significant transmission paths. Moreover, the identification of Germany as a dominant net transmitter and Japan, OVX, and GVX as net receivers is consistent with Hypothesis 2 (H2), which anticipates evolving transmitter/receiver roles across market states.

For the median quantile ($q = 0.50$), which reflects normal market conditions, Panel B of Table 3 shows that own-share spillovers are generally higher compared to bear markets. The own-share spillovers for G7 stock markets range from 25.20 % for Germany to 37.80 % for Japan, indicating a substantial portion of forecast variance is explained by each market's own past returns. However, the majority of these own-share estimates for the G7 are not statistically significant at the 10 % level (except for the US and the UK). In contrast, GVX exhibits a significant own-share spillover of 68.41 % ($p = 0.00$), highlighting the persistent self-dependence of gold market volatility in normal times. Among the cross-market dynamics, Italy appears particularly exposed, receiving statistically significant spillovers from both France (18.23 %, $p = 0.01$) and Germany (17.64 %, $p = 0.00$). These results underscore Italy's heightened sensitivity to broader European financial movements, especially under stable conditions. Furthermore, Japan exerts a statistically significant spillover to the US stock market (14.41 %, $p = 0.00$), highlighting a notable East-to-West information flow. Meanwhile, the US exhibits a significant own-share spillover of 36.57 % ($p = 0.00$), reflecting a strong degree of internal return predictability. Although several other spillovers appear economically meaningful—such as those between Germany and France (19.63 % and 18.98 %, respectively), or from the UK to Italy (13.85 %)—they do not meet conventional significance thresholds and should thus be interpreted with caution. Furthermore, spillovers from OVX and GVX to G7 equity markets remain generally limited and statistically insignificant, with no clear evidence of commodity markets transmitting volatility to equities in this regime. The reverse spillover effects from G7 stock markets to OVX and GVX are more pronounced, ranging from 1.64 % to 8.13 %, yet remain statistically insignificant. From a systemic risk perspective, and in line with Panel A, the network structure indicates that all G7 stock markets, except Japan, function as net transmitters of shocks, while Japan (–47.10 %), OVX (–13.95 %), and GVX (–11.39 %) act as net receivers. The TCI of 62.40 % affirms the persistence of substantial interdependence, though the magnitude of interconnectedness is lower than in bear market regimes. This structural drop in spillover intensity under normal market conditions offers additional support for H1, confirming that connectedness is weaker in the median quantile than in the tails. The reversal of Japan's role—from net transmitter to net receiver—also illustrates Hypothesis 2 (H2), which anticipates dynamic role changes in directional spillovers across quantiles.

Panel C of Table 3 presents spillover dynamics at the upper return quantile ($q = 0.95$), which corresponds to bullish market conditions. The observed patterns mirror those identified under bearish regimes, suggesting that both positive and negative extremes in the return distribution associate with heightened volatility transmission. Own-share spillovers are statistically significant for several major economies, including Italy (13.34 %, $p = 0.00$), Japan (13.52 %, $p = 0.04$), and the United States (14.42 %, $p = 0.00$). These values indicate a notable degree of return predictability. However, while OVX and GVX show own-share spillovers of 17.21 % and

16.61 %, respectively, neither of these is statistically significant. Among the cross-market spillovers, a few statistically significant links emerge. France and Italy exhibit statistically significant bidirectional spillovers—France transmits 12.12 % to Italy (p = 0.02), and Italy transmits 11.89 % to France (p = 0.01)—highlighting a persistent and reciprocal linkage. The United States also transmits 10.92 % to Japan (p = 0.00), reinforcing its structurally dominant role. In contrast, other spillovers—such as Canada to Germany (11.03 %, p = 0.43) or UK to Japan (10.68 %, p = 0.96)—though economically moderate, are not statistically significant and should be interpreted with caution. Overall, the TCI stands at 85.69 %, confirming a strong level of systemic integration. France emerges as a dominant net transmitter of shocks (+3.29 %), while Japan (–7.81 %), GVX (–2.01 %), and the US (–0.75 %) serve as net recipients.

Together with the lower quantile findings, this elevated spillover intensity under bullish conditions further substantiates Hypothesis 1 (H1). Moreover, the shift in directional roles—particularly France becoming a strong net transmitter—reaffirms Hypothesis 2 (H2), which posits that transmitter/receiver status varies across quantiles in response to market conditions.

These findings underscore the asymmetric behavior of risk transmission and emphasize the importance of active monitoring and policy coordination. Japan and GVX's roles as persistent net recipients suggest that global investors must carefully consider risk transmission pathways. Additionally, the influence of energy prices and macroeconomic uncertainty highlights critical implications for systemic risk and financial stability. Policymakers should actively monitor these linkages and design macroprudential policies aimed at mitigating contagion and reinforcing resilience.

5.2. Time-varying in quantiles spillover analysis among G7 stock returns, OVX and GVX

In this section, we aim to examine the dynamic connectedness between the markets based on the evidence suggesting that average values of total connectedness may obscure time-varying and time-specific effects. Specifically, we focus on the middle quantile (Fig. 4) as well as the lower and upper quantiles (Fig. 5). To capture the spillover over time, we employ a 100-day rolling window at a forecast horizon of 10-step ahead.

Fig. 4 presents the dynamic connectedness in the middle quantile (q = 0.50), capturing market interdependencies under normal conditions. The results reveal substantial fluctuations in total spillover, ranging between 50 and 91 over the study period. These variations highlight that spillovers are time-dependent and respond to economic events. Several notable peaks emerge. In 2018, spillovers exceed 70, coinciding with global trade tensions, rising interest rates, and Brexit-related uncertainties. This pattern aligns with previous research indicating that political and economic instability amplifies financial market spillovers (Cui et al., 2021). After a stable period from late 2018–2020, connectedness spikes again, exceeding 90 in early 2020, at the onset of the COVID-19 pandemic. Following an initial decline in mid-2020, spillovers rise again to around 80 in early 2021, reflecting heightened market reactions to the global vaccine rollout and economic recovery expectations. The index remains elevated through 2021 and early 2022, driven by renewed uncertainty in oil markets and the Russia-Ukraine war. These findings indicate that financial market integration intensifies during global crises, reducing portfolio diversification benefits during economic uncertainty. These findings of extreme connectedness during high-stress periods align with previous studies (Adekoya and Oliyide, 2021; Mensi et al., 2021). This supports H1, as spillovers intensify even under normal conditions when external shocks occur, highlighting the nonlinearity of systemic risk.

Fig. 5 examines spillovers in the lower (q = 0.05) and upper (q = 0.95) quantiles, capturing market behavior during bearish and bullish conditions. The results show even higher connectedness than in the median quantile, with spillovers fluctuating between 90 and 103. This confirms that extreme market conditions amplify interdependencies, making risk management more challenging. Under the lower quantile (q = 0.05), spillovers surge in 2018, 2020, 2021, and 2022, coinciding with major economic shocks. The peak of 103

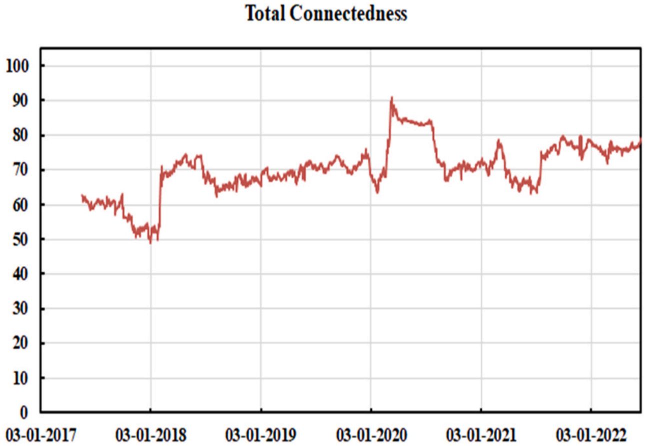


Fig. 4. Time varying total spillover index (median quantile q=0.50). Note: This figure illustrates the dynamic evolution of total connectedness. The Total Connectedness Index (TCI) is computed using the quantile-based connectedness approach described in Section 3.1, specifically Eq. (6), based on the Generalized Forecast Error Variance Decomposition (GFEVD). The TCI is calculated at the median quantile (q=0.50), using a rolling window of 100 observations and a 10-step-ahead forecast horizon to capture time variation in spillover intensity. The sample period spans from January 2017 to June 2022.

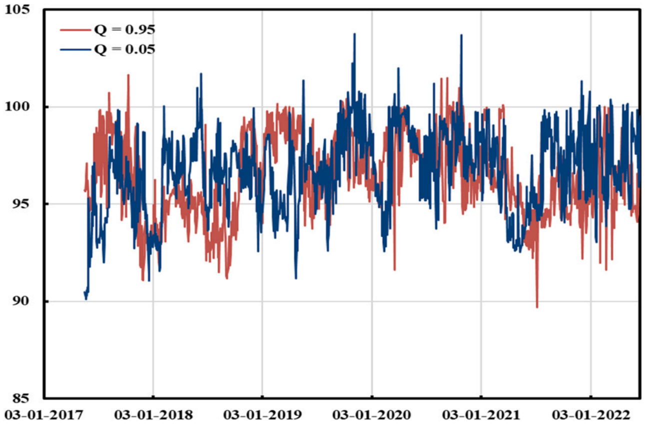


Fig. 5. Time varying quantile spillover index in the lower quantile (q = 0.05) and upper quantile (q = 0.95). Note: This figure presents the dynamic evolution of total connectedness under extreme market conditions. The Total Connectedness Index (TCI) is computed using the quantile-based connectedness framework outlined in Section 3.1, specifically Eq. (6), which relies on the Generalized Forecast Error Variance Decomposition (GFEVD). The index is estimated separately for the lower quantile (q=0.05) to capture spillovers during bearish market phases, and for the upper quantile (q=0.95) to reflect spillovers during bullish conditions. A rolling window of 100 observations and a 10-step-ahead forecast horizon is used. The sample period spans from January 2017 to June 2022.

in late 2019 and 2020 corresponds to the COVID-19 outbreak and its severe economic disruptions. Fear-driven trading intensifies market linkages, limiting diversification options (Beine et al., 2010). Similarly, in the upper quantile ($q = 0.95$), spillovers spike to 101 during these periods, suggesting that financial markets become more interconnected even during bullish conditions. This result aligns with previous studies that identify unprecedented levels of connectedness between markets during the pandemic, regardless of asset type and time horizons (Liao et al., 2021). The flight-to-safety effect likely plays a role, as investors reallocate capital in response to shifting risk perceptions. The trends in both quantiles mirror those in the median quantile, where spillovers decline after February 2021, only to rise again following the Russia-Ukraine war. These results provide strong evidence for H1, confirming that spillovers are highest in the tails of the return distribution. The temporal variation also supports H2, reflecting shifts in connectedness across crises.

These findings provide important insights into financial stability, portfolio management, and systemic risk. The evidence confirms that market spillovers intensify during economic turbulence, reducing diversification benefits for investors. The heightened spillovers in bearish and bullish market conditions suggest that extreme conditions disrupt normal risk-return relationships, requiring investors to adjust their hedging and portfolio strategies to account for these nonlinear dynamics. The time-series evidence also indicates that spillovers fluctuate based on global events and financial stress levels. This highlights the importance of continuous monitoring and adaptive investment strategies that respond to changing market conditions. For policymakers, the results suggest that financial

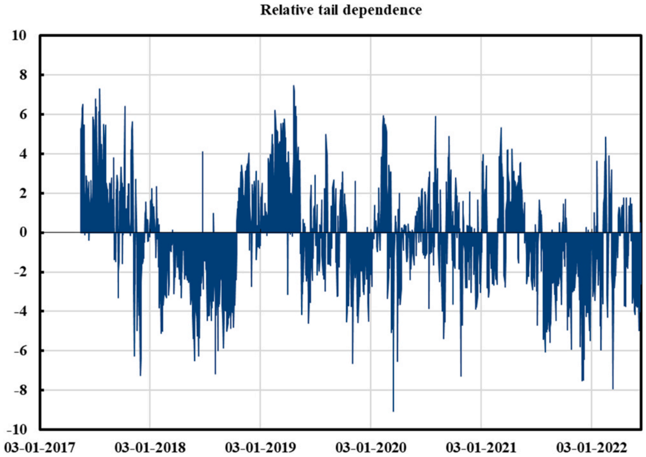


Fig. 6. Time varying relative tail dependence index $\left(TCI_{q=0.95} - TCI_{q=0.05}\right)$. Note: This figure depicts the relative tail dependence index, computed as the difference between the Total Connectedness Index (TCI) at the upper quantile (q=0.95) and the lower quantile (q=0.05). This measure reflects the asymmetry in spillover intensity across extreme market states. A positive value indicates stronger spillovers during bullish conditions, while a negative value reflects higher connectedness during bearish periods. The TCI values are obtained using the quantile-based connectedness framework described in Section 3.1, with a rolling window of 100 days and a 10-step-ahead forecast horizon. The sample period spans from January 2017 to June 2022.

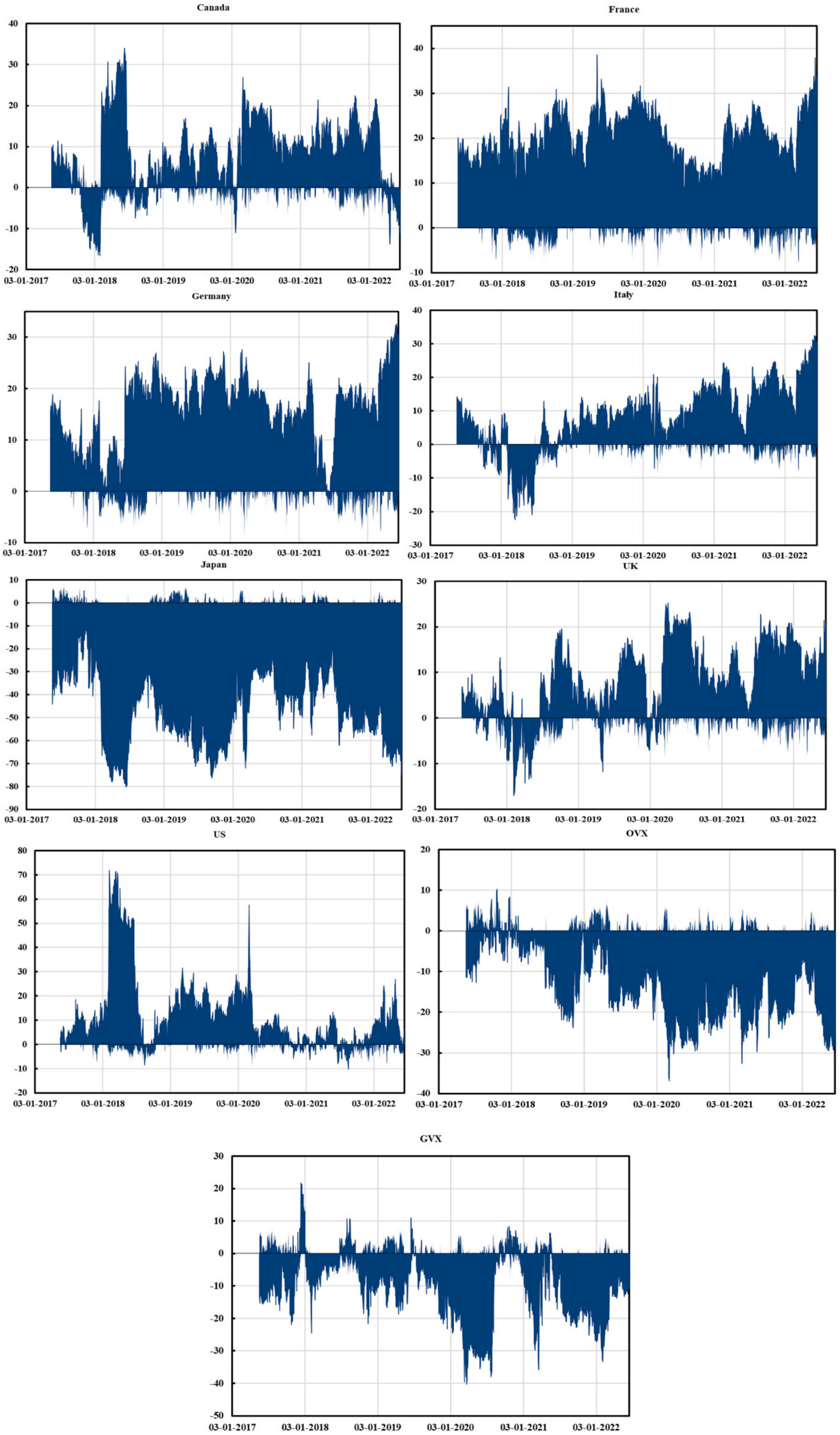
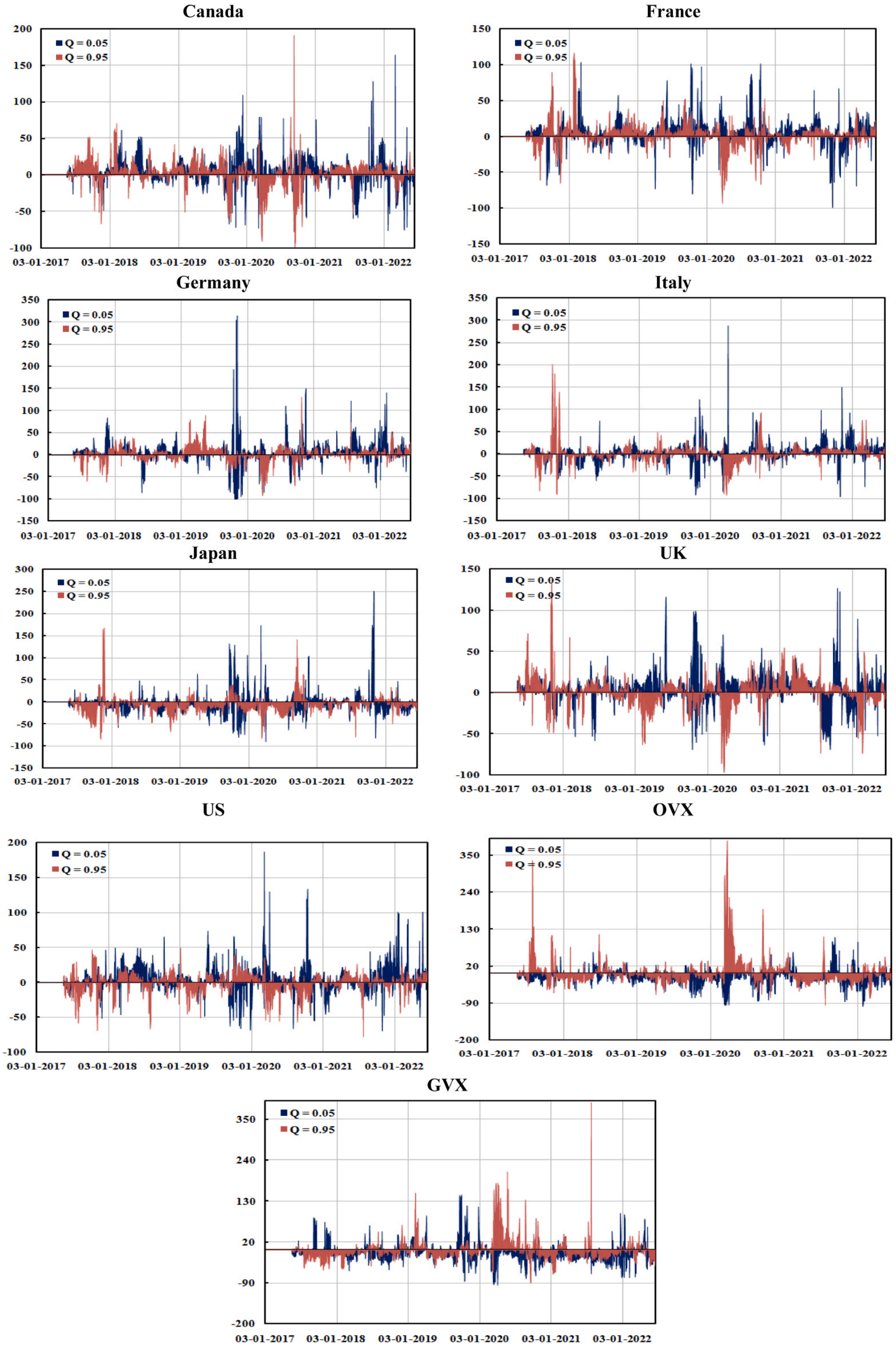


Fig. 7. Time varying net spillover indices (median quantileq = 0.5). Note: This figure presents the evolution of net spillover indices across G7 stock markets, oil, and gold at the median quantile (q=0.50). See Table 1 for definitions of all variables. The net spillover for each market is calculated as the difference between shocks transmitted to others and shocks received from others, based on the quantile-based connectedness approach detailed in Section 3.1 (see Eq. (11)). Positive values indicate that the market acts as a net transmitter of return shocks, while negative values indicate that it functions as a net receiver. The estimates are generated using a rolling window of 100 observations and a 10-step-ahead forecast horizon. The sample period spans from January 2017 to June 2022.


Canada

France

Germany

Italy

Japan

UK

US

OVX

GVX

Fig. 8. Net spillover in quantile VAR (lower quantile q = 0.05; upper quantile q = 0.95). Note: This figure illustrates the net spillover positions of all variables under extreme market conditions. See Table 1 for definitions of all variables. The lower quantile (q=0.05) corresponds to bearish states, while the upper quantile (q=0.95) reflects bullish states. The net spillover index is computed using the quantile-based connectedness framework described in Section 3.1 (see Eq. (11)), and is calculated as the difference between directional spillovers transmitted and received. Positive values indicate net transmitters of return shocks; negative values indicate net receivers. The sample period spans from January 2017 to June 2022.

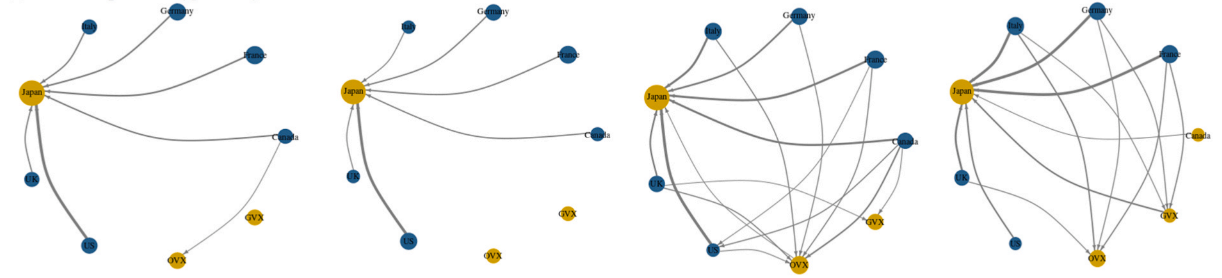
contagion risks are asymmetric and crisis-dependent, reinforcing the need for stronger systemic risk monitoring and coordinated interventions during periods of extreme financial stress.

Fig. 6 illustrates the evolution of the relative tail dependence index, calculated as the difference between the Total Connectedness Index (TCI) at the upper and lower quantiles. A positive index value indicates stronger dependence in the upper quantile, while a negative value signifies stronger dependence in the lower quantile. The results highlight substantial fluctuations and reciprocity between the two quantiles throughout the sample period, reinforcing the notion that financial markets react asymmetrically to extreme market conditions. Periods of heightened connectedness in the lower quantile, particularly in 2018, late 2019, March–April 2020, and mid-2021 onward, coincide with major economic disruptions such as trade tensions, the COVID-19 outbreak, and post-pandemic economic uncertainty. In contrast, upper quantile connectedness appears stronger in 2017, 2019, and intermittently from 2020 onward, suggesting that certain periods see increased co-movement in bullish market conditions. These findings confirm that G7 stock markets, along with oil and gold markets, remain highly sensitive to external shocks, necessitating active risk management. This further reinforces H1 by demonstrating spillover asymmetry across market extremes, and supports H2 as dominance shifts over time.

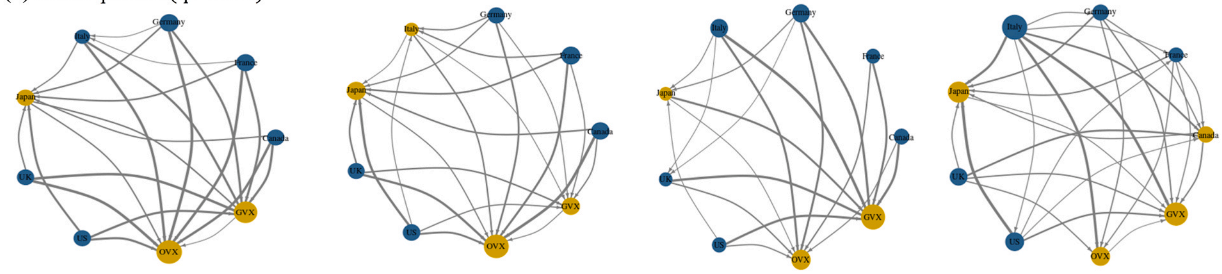
Fig. 7 provides real-time insights into the contribution of each market to the overall connectedness system, focusing on the median return quantile (q = 0.50). Based on the net directional spillover index, the figure captures shifts in market roles as net transmitters or recipients of shocks across the sample period. France, Germany, and the USA consistently emerge as net transmitters of shocks. While France and Germany exhibit moderate spillover magnitudes (generally below 40), the USA shows stronger effects, with net spillovers exceeding 70 at certain points. Canada, Italy, and the UK display alternating roles, shifting between transmitter and recipient status

Panel A. Full sample **Panel B. Pre COVID-19** **Panel C. COVID-19** **Panel D. Russia-Ukraine War**

(a) Median quantile (q = 0.5)



(b) Lower quantile (q = 0.05)



(c) Upper quantile (q = 0.95)

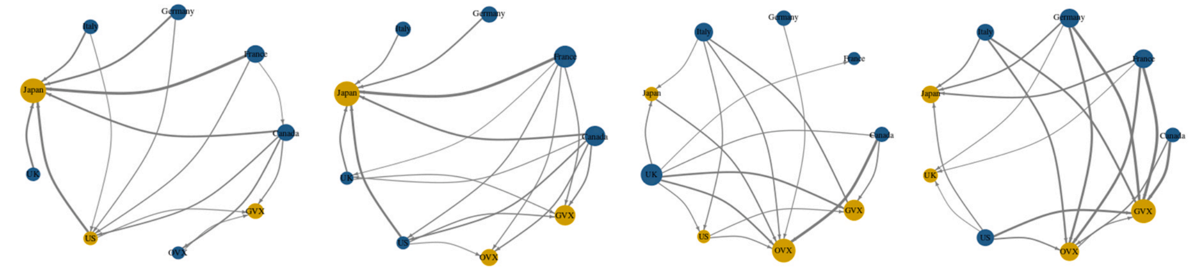


Fig. 9. Net pairwise directional connectedness network at different quantiles of the return distribution. Note: Panels A–D depict the net pairwise directional connectedness networks among variables for four subsample periods: (A) full sample, (B) pre-COVID-19, (C) COVID-19, and (D) Russia–Ukraine war. See Table 1 for definitions of all variables Within each panel, the networks are presented for three quantiles: (a) lower quantile (q=0.05), (b) median quantile (q=0.50), and (c) upper quantile (q=0.95).The net directional connectedness is computed using the quantile-based connectedness framework described in Section 3.1. The network graphs visualize the net transmission of shocks between markets, where the direction and magnitude of the connections indicate whether a market is a net transmitter or receiver of return spillovers under different risk conditions and periods.

during periods of uncertainty. Japan, OVX, and GVX consistently appear as net recipients, with Japan recording net shock reception levels above 50 across most of the period. Between late 2017 and 2018, characterized by US–China trade tensions and Brexit uncertainty, the USA and Canada play leading roles in risk transmission, with the USA's net index peaking above 70. During the COVID-19 crisis, all G7 markets except Japan become major transmitters of shocks, emphasizing the amplification of market interdependence during systemic events. OVX—typically a net recipient—temporarily acts as a transmitter in the early sample period, likely due to structural shifts following the Shale Oil revolution and OPEC's 2016 production adjustments. Japan's persistent status as a shock recipient can be attributed to its safe-haven appeal and its export-driven economy, which is particularly vulnerable to global supply chain disruptions—a trend exacerbated during the pandemic. OVX remains a net recipient of shocks due to its function as a volatility index rather than a price determinant. Events such as the April 2020 collapse in WTI prices reflect how market stress inflates OVX volatility without it becoming a source of contagion. Similarly, GVX consistently absorbs shocks rather than transmitting them. As an implied volatility measure, GVX captures shifts in investor risk aversion toward gold during crises, reinforcing gold's role as a refuge. These findings underscore the heterogeneity of spillover roles: while G7 stock markets actively propagate shocks, assets like Japan, OVX, and GVX serve as stress barometers. These distinctions are critical for investors and policymakers when constructing diversified portfolios and implementing macroprudential safeguards under crisis conditions. These evolving roles align with H2. The persistent shock absorption by GVX and OVX also provides initial support for H3, suggesting their value as hedging instruments.

Fig. 8 presents the patterns of net spillovers in the lower and upper return quantiles, revealing significant fluctuations across all G7 stock markets, OVX, and GVX throughout the sample period. These fluctuations highlight the dynamic nature of market interdependencies and the varying intensity of risk transmission under different economic conditions. In bullish market states during the early part of the sample, strong spillovers originate from France, Italy, Japan, the UK, and OVX. These patterns reflect persistent political uncertainties in Europe, such as Brexit, combined with rising oil prices that shape investor sentiment. The upper quantile results also show that Canada, GVX, and OVX transmit more shocks during the COVID-19 period, highlighting their influence on other markets during optimistic conditions and reinforcing the flight-to-safety phenomenon. Conversely, under bearish market conditions, all G7 countries emerge as net transmitters of shocks, particularly during the COVID-19 pandemic and the Russia–Ukraine conflict. The effect is most pronounced for Germany, Italy, Japan, and the USA, where spillover indices exceed 200, signaling strong shock propagation. These economies are especially exposed to global disruptions, amplifying risk spillovers across markets. Germany, Japan, and the USA play central roles in financial stress transmission during downturns, particularly in the lower quantile. In contrast, Canada, France, Italy, and the UK exhibit more bidirectional spillover behavior, shifting between net transmitter and receiver roles across market states. These patterns support H2 by confirming role reversals across quantiles. The behavior of GVX and OVX under stress supports H3, emphasizing their conditional hedging effectiveness.

These results confirm that spillover dynamics are heavily influenced by episodes of market turbulence and investor sentiment during global crises. Periods such as Brexit, the COVID-19 pandemic, and the Russia–Ukraine war exacerbate spillover effects, increasing interconnectedness and reducing resilience to shocks. These findings emphasize the necessity of continuous monitoring of systemic linkages and the adoption of proactive risk management tools. Investors must recognize that extreme conditions weaken diversification benefits, making frequent portfolio rebalancing crucial. Evaluating tail dependencies and market-specific contributions to systemic risk can help guide informed investment and policy decisions, ultimately supporting financial stability and market resilience.

5.3. Pairwise spillover analysis among G7 stock returns, OVX and GVX

In this section, we delve into the network connectedness among G7 stock market returns and oil and gold volatilities in sub-samples. The directional connectedness at three return quantiles is shown graphically in Fig. 9. Fig. 9's panels A, B, C, and D, respectively, represent the full sample, the time before Covid-19, the Covid-19 era, and the Russia-Ukraine war. The size of each node reveals the extent of the net system connectedness spillover of each index. The average spillover interaction between pairs is represented by arrows between markets; the strength of the pairwise connectedness is indicated by the width of the arrow. Net shock transmitters and receivers are represented by the colors blue and yellow, respectively.

Examining the results for the full sample period in Panel A, we uncover complementary findings compared to those derived from Table 3. Notably, the strongest pairwise spillover in the median quantile originates from the USA to Japan. This aligns with the findings of Chang (2021), who emphasizes the strong responsiveness of the Japanese stock market to shocks in the US equity market, regardless of market conditions. Additionally, significant spillovers from other G7 countries to Japan position it as the most crucial net receiver of shocks in the system. This finding reinforces the notion that Japan absorbs external shocks rather than transmitting them, consistent with its safe-haven status. Another key connection is the risk transmission from Canada to OVX, which supports the role of North American oil production as a major driver of global crude oil dynamics. The importance of Canada in oil-related financial markets stems from its status as one of the world's largest crude oil producers, meaning that shocks in Canadian markets can directly affect oil price volatility. This transmission further highlights the integration of commodity-linked financial instruments into global risk networks. Overall, in the median quantile, Japan, OVX, and GVX emerge as the primary net recipients of shocks, while the stock markets of Italy, Germany, France, Canada, the UK, and the USA serve as net transmitters. This asymmetry suggests that major European and North American financial markets act as dominant sources of global financial turbulence, while Japan and commodity-related volatility indices (OVX and GVX) primarily absorb financial stress. This pattern is consistent with H2, as it reveals time-varying roles of markets in transmitting or receiving shocks across quantiles.

The connectedness system for the lower and upper quantiles, shown in Graphs (b) and (c) of Panel A, reveals important differences compared to the median quantile. Under bearish market conditions (q=0.05), all pairwise connections between markets intensify, reflecting heightened market uncertainty. OVX, GVX, and Japan emerge as the main recipients of shocks, experiencing significant spillover effects from the stock markets of all G7 nations. The strong spillover from the USA to Japan, consistent across quantiles, suggests that Japan's stock market remains highly sensitive to external financial shocks, reinforcing its limited role as a diversification asset. For OVX, the most significant spillovers originate from the UK, Germany, Italy, France, and Canada, highlighting the impact of European and North American financial conditions on oil market volatility. This supports H1, indicating that extreme (tail) market states result in stronger spillovers and reduced diversification. However, in bullish market conditions ($q=0.95$), OVX transitions into a net transmitter of shocks, with a primary transmission link to GVX. This shift aligns with increased speculative trading in oil markets during periods of optimism, where heightened oil price volatility propagates uncertainty into gold markets.

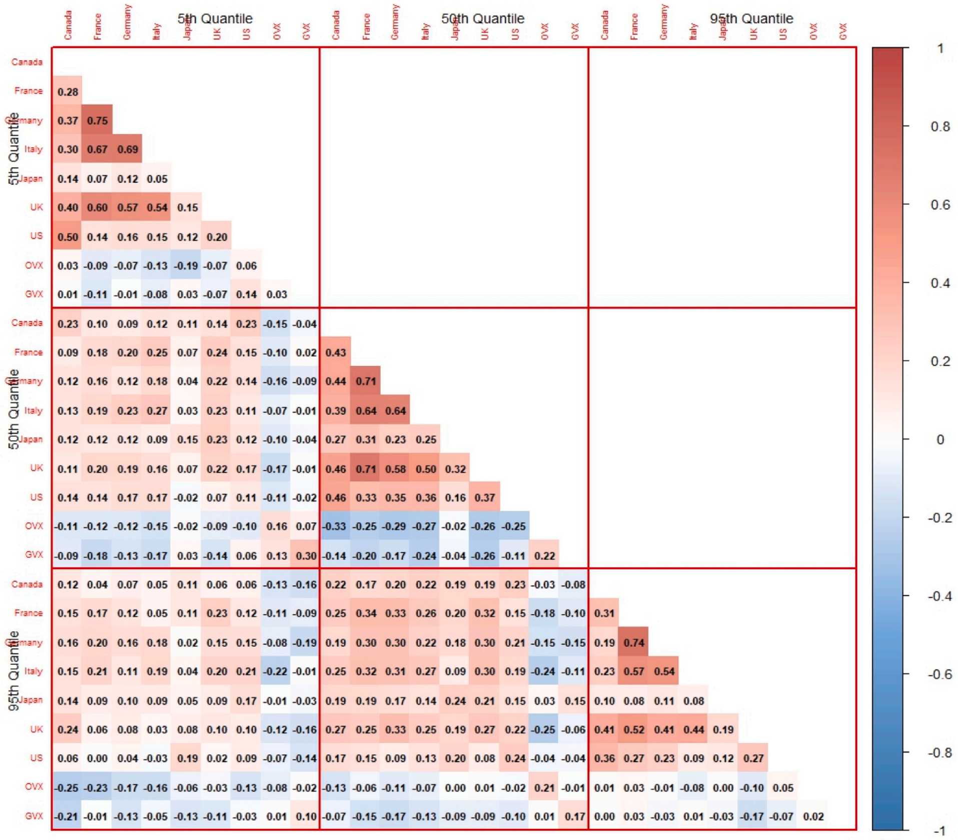
The differences in net transmitters and receivers across quantiles underscore the asymmetric nature of risk transmission under varying market conditions. Under normal market conditions ($q = 0.5$), spillovers remain relatively stable, and markets exhibit moderate fluctuations. However, in extreme quantiles ($q = 0.05$ and $q = 0.95$), the structure of net spillovers shifts significantly due to financial distress or speculative activity, revealing non-linear contagion patterns. In bearish market conditions, financial distress amplifies the transmission of shocks from more globally integrated markets such as the USA, Germany, and France. These markets, which serve as key nodes in global capital flows, act as dominant net transmitters, intensifying risk spillovers during downturns. Conversely, assets perceived as safe havens—namely Japan, OVX, and GVX—absorb financial stress as investors seek stability. This pattern reflects a broader flight-to-safety mechanism typically observed during crises. In bullish conditions, risk transmission mechanisms evolve due to optimism, leverage, and momentum-driven trading. While the USA and other major stock markets continue to play a prominent role as transmitters, OVX transitions into a net transmitter. This shift highlights the growing influence of commodity-related volatility on financial spillovers during demand-driven rallies and speculative phases in energy markets. As speculative trading in oil markets intensifies, oil price volatility captured by OVX begins to propagate into broader financial markets. This process is closely linked to GVX, which reflects uncertainty in gold markets. The interplay between commodity volatility and financial markets becomes especially relevant during periods of macroeconomic optimism and high liquidity, when investor risk appetite increases. These findings highlight the dynamic and context-dependent nature of financial contagion. Risk transmission mechanisms are not static but evolve with market sentiment and macroeconomic conditions. The variations observed across quantiles demonstrate that contagion intensifies during crises and speculative bubbles, reshaping the traditional roles of stock markets and commodities in global risk propagation.

From an economic and financial perspective, these results carry important implications. The persistent role of Japan, OVX, and GVX as net recipients of shocks suggests that these markets primarily reflect investor uncertainty rather than actively transmitting contagion. This aligns with H3, as it underscores the role of gold and oil volatility as systemic stress indicators rather than sources of financial contagion. Their behavior during crises helps investors and policymakers distinguish between signalers of stress and sources of systemic risk. Japan's safe-haven status remains a defining feature of its financial market. It consistently attracts capital inflows during periods of heightened uncertainty. However, its recurrent position as a net receiver also implies that its stock market may not always deliver the diversification benefits often assumed in turbulent times, due to its sensitivity to global risk aversion. Similarly, OVX and GVX operate more as indicators of financial stress than as transmitters of instability. OVX, which captures oil market uncertainty, reacts strongly to external shocks such as supply chain disruptions or geopolitical tensions. Yet, it does not typically serve as a conduit for volatility into stock markets. Its role aligns with demand-driven oil price shocks and broader commodity speculation cycles. Gold market volatility, as measured by GVX, similarly mirrors investor sentiment. During systemic crises, investors often flock to gold, causing spikes in implied volatility. This behavior is notably evident during the COVID-19 pandemic and the Russia-Ukraine war, where GVX surges in response to elevated uncertainty. These findings reinforce the interpretation of GVX as a barometer of financial anxiety rather than a vector of contagion.

Notably, Graph (c) of Panel A also reveals that the USA becomes a net receiver of shocks under bullish conditions, receiving spillovers from Italy, Germany, France, and Canada. This finding challenges traditional perspectives on the dominant role of the US stock market in global financial systems (Arshanapalli and Doukas, 1993; Becker et al., 1990; Morana and Beltratti, 2008). While the USA historically functions as a key transmitter of shocks, this result suggests that during speculative bubbles and high-risk environments, external shocks from European markets can influence US financial conditions. Moving to Panels B to D, we extend our analysis to the pre-COVID-19 period, the COVID-19 period, and the Russia-Ukraine war, respectively. While several core spillover relationships persist across sub-samples, notable changes in net spillover positions and the magnitude of pairwise spillovers highlight the impact of major global events on market interconnectedness.

Starting with the pre-COVID-19 period in Panel B, we observe notable shifts in the connectedness structure. The connection between Canada and OVX disappears in the median quantile, suggesting a reduction in direct oil-related spillovers from Canada during this period. Besides Japan, OVX, and GVX, Italy emerges as a net recipient of shocks under bearish market conditions, receiving significant spillovers from Germany, France, and the USA. This finding highlights Italy's vulnerability to external shocks and its relatively weaker position in transmitting risk compared to its European counterparts. In the upper quantile, OVX acts as a net receiver of shocks, primarily from the USA, Canada, France, and Japan. Interestingly, this reverses during bullish market conditions, where OVX transitions into a transmitter. This pattern suggests that oil market volatility plays a dual role depending on market sentiment—absorbing risk during downturns and propagating uncertainty during speculative upswings. Additionally, the observed spillovers between OVX and the French stock market may reflect an indirect link between European financial conditions and North American oil market fluctuations. Given France's historical financial ties with the USA, the back-and-forth spillover dynamics between these markets further reinforce the interconnectedness of financial and commodity markets in the pre-pandemic period.

The results for the COVID-19 period (Panel C) reveal a more interconnected financial landscape, with stronger spillovers across markets. The USA, Japan, OVX, and GVX emerge as key net recipients of shocks, suggesting that global uncertainty during the pandemic leads to heightened market interdependencies. OVX receives shocks from all G7 countries, reflecting the widespread impact of pandemic-induced disruptions on the oil market. Similarly, GVX absorbs risk primarily from Canada and the UK, reinforcing gold's function as a financial stress indicator. Significant spillovers from Canada and France to the USA also indicate a shift in global risk transmission, challenging the conventional notion of the USA as the dominant shock transmitter. Japan receives spillovers from OVX in addition to other G7 stock markets, further confirming its role as a key absorber of external shocks. However, in the lower quantile, we observe lower but significant spillovers from Germany and Italy to the UK. This suggests that while market distress intensifies during the pandemic, certain spillover pathways weaken, possibly due to government interventions and liquidity measures aimed at stabilizing financial markets. The declining connectedness between Canada and Japan, as well as between Canada and OVX, during the pandemic period suggests that risk transmission patterns are altered by economic shocks that disproportionately affect certain markets. Interestingly, investing in Japanese stocks appears to be a safer strategy during the pandemic, even in bullish market conditions. This further supports H3, highlighting Japan's structural position as a net recipient and reinforcing its safe-haven reputation in volatile regimes. Japan exhibits weaker linkages with other markets, reinforcing its safe-haven status. However, OVX continues to receive substantial spillovers from G7 markets, particularly from Canada, highlighting the deep interdependence between oil price volatility and financial market stability during global crises. Italy stands out as a major risk transmitter during the pandemic, sending significant spillovers to GVX, OVX, Japan, and the USA. This finding aligns with Italy's position as one of the hardest-hit economies by COVID-19, suffering severe economic disruptions following the outbreak in China. The transmission of shocks from Italy to GVX and OVX also suggests that European financial stress is a key driver of commodity market volatility. The role of Japan and OVX as net shock recipients during the pandemic can be explained by structural and economic factors. Japan's stock market, dominated by domestic institutional investors and government interventions from the Bank of Japan, is less prone to outward risk transmission. Instead, its financial system absorbs global economic turbulence, making it a net recipient of shocks. Similarly, OVX's position as a net receiver rather than a transmitter stems from the unique nature of oil market volatility during the pandemic. Unlike traditional financial contagion, pandemic-induced oil price fluctuations are primarily driven by exogenous factors such as travel restrictions, industrial slowdowns, and supply chain disruptions. This means that OVX largely reflects investor uncertainty rather than actively propagating



		5th Quantile									50th Quantile									95th Quantile								
		Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX
5th Quantile	Canada																											
	France	0.28																										
	Germany	0.37	0.75																									
	Italy	0.30	0.67	0.69																								
	Japan	0.14	0.07	0.12	0.05																							
	UK	0.40	0.60	0.57	0.54	0.15																						
	US	0.50	0.14	0.16	0.15	0.12	0.20																					
	OVX	0.03	-0.09	-0.07	-0.13	-0.19	-0.07	0.06																				
	GVX	0.01	-0.11	-0.01	-0.08	0.03	-0.07	0.14	0.03																			
50th Quantile	Canada	0.23	0.10	0.09	0.12	0.11	0.14	0.23	-0.15	-0.04																		
	France	0.09	0.18	0.20	0.25	0.07	0.24	0.15	-0.10	0.02	0.43																	
	Germany	0.12	0.16	0.12	0.18	0.04	0.22	0.14	-0.16	-0.09	0.44	0.71																
	Italy	0.13	0.19	0.23	0.27	0.03	0.23	0.11	-0.07	-0.01	0.39	0.64	0.64															
	Japan	0.12	0.12	0.12	0.09	0.15	0.23	0.12	-0.10	-0.04	0.27	0.31	0.23	0.25														
	UK	0.11	0.20	0.19	0.16	0.07	0.22	0.17	-0.17	-0.01	0.46	0.71	0.58	0.50	0.32													
	US	0.14	0.14	0.17	0.17	-0.02	0.07	0.11	-0.11	-0.02	0.46	0.33	0.35	0.36	0.16	0.37												
	OVX	-0.11	-0.12	-0.12	-0.15	-0.02	-0.09	-0.10	0.16	0.07	-0.33	-0.25	-0.29	-0.27	-0.02	-0.26	-0.25											
	GVX	-0.09	-0.18	-0.13	-0.17	0.03	-0.14	0.06	0.13	0.30	-0.14	-0.20	-0.17	-0.24	-0.04	-0.26	-0.11	0.22										
95th Quantile	Canada	0.12	0.04	0.07	0.05	0.11	0.06	0.06	-0.13	-0.16	0.22	0.17	0.20	0.22	0.19	0.19	0.23	-0.03	-0.08									
	France	0.15	0.17	0.12	0.05	0.11	0.23	0.12	-0.11	-0.09	0.25	0.34	0.33	0.26	0.20	0.32	0.15	-0.18	-0.10	0.31								
	Germany	0.16	0.20	0.16	0.18	0.02	0.15	0.15	-0.08	-0.19	0.19	0.30	0.30	0.22	0.18	0.30	0.21	-0.15	-0.15	0.19	0.74							
	Italy	0.15	0.21	0.11	0.19	0.04	0.20	0.21	-0.22	-0.01	0.25	0.32	0.31	0.27	0.09	0.30	0.19	-0.24	-0.11	0.23	0.57	0.54						
	Japan	0.14	0.09	0.10	0.09	0.05	0.09	0.17	-0.01	-0.03	0.19	0.19	0.17	0.14	0.24	0.21	0.15	0.03	0.15	0.10	0.08	0.11	0.08					
	UK	0.24	0.06	0.08	0.03	0.08	0.10	0.10	-0.12	-0.16	0.27	0.25	0.33	0.25	0.19	0.27	0.22	-0.25	-0.06	0.41	0.52	0.41	0.44	0.19				
	US	0.06	0.00	0.04	-0.03	0.19	0.02	0.09	-0.07	-0.14	0.17	0.15	0.09	0.13	0.20	0.08	0.24	-0.04	-0.04	0.36	0.27	0.23	0.09	0.12	0.27			
	OVX	-0.25	-0.23	-0.17	-0.16	-0.06	-0.03	-0.13	-0.08	-0.02	-0.13	-0.06	-0.11	-0.07	0.00	0.01	-0.02	0.21	-0.01	0.01	0.03	-0.01	-0.08	0.00	-0.10	0.05		
	GVX	-0.21	-0.01	-0.13	-0.05	-0.13	-0.11	-0.03	0.01	0.10	-0.07	-0.15	-0.17	-0.13	-0.09	-0.09	-0.10	0.01	0.17	0.00	0.03	-0.03	0.01	-0.03	-0.17	-0.07	0.02	

Fig. 10. Short-term quantile coherence matrices among G-7 stock markets, oil and gold volatilities. Note: This figure presents the short-term (5-day) quantile coherence matrices computed at the 5th, 50th, and 95th quantiles of the return distribution (q=0.05,0.50,0.95), which correspond to bearish, normal, and bullish market conditions, respectively. See Table 1 for definitions of all variables. The coherence is estimated using the quantile coherence framework described in Section 3.2. These matrices capture pairwise dependence structures under distinct market regimes. Only statistically significant coherence values (at the 5 % level) are shown above the diagonal for interpretive clarity. Non-significant entries are set to zero, and duplicate values below the diagonal are omitted to reduce redundancy.

volatility into financial markets.

Moving to Panel D, which covers the Russia-Ukraine war period, we observe heightened market interdependencies, particularly in the median quantile. Canada becomes the system's primary net recipient of shocks, while OVX and GVX absorb more volatility from external markets. European markets, including Italy, Germany, France, and the UK, send strong spillovers to OVX, while Germany, France, and Italy significantly impact GVX. These findings highlight the impact of geopolitical risks on commodity volatility, as oil and gold markets respond sharply to uncertainty following Russian crude oil supply disruptions. The war-induced disruptions in global energy markets amplify oil price volatility, which in turn affects the gold market. The new spillovers from Italy to Germany, France, Canada, and the USA indicate that European financial stress plays a crucial role in global market contagion during this period. The increased size of Italy's node in the connectedness network further underscores its prominent role as a shock transmitter. This suggests that Italy's economic exposure to energy market volatility, combined with financial uncertainty in the eurozone, intensifies risk transmission across global markets. Additionally, new spillover pathways emerge among G7 stock markets, with significant connections between all G7 countries (except Japan) and Canada. This development positions Canada as a key recipient of external shocks, which may reflect its economic dependence on global commodity trade and exposure to oil price fluctuations. The most intense spillovers occur from Italy to GVX, OVX, and Japan, reinforcing the interconnectedness between financial markets and commodity price volatility. The USA also transmits strong shocks to Japan, further consolidating Japan's role as a financial stress absorber rather than a shock transmitter. In bullish market conditions, spillover effects appear to weaken. However, GVX remains the strongest recipient of shocks, followed by OVX, with spillovers originating from Germany, France, Italy, and Canada. This finding highlights the continued influence of European financial instability on commodity market volatility, particularly in response to energy supply disruptions. The UK also becomes a net recipient of shocks from France, Germany, and the USA, suggesting that geopolitical uncertainties further heighten financial interdependencies within developed economies.

Despite variations across sub-samples, certain findings remain consistent. Japan, OVX, and GVX persistently serve as net recipients of shocks, while Italy, Germany, and France consistently act as net transmitters. This reinforces the idea that European markets play a dominant role in risk transmission, while Japan and commodity-related volatility indices function as absorbers of financial stress. From an economic and financial standpoint, these findings carry significant implications. The persistent role of OVX and GVX as net recipients suggests that oil and gold volatility indices primarily reflect investor sentiment rather than actively spread financial contagion. Similarly, Japan's consistent position as a net recipient highlights that its stock market, despite being a major global financial hub, may not always offer the expected diversification benefits in times of crisis. The results also emphasize the need for dynamic risk management strategies. Investors should recognize that spillover intensities shift depending on market conditions and global crises. The Russia-Ukraine war, for example, significantly alters risk transmission pathways, reinforcing the importance of continuously reassessing market interdependencies. Policymakers should take these evolving risk transmission dynamics into account when designing financial stability measures, particularly during geopolitical conflicts. Overall, aside from the connections established between specific markets, Fig. 9 reveals intriguing diversification opportunities under normal, bearish, and bullish market conditions. The ability to identify key net transmitters and receivers of shocks allows investors to adjust portfolio strategies accordingly, mitigating risk exposure in response to evolving global uncertainties. These findings collectively reinforce H1–H3, by demonstrating regime-dependent connectedness, evolving market roles, and the conditional hedging characteristics of OVX and GVX.

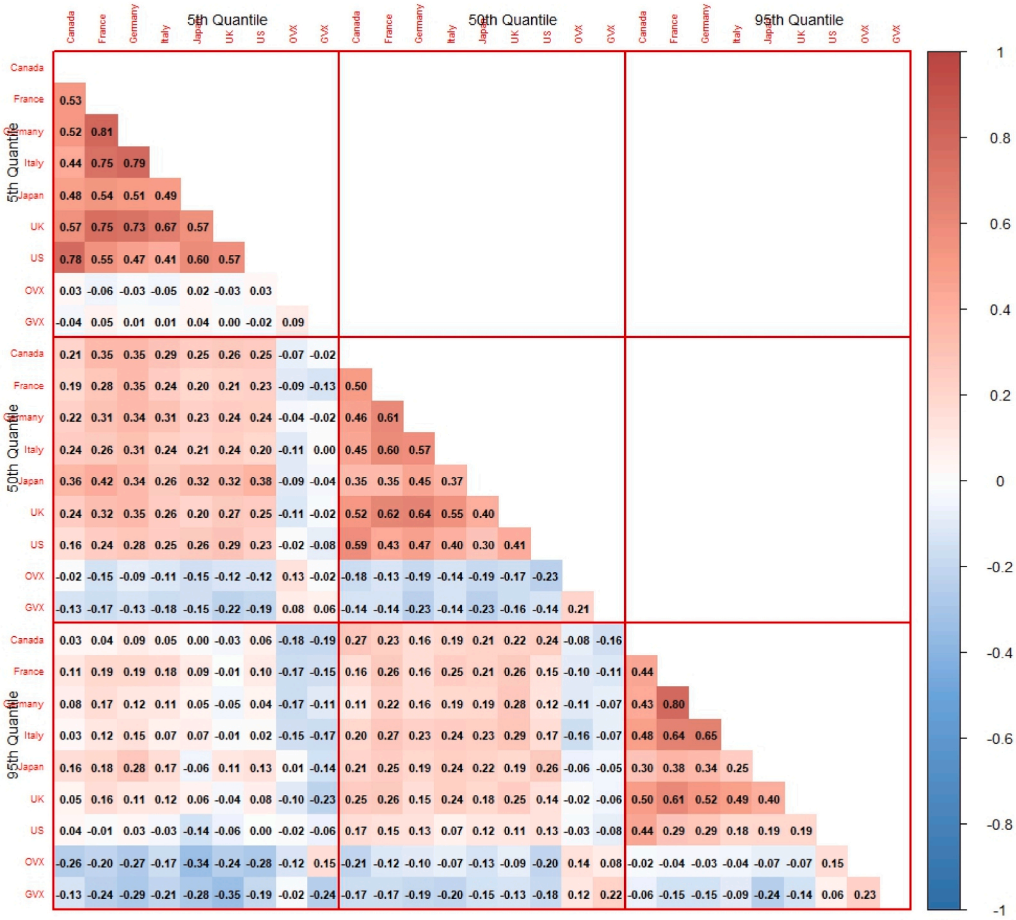
5.4. *Results of the quantile coherence approach*

We use the quantile cross-spectral analysis proposed by Barunik and Kley (2015) to examine the interdependencies among G7 stock markets, OVX, and GVX across different frequencies and quantiles. Figs. 10–12 present quantile coherence matrices that illustrate short-, medium-, and long-term return horizons, respectively. The results for the three quantiles—the 5th, 50th, and 95th—as well as their various combinations, appear in each coherence matrix. By measuring the interdependence between the lower, median, and upper return quantiles, this analytical method enables detailed visualization of the connections between markets across quantiles and frequencies. It is important to emphasize that the 5th and 95th quantiles represent distinct and non-overlapping market conditions—bearish and bullish, respectively—and their comparison does not imply concurrent market states or simultaneous portfolio actions. Rather, these comparisons highlight how extreme downside and upside risks evolve and interact over time, offering a broader perspective on market instability and informing long-term risk management strategies. Notably, this method surpasses the limitations of traditional invariant dependence models, as noted by Jain et al. (2022). Such analysis proves particularly insightful for investors with diverse investment horizons and those operating within a dynamic market environment. The color spectrum, from blue to red, represents the degree of coherence between the various markets under examination, from strongly negative to strongly positive.

The short-term coherence matrix (5-day horizon) in Fig. 10 provides insight into immediate market reactions and the dynamic nature of short-term risk spillovers. The results reveal a negative interdependence between OVX, GVX, and G7 stock returns at the median quantile (0.5, 0.5). However, in extreme market conditions (0.05, 0.05 and 0.95, 0.95), interlinkages between G7 stock markets and commodity volatilities weaken, suggesting potential diversification opportunities. During bearish market conditions, gold does not offer significant downside protection for G7 stock investors, contradicting the conventional belief in its safe-haven properties. However, it provides some diversification benefits due to the absence of strong interdependence. Oil, on the other hand, exhibits a strong safe-haven attribute for short-term investors, particularly in Italy and Japan, where negative coherence values (–0.13 and –0.19, respectively) indicate its ability to hedge against stock market downturns. During bullish periods, gold appears as a viable hedge for UK investors (–0.17 coherence), suggesting that its hedging effectiveness varies depending on market conditions. Both gold and oil exhibit the most pronounced hedging benefits under normal market conditions (0.5, 0.5), reinforcing their role as stabilizers in standard trading environments. Overall, the short-term analysis suggests that while both assets can serve as safe havens, oil may offer more immediate downside protection in certain markets, whereas gold's hedging effectiveness is more market-specific—supporting H3 regarding the asset-specific hedging behavior under high-volatility conditions. These findings carry implications for short-term traders and portfolio managers, who should account for varying asset interdependencies when adjusting hedging strategies.

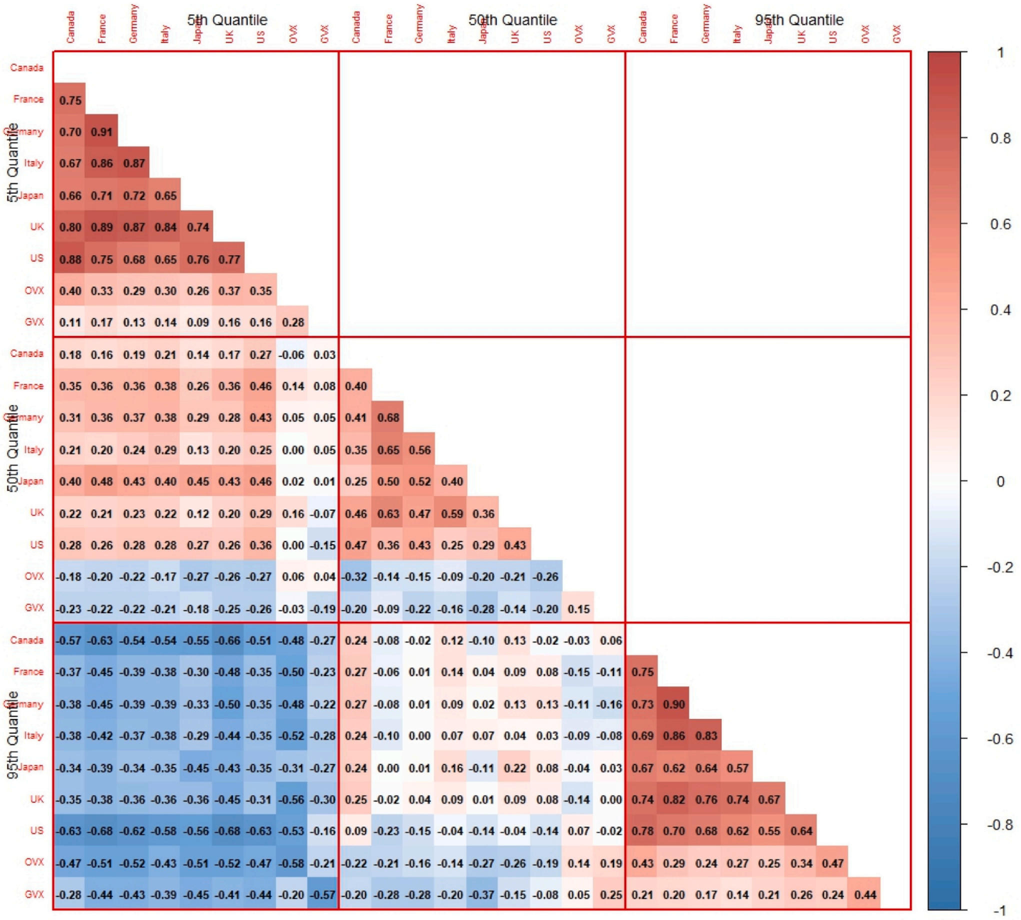
In the medium term (22-day horizon) in Fig. 11, the interdependence between OVX (and GVX) and G7 stock markets becomes more apparent. During stable market conditions, the results indicate a strong negative relationship between commodity volatilities and stock markets (coherences ranging from –0.23 to –0.14), reinforcing the hedging potential of oil and gold. Under bearish market conditions, gold and oil exhibit minimal interdependence with stock markets, suggesting their suitability for diversification—particularly for medium-term investors seeking assets with low equity correlation. Interestingly, gold emerges as a more effective hedge during bullish periods—especially for French, German, Japanese, and UK stock investors. The observed negative coherence values suggest that gold's role as a hedging instrument strengthens in medium-term horizons. These findings suggest that investors with a medium-term outlook should incorporate both gold and oil into their portfolios to manage risk exposure across different market conditions. The negative coherence between OVX/GVX and stock markets under stable conditions further supports their use as hedging tools.

The long-term coherence matrix (250-day horizon) in Fig. 12 presents a different picture. Compared to short- and medium-term horizons, the diversification benefits of gold and oil diminish significantly over extended periods. While stock-commodity interdependencies weaken in extreme market conditions, certain exceptions arise. In the lower quantile, GVX exhibits some diversification potential for Canada, Germany, Italy, and Japan, while in the upper quantile, gold provides hedging benefits for Italian investors. These findings indicate that, although limited, gold and oil can still offer long-term portfolio benefits under specific conditions. Under normal market conditions, oil and gold exhibit weak or negative interdependencies with stock markets, suggesting that they still provide risk reduction benefits over long investment horizons. However, their hedging capabilities appear more robust in shorter time frames, highlighting the importance of dynamic asset allocation.



		5th Quantile									50th Quantile									95th Quantile								
		Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX
5th Quantile	Canada																											
	France	0.53																										
	Germany	0.52	0.81																									
	Italy	0.44	0.75	0.79																								
	Japan	0.48	0.54	0.51	0.49																							
	UK	0.57	0.75	0.73	0.67	0.57																						
	US	0.78	0.55	0.47	0.41	0.60	0.57																					
	OVX	0.03	-0.06	-0.03	-0.05	0.02	-0.03	0.03																				
	GVX	-0.04	0.05	0.01	0.01	0.04	0.00	-0.02	0.09																			
50th Quantile	Canada	0.21	0.35	0.35	0.29	0.25	0.26	0.25	-0.07	-0.02																		
	France	0.19	0.28	0.35	0.24	0.20	0.21	0.23	-0.09	-0.13	0.50																	
	Germany	0.22	0.31	0.34	0.31	0.23	0.24	0.24	-0.04	-0.02	0.46	0.61																
	Italy	0.24	0.26	0.31	0.24	0.21	0.24	0.20	-0.11	0.00	0.45	0.60	0.57															
	Japan	0.36	0.42	0.34	0.26	0.32	0.32	0.38	-0.09	-0.04	0.35	0.35	0.45	0.37														
	UK	0.24	0.32	0.35	0.26	0.20	0.27	0.25	-0.11	-0.02	0.52	0.62	0.64	0.55	0.40													
	US	0.16	0.24	0.28	0.25	0.26	0.29	0.23	-0.02	-0.08	0.59	0.43	0.47	0.40	0.30	0.41												
	OVX	-0.02	-0.15	-0.09	-0.11	-0.15	-0.12	-0.12	0.13	-0.02	-0.18	-0.13	-0.19	-0.14	-0.19	-0.17	-0.23											
	GVX	-0.13	-0.17	-0.13	-0.18	-0.15	-0.22	-0.19	0.08	0.06	-0.14	-0.14	-0.23	-0.14	-0.23	-0.16	-0.14	0.21										
95th Quantile	Canada	0.03	0.04	0.09	0.05	0.00	-0.03	0.06	-0.18	-0.19	0.27	0.23	0.16	0.19	0.21	0.22	0.24	-0.08	-0.16									
	France	0.11	0.19	0.19	0.18	0.09	-0.01	0.10	-0.17	-0.15	0.16	0.26	0.16	0.25	0.21	0.26	0.15	-0.10	-0.11	0.44								
	Germany	0.08	0.17	0.12	0.11	0.05	-0.05	0.04	-0.17	-0.11	0.11	0.22	0.16	0.19	0.19	0.28	0.12	-0.11	-0.07	0.43	0.80							
	Italy	0.03	0.12	0.15	0.07	0.07	-0.01	0.02	-0.15	-0.17	0.20	0.27	0.23	0.24	0.23	0.29	0.17	-0.16	-0.07	0.48	0.64	0.65						
	Japan	0.16	0.18	0.28	0.17	-0.06	0.11	0.13	0.01	-0.14	0.21	0.25	0.19	0.24	0.22	0.19	0.26	-0.06	-0.05	0.30	0.38	0.34	0.25					
	UK	0.05	0.16	0.11	0.12	0.06	-0.04	0.08	-0.10	-0.23	0.25	0.26	0.15	0.24	0.18	0.25	0.14	-0.02	-0.06	0.50	0.61	0.52	0.49	0.40				
	US	0.04	-0.01	0.03	-0.03	-0.14	-0.06	0.00	-0.02	-0.06	0.17	0.15	0.13	0.07	0.12	0.11	0.13	-0.03	-0.08	0.44	0.29	0.29	0.18	0.19	0.19			
	OVX	-0.26	-0.20	-0.27	-0.17	-0.34	-0.24	-0.28	-0.12	0.15	-0.21	-0.12	-0.10	-0.07	-0.13	-0.09	-0.20	0.14	0.08	-0.02	-0.04	-0.03	-0.04	-0.07	-0.07	0.15		
	GVX	-0.13	-0.24	-0.29	-0.21	-0.28	-0.35	-0.19	-0.02	-0.24	-0.17	-0.17	-0.19	-0.20	-0.15	-0.13	-0.18	0.12	0.22	-0.06	-0.15	-0.15	-0.09	-0.24	-0.14	0.06	0.23	

Fig. 11. Medium-term quantile coherence matrices among G-7 stock markets, oil and gold volatilities. Note: This figure presents the medium-term (22-day) quantile coherence matrices computed at the 5th, 50th, and 95th quantiles of the return distribution (q=0.05,0.50,0.95), which correspond to bearish, normal, and bullish market conditions, respectively. See Table 1 for definitions of all variables. The coherence is estimated using the quantile coherence framework described in Section 3.2. These matrices capture pairwise dependence structures under distinct market regimes. Only statistically significant coherence values (at the 5 % level) are shown above the diagonal for interpretive clarity. Non-significant entries are set to zero, and duplicate values below the diagonal are omitted to reduce redundancy.



		5th Quantile									50th Quantile									95th Quantile								
		Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX	Canada	France	Germany	Italy	Japan	UK	US	OVX	GVX
5th Quantile	Canada																											
	France	0.75																										
	Germany	0.70	0.91																									
	Italy	0.67	0.86	0.87																								
	Japan	0.66	0.71	0.72	0.65																							
	UK	0.80	0.89	0.87	0.84	0.74																						
	US	0.88	0.75	0.68	0.65	0.76	0.77																					
	OVX	0.40	0.33	0.29	0.30	0.26	0.37	0.35																				
	GVX	0.11	0.17	0.13	0.14	0.09	0.16	0.16	0.28																			
50th Quantile	Canada	0.18	0.16	0.19	0.21	0.14	0.17	0.27	-0.06	0.03																		
	France	0.35	0.36	0.36	0.38	0.26	0.36	0.46	0.14	0.08	0.40																	
	Germany	0.31	0.36	0.37	0.38	0.29	0.28	0.43	0.05	0.05	0.41	0.68																
	Italy	0.21	0.20	0.24	0.29	0.13	0.20	0.25	0.00	0.05	0.35	0.65	0.56															
	Japan	0.40	0.48	0.43	0.40	0.45	0.43	0.46	0.02	0.01	0.25	0.50	0.52	0.40														
	UK	0.22	0.21	0.23	0.22	0.12	0.20	0.29	0.16	-0.07	0.46	0.63	0.47	0.59	0.36													
	US	0.28	0.26	0.28	0.28	0.27	0.26	0.36	0.00	-0.15	0.47	0.36	0.43	0.25	0.29	0.43												
	OVX	-0.18	-0.20	-0.22	-0.17	-0.27	-0.26	-0.27	0.06	0.04	-0.32	-0.14	-0.15	-0.09	-0.20	-0.21	-0.26											
	GVX	-0.23	-0.22	-0.22	-0.21	-0.18	-0.25	-0.26	-0.03	-0.19	-0.20	-0.09	-0.22	-0.16	-0.28	-0.14	-0.20	0.15										
95th Quantile	Canada	-0.57	-0.63	-0.54	-0.54	-0.55	-0.66	-0.51	-0.48	-0.27	0.24	-0.08	-0.02	0.12	-0.10	0.13	-0.02	-0.03	0.06									
	France	-0.37	-0.45	-0.39	-0.38	-0.30	-0.48	-0.35	-0.50	-0.23	0.27	-0.06	0.01	0.14	0.04	0.09	0.08	-0.15	-0.11	0.75								
	Germany	-0.38	-0.45	-0.39	-0.39	-0.33	-0.50	-0.35	-0.48	-0.22	0.27	-0.08	0.01	0.09	0.02	0.13	0.13	-0.11	-0.16	0.73	0.90							
	Italy	-0.38	-0.42	-0.37	-0.38	-0.29	-0.44	-0.35	-0.52	-0.28	0.24	-0.10	0.00	0.07	0.07	0.04	0.03	-0.09	-0.08	0.69	0.86	0.83						
	Japan	-0.34	-0.39	-0.34	-0.35	-0.45	-0.43	-0.35	-0.31	-0.27	0.24	0.00	0.01	0.16	-0.11	0.22	0.08	-0.04	0.03	0.67	0.62	0.64	0.57					
	UK	-0.35	-0.38	-0.36	-0.36	-0.36	-0.45	-0.31	-0.56	-0.30	0.25	-0.02	0.04	0.09	0.01	0.09	0.08	-0.14	0.00	0.74	0.82	0.76	0.74	0.67				
	US	-0.63	-0.68	-0.62	-0.58	-0.56	-0.68	-0.63	-0.53	-0.16	0.09	-0.23	-0.15	-0.04	-0.14	-0.04	-0.14	0.07	-0.02	0.78	0.70	0.68	0.62	0.55	0.64			
	OVX	-0.47	-0.51	-0.52	-0.43	-0.51	-0.52	-0.47	-0.58	-0.21	-0.22	-0.21	-0.16	-0.14	-0.27	-0.26	-0.19	0.14	0.19	0.43	0.29	0.24	0.27	0.25	0.34	0.47		
	GVX	-0.28	-0.44	-0.43	-0.39	-0.45	-0.41	-0.44	-0.20	-0.57	-0.20	-0.28	-0.28	-0.20	-0.37	-0.15	-0.08	0.05	0.25	0.21	0.20	0.17	0.14	0.21	0.26	0.24	0.44	

Fig. 12. Long-term quantile coherence matrices among G-7 stock markets, oil and gold volatilities. Note: This figure presents the long-term (250-day) quantile coherence matrices computed at the 5th, 50th, and 95th quantiles of the return distribution (q=0.05,0.50,0.95), which correspond to bearish, normal, and bullish market conditions, respectively. See Table 1 for definitions of all variables. The coherence is estimated using the quantile coherence framework described in Section 3.2. These matrices capture pairwise dependence structures under distinct market regimes. Only statistically significant coherence values (at the 5 % level) are shown above the diagonal for interpretive clarity. Non-significant entries are set to zero, and duplicate values below the diagonal are omitted to reduce redundancy.

These findings have significant implications for investors and policymakers. The results confirm that the hedging and diversification properties of gold and oil are time-dependent, with their effectiveness varying across short-, medium-, and long-term investment horizons. Our findings align with previous studies that highlight the safe-haven attributes of oil and gold when combined with stocks (Disli et al., 2021). However, the results provide a more nuanced perspective, showing that the strength of these safe-haven properties differs depending on the time frame and market conditions. For short-term investors, oil appears to provide stronger safe-haven benefits than gold, particularly for the Italian and Japanese stock markets. This suggests that traders seeking immediate downside protection may find oil-related assets more effective during financial distress. For medium-term investors, both gold and oil demonstrate strong hedging potential, particularly under normal and bullish market conditions. Investors with a 22-day investment horizon should consider incorporating these commodities into their portfolios to mitigate risk and improve portfolio resilience. For long-term investors, the diversification benefits of gold and oil tend to decline, though some opportunities persist in specific markets. This finding implies that long-term portfolio strategies should not rely solely on commodity-based hedging. Instead, investors should complement gold and oil with additional risk management tools to ensure resilience against prolonged market shocks and structural changes in global financial markets. These insights emphasize the need for dynamic investment strategies, where investors adjust their hedging instruments based on market conditions and investment horizons, in line with H3's proposition that gold and oil provide effective hedging particularly during high-risk states and crisis periods. Policymakers should also consider these dynamics when designing financial stability measures, particularly in times of economic uncertainty and geopolitical instability.

6. Conclusion and implications

This study provides a comprehensive analysis of spillover effects between G7 stock markets, oil, and gold volatilities, covering the period from January 1, 2017, to June 16, 2022. By employing a quantile-based connectedness approach and quantile coherence analysis, we uncover asymmetric spillovers across different market conditions and time horizons, offering new insights into financial contagion, risk transmission, and portfolio diversification strategies. These results are directly aligned with our study's hypotheses: H1, which posits stronger spillovers during extreme market states; H2, concerning the regime-dependent roles of markets as net transmitters or receivers; and H3, which highlights the time-varying hedging effectiveness of oil and gold volatility.

Our analysis yields several key findings. First, Japan and GVX consistently act as net recipients of shocks, while Canada, France, Germany, Italy, and the UK serve as net transmitters across the middle, lower, and upper quantiles. This supports H2, showing consistent role asymmetries across regimes.This suggests that some markets are more influential in transmitting financial turbulence, whereas others absorb external shocks. The strong risk transmission between France and Germany, as well as from France and Germany to Italy, highlights the close financial ties within European markets. Additionally, the reciprocal effects between OVX, GVX, and G7 stock markets remain low in the median quantile but become more pronounced in both the lower and upper quantiles.

Second, spillover structures differ significantly between normal, bullish, and bearish market conditions. Under normal conditions, G7 stock markets exhibit higher spillovers to their own shares. However, during bullish and bearish phases, they tend to receive more spillovers from other markets, indicating greater market interdependence in times of financial turbulence. This is consistent with H1, which anticipates stronger cross-market spillovers under tail conditions. Certain markets, such as Canada, GVX, and OVX, exhibit a more pronounced influence on other markets during specific periods, reinforcing their role in risk propagation.

Third, the dynamic connectedness analysis reveals high fluctuations in spillover magnitudes over time. We observe peaks in spillover intensity during periods of trade tensions, rising interest rates, the COVID-19 pandemic, and the Russia-Ukraine war. These findings underscore that market turbulence amplifies interdependencies, limiting diversification benefits. Investors should recognize that during high-risk periods, portfolio diversification becomes less effective, necessitating alternative hedging strategies.

Fourth, the study highlights strong tail dependencies, with spillovers intensifying under both extreme negative (bearish) and extreme positive (bullish) conditions. Tail risks propagate differently than median-level risks, suggesting that financial markets become more sensitive to extreme shocks. This reinforces H1, highlighting that spillover intensity rises under extreme downside and upside risk conditions.This leads to higher volatility and increased exposure to systemic risks, reinforcing the importance of continuous portfolio rebalancing to account for market asymmetries.

Fifth, our network directional connectedness analysis shows that the USA plays a dominant role in shock transmission during stable market phases, particularly between 2017 and 2018. However, during the COVID-19 pandemic, all G7 countries—except Japan—emerge as significant net contributors to risk transmission. In contrast, during the Russia-Ukraine war, European stock markets assume a more prominent role in risk transmission, affecting both oil and gold markets. These evolving spillover patterns suggest that global crises alter traditional risk transmission channels, reinforcing the need for continuous assessment of systemic risks. Again supporting H2, these shifts demonstrate the regime-dependent evolution of market influence.

Sixth, when analyzing net connectedness, our results show that specific countries significantly contribute to information transmission during major global events. For example, the US-China trade tensions and Brexit uncertainty in 2018 lead to increased spillover effects. Similarly, during the COVID-19 pandemic, all G7 countries (except Japan) contribute to risk transmission. Fluctuations in spillovers persist throughout the entire sample period, with significant spillovers originating from different markets depending on prevailing market conditions.

Seventh, the network directional connectedness analysis underscores the stability of connections between Japan and other G7 countries, as well as between OVX and Canada, across different quantiles. Under bearish conditions, all pairwise connections become significant, with OVX, GVX, and Japan acting as the main recipients of shocks. However, in bullish conditions, OVX becomes a net transmitter, while the USA shifts to a net receiver. These findings suggest that some G7 markets exhibit risk mitigation properties, offering diversification opportunities for investors.

The study also reveals shifting market interdependencies over different periods, particularly pre-COVID-19, the COVID-19 crisis, and the Russia-Ukraine war. These findings highlight that global financial relationships continually evolve due to geopolitical and economic shocks. During the COVID-19 pandemic, network connectedness intensifies, with the USA, Japan, OVX, and GVX receiving more shocks from other markets. While Japan appears to be a safer investment, Italy emerges as a key risk transmitter, increasing spillovers to other G7 markets. Similarly, the Russia-Ukraine war disrupts oil and gold markets, causing new spillover dynamics. European stock markets play a stronger role in transmitting shocks to OVX and GVX, reinforcing the connection between geopolitical risk and commodity volatility. Across all sub-periods, Japan, OVX, and GVX consistently act as net recipients of shocks, while other G7 markets, particularly the USA and European stock markets, influence risk transmission. These findings underscore the strong interdependence between G7 stock markets, especially between the USA and Japan. The diversification potential of Japanese stocks may be limited, as they remain highly susceptible to external shocks. Policymakers should account for financial interconnectedness and systemic risks, particularly during economic crises and geopolitical conflicts. The changing role of the US stock market suggests a need to reassess traditional assumptions about global financial stability and risk transmission mechanisms.

Eighth, employing the quantile coherence approach, we provide valuable insights to traders and investors with different investment horizons and market conditions. The results show that market interdependence varies across quantiles and frequencies, confirming H3, as the hedging potential of gold and oil varies across time horizons and quantile-based regimes, offering practical guidance for portfolio management and risk optimization. Short-term analysis reveals that gold exhibits weak safe-haven characteristics but still provides some diversification benefits. Conversely, oil demonstrates strong safe-haven properties, particularly for short-term investors in certain G7 stock markets. Medium-term analysis shows that both oil and gold act as effective hedging instruments under stable market conditions and present strong hedging opportunities during bullish phases. Long-term analysis suggests that gold retains limited diversification benefits for specific G7 countries, while oil's hedging capabilities decline over extended periods. These findings highlight the importance of accounting for time-varying dependencies when designing portfolio strategies. By incorporating gold and oil into investment strategies, investors enhance risk management and portfolio diversification, particularly in volatile market conditions.

Our findings carry critical implications for investors, policymakers, and financial regulators, particularly in the context of risk management, portfolio diversification, and financial stability policies. From an investment perspective, the evidence of asymmetric spillovers suggests that traditional diversification strategies prove insufficient during periods of financial turbulence. Investors should adopt dynamic hedging strategies that account for changing market interdependencies under different economic conditions. For instance, while gold and oil serve as effective hedges in certain contexts, their risk mitigation potential varies depending on the market state—whether bullish, bearish, or normal. Short-term investors may benefit from tactical asset allocation adjustments, whereas long-term investors should monitor structural shifts in spillover dynamics. These adjustments enhance portfolio resilience in the face of evolving financial risks. For portfolio managers, our findings emphasize the importance of monitoring tail dependencies, as risk transmission intensifies in extreme market conditions. This underscores the need for incorporating quantile-based risk assessment models alongside conventional risk measures such as Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). The time-varying nature of spillovers calls for the use of rolling-window analysis and real-time monitoring tools. These tools should be integrated into portfolio decision-making frameworks to ensure timely responses to financial shocks. By doing so, asset managers better navigate periods of heightened market stress and reduce vulnerability to systemic events. Quantile-based models also improve the detection of asymmetries in risk exposure, allowing for more robust risk management strategies.

For policymakers and financial regulators, the results indicate that systemic risk amplifies during crises, necessitating closer supervision of cross-market interdependencies. The reshaping of financial contagion channels during the Russia-Ukraine war and the COVID-19 pandemic suggests that regulatory frameworks must remain adaptive to emerging risks rather than static. Policymakers may need to strengthen macroprudential regulations to mitigate financial vulnerabilities arising from geopolitical uncertainty and commodity price shocks. In addition, central banks should consider commodity market volatilities when designing monetary policy frameworks, as these fluctuations increasingly affect financial system stability and investor behavior.

Overall, our results validate all three hypotheses: H1, confirming intensified spillovers in tail regimes; H2, identifying structural differences in transmission roles across time and regimes; and H3, illustrating the conditional hedging power of commodity volatilities depending on market phase and investment horizon.

While this study provides a comprehensive analysis of financial spillovers, several areas remain open for future investigation. Extending the analysis to emerging markets may yield insights into whether spillover effects behave similarly in economies with different financial structures and regulatory frameworks. Since developing markets often exhibit higher volatility and lower integration, understanding risk transmission in these contexts enhances global financial stability research. Another promising avenue involves the examination of sectoral and industry-level spillovers. Different industries respond uniquely to macroeconomic and geopolitical shocks. For instance, sectors such as technology, energy, and financial services may exhibit distinct contagion patterns. Analyzing these differences may offer a more nuanced understanding of systemic risk and improve sector-specific risk mitigation strategies. Given the growing emphasis on environmental, social, and governance (ESG) factors, future research may also explore whether sustainable investments exhibit different spillover dynamics compared to traditional assets. Studying the role of green finance and ESG-oriented strategies in shaping financial contagion provides valuable insights for both institutional investors and regulatory bodies. Additionally, including alternative asset classes—such as cryptocurrencies, sovereign and corporate bonds, and real estate—into spillover models enhances the assessment of contagion mechanisms. This becomes particularly relevant as institutional investors increasingly diversify into digital assets and non-traditional instruments, potentially altering the structure of financial interdependencies. Higher-frequency data analysis presents another promising direction. Since financial shocks propagate rapidly within a trading day, examining intraday spillovers may shed light on volatility clustering, especially during market open and close periods. These insights may help refine real-time risk management tools. Lastly, assessing the influence of macroeconomic policy interventions on spillover intensity remains a key research frontier. Central bank actions, interest rate changes, and fiscal stimulus measures may moderate or amplify contagion effects. Evaluating their effectiveness in mitigating systemic risk carries practical implications for policy design. By pursuing these directions, future research contributes to a deeper understanding of market interdependencies, enhances portfolio diversification strategies, and supports more effective responses to financial instability in an increasingly interconnected global economy.

CRediT authorship contribution statement

Sinda Hadhri: Writing – review & editing, Writing – original draft, Validation, Supervision, Investigation, Conceptualization. **Waqas Hanif:** Writing – original draft, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Elkhoury Rim:** Writing – review & editing, Writing – original draft, Validation, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The first author is pleased to acknowledge financial support from Fundação para a Ciência e a Tecnologia under a project (Grant UIDB/04007/2020).

Appendix-A

A1 – Explanation of Quantile Connectedness approach

Consider a system of $N -$ variables with $i = 1, 2, 3, 4, \ldots, N$ and time t periods with $t = 1, 2, 3, 4, \ldots, T$. Let $y_t = (\mathrm{y}_{1t},\ \mathrm{y}_{2t},\ \ldots,\ \mathrm{y}_N)^{'}$ is $N \times 1$ matrix of $N -$ variables. Following a simple Quantile Vector Autoregressive (QVAR) framework, we can estimate the model at quantile $q \in (0, 1)$ is written as:

$$y_{i\tau} = c \quad (q) + \sum_{i=1}^{p} \phi_i(q) y_{t-i} + \varepsilon_t(q) \tag{A.1}$$

Where $c(q)$ is the $N \times 1$ intercept vector. $\phi_i(q)$ is the $N \times N$ lag coefficient matrix, and $\varepsilon_t(q)$ is the residual vector with quantile-specific-variance-covariance matrix $\Sigma(q)$.

Ando et al. (2022) present the quantile-specific conditional function as:

$$Q_q(y_{it} \mid \mathrm{y}_{t-1}, \quad \ldots, \quad \mathrm{y}_{t-p}) = \widehat{c}(q) + \sum_{i=1}^{p} \widehat{\phi}_i(q) y_{t-i} \tag{A.2}$$

The infinite-order QVAR moving average (QVAR(∞)) representation is:

$$y_t = \mu(q) + \quad \sum_{i=1}^{\infty} \Psi_i(q) \varepsilon_{t-i}(q) \tag{A.3}$$

To estimate QVAR, we assume the quantile residuals satisfy:

$$Q_q(\varepsilon_t(q) \mid \mathrm{y}_{t-1}, \quad \ldots, \quad \mathrm{y}_{t-p}) = 0 \tag{A.4}$$

To check loss function $\rho_p(y)$ is used to estimate quantile-specific parameters via:

$$\min_{c(q), \phi(q)} \sum\nolimits_{t=1}^{T} \sum\nolimits_{i=1}^{N} \rho_p (y_{it} - c_i(q) - \sum_{j=1}^{p} \phi_{ij}(q) y_{i,t-j}) \tag{A.5}$$

$$\text{Where} \rho_p(\mu) = \mu[q - I(\mu - \quad < 0]$$

To assess volatility connectedness, we compute the Generalized Forecast Error Variance Decomposition (GFEVD) at horizon H using Koop et al. (1996) and Pesaran and Shin (1998)

$$\widetilde{C}_{ij}^{g}(H) = \frac{\sum q_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h(q) \sum(q) e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h(q) \sum \tau \Psi_h(q' e_i)} \tag{A.6}$$

Where e_i is a selection vector with 1 at i-th position. The normalized spillover is:

$$\widetilde{C}_{ij}^{g}(H) = \frac{\varTheta_{ij}^{g}(H)}{\sum\limits_{j=1}^{N} \varTheta_{ij}^{g}(H)}, \sum\nolimits_{j=1}^{N} \widetilde{C}_{ij}^{g} = 1 \tag{A.7}$$

The total connectedness index (TCI):

$$TCI(q) = \frac{\sum\limits_{i=1}^{N} \sum\limits_{j=1, i \neq j}^{N} \widetilde{C}_{ij}^{g}(q)}{\sum\limits_{i=1}^{N} \sum\limits_{j=1}^{N} \widetilde{C}_{ij}^{g}(q)} \quad \times 100 \tag{A.8}$$

Directional Spillovers:

$$TO_{i \to j} \quad (q) = \frac{\sum\limits_{j=1, i \neq j}^{N} \widetilde{C}_{ji}^{g}(q)}{\sum\limits_{j=1}^{N} \widetilde{C}_{ji}^{g}(q)} \quad \times 100 \tag{A.9}$$

$$FROM_{i\leftarrow j}\quad(q)=\frac{\sum_{j=1,i\neq j}^{N}\widetilde{C}_{ij}^{g}(q)}{\sum_{j=1}^{N}\widetilde{C}_{ij}^{g}(q)}\quad\times 100 \tag{A.10}$$

$$NET_{i}\ (q)=TO_{i\rightarrow j}\ (q)-FROM_{i\leftarrow j}\ (q) \tag{A.11}$$

Positive values of $NET_i\ (q)$ indicate net transmitters, negative indicate net receivers.

A2 – Explanation of Quantile coherence approach

Following a stationary process along-with components $y_{t,j}, j=1,\ldots,d$: i.e., $y_t\ =(y_t,1,\ldots,y_{t,d})\prime$.The marginal distribution function $y_{t,j}$ will be denoted by F_j, and the corresponding quantile by $q_j(\tau)\ =F_j^{-1}(\tau)\ =\inf\{q\in\mathbb{R}:\tau\leq F_j(q)\}$, where $\tau\in(0,1)$. We use the convention $\inf\varnothing=+\infty$, allowing $q_j(\tau)$ to equal $-\infty$ if $\tau=0$ and $+\infty$ if $\tau\ =1$. We will write z for the complex conjugate, R_Z for the real part, and z for the imaginary part of $z\in C$. Matrix A will be represented by $A\prime$, and the inverse of a regular matrix B will be B^{-1}. We explain the quantile cross-covariance kernels matrix to measure the serial and cross-dependency structure of $(y_t)t\in z$ as $\Gamma_k(\tau_1,\tau_2):=\left(\Upsilon_k^{j1,j2}(\tau_1,\ \tau_2)\right)_{j1,j2=1,\ldots d}$,where

$$\Upsilon_k^{j1,j2}(\tau_1,\tau_2):=Cov\left(I\left\{y_{t+k,j1}\ \leq q_{j1}(\tau_1)\right\},I\left\{y_{t,j2}\leq q_{j2}(\tau_2)\right\}\right), \tag{A.12}$$

$j_1,j_2\in\{1,\ldots,d\}$, $k\in\ \mathbb{Z}$, $\tau_1,\tau_2\in(0,1)$, and $I\{A\}$ indicates the indicator function of the event A. In the frequency domain, this yields (under appropriate mixing conditions) the matrix of quantile cross-spectral density kernels $\mathfrak{f}^{j1,j2}(\omega;\tau_1,\tau_2):=(\mathfrak{f}^{j1,j2}(;\tau_1,\tau_2))j_1,j_2\ =1,\ldots,d$, where $\mathfrak{f}^{j1,j2}(\omega;\tau_1,\tau_2):=(2\pi)^{-1}\sum_{k=-\infty}^{\infty}\Upsilon_k^{j1,j2}(\tau_1,\tau_2)e^{-ik\omega}$,

$j_1,j_2\in\{1,\ldots,d\}$, $\omega\in\ \mathbb{R}$, $\tau_1,\tau_2\in(0,1)$. A closely related quantity that can be used as a measure for the dynamic dependence of the two processes $(y_{t,j1})_{t\in\mathbb{Z}}$ and $(y_{t,j2})_{t\in\mathbb{Z}}$ is quantile coherence kernel of $(y_{t,j1})_{t\in\mathbb{Z}}$ and $(y_{t,j2})_{t\in\mathbb{Z}}$, which define as follows:

$$\Re^{j1,j2}(\omega;\tau_1,\tau_2):=\ =\ \frac{\mathfrak{f}^{j1,\ j2}(\omega;\tau_1,\tau_2)}{\left(\mathfrak{f}^{j1,\ j1}(\omega;\tau_1,\tau_2)\mathfrak{f}^{j2,\ j2}(\omega;:\tau_1,\tau_2)\right)1\Big/2}, \tag{A.13}$$

$(\tau_1,\tau_2)\in(0,1)^2$. We explain the estimator for the quantile cross-spectral density as the collection

$$I_{n,R}^{j1,j2}(\omega;\tau_1,\tau_2):=\frac{1}{2\pi n}d_{n,R}^{j1}(\omega;\tau_1)d_{n,R}^{j2}(-\omega;\tau_2), \tag{A.14}$$

$j_1,j_2\ =1,\ldots,d$, $\omega\in\ \mathbb{R}$, $\tau_1,\tau_2\in(0,1)^2$, and call it ranked-based copula cross-periodograms or the CCR-periodograms, where

$$d_{n,R}^{j}(\omega;\tau):=\sum_{t=0}^{n-1}I\left\{\widehat{F_{n,j}}\left(y_{t,j}\right)\ \leq\tau\right\}e^{-i\omega t}=\sum_{t=0}^{n-1}I\{R_{n;t,j}\leq n\tau\}e^{-i\omega t}, \tag{A.15}$$

$j=1,\ldots,d$, $\omega\in\ \mathbb{R}$, $\tau\ \in(0,1)$ and $\widehat{F_{n,j}}(x):=n^{-1}\sum_{t=0}^{n-1}I\left\{y_{t,j}\leq x\right\}$ indicates the empirical distribution function of $y_{t,j}$ and $R_{n;t,j}$ indicates the maximum rank of $y_{t,j}$ among $y_{0,j},\ldots,y_{n-1,j}$. The matrix of CCR-periodograms is written as:

$$I_{n,R}(\omega;\tau_1,\tau_2):=\left(I_{n,R}^{j1,j2}(\omega;\tau_1,\tau_2)\right)_{j1,j2=1,\ldots d}. \tag{A.16}$$

Constantly, the CCR-periodograms fail to calculate $\mathfrak{f}^{j1,j2}(\omega;\tau_1,\tau_2)$ for univariate case. This can be achieved by smoothing $I_{n,R}^{j1,j2}(\omega;\tau_1,\tau_2)$ across frequencies. In short, we take into consideration

$$\widehat{G_{n,R}^{j1,j2}}(\omega;\tau_1,\tau_2):=\ \frac{2\pi}{n}\sum_{s=1}^{n-1}W_n\left(\omega-\frac{2\pi s}{n}\right)I_{n,R}^{j1,j2}\left(\frac{2\pi s}{n},\tau_1,\tau_2\right), \tag{A.17}$$

Where W_n indicates a sequence of weight functions. We denote the matrix of smooth CCR-periodgrams as

$$\widehat{G}_{n,R}(\omega;\tau_1,\tau_2):=\left(\widehat{G}_{n,R}^{j1,j2}(\omega;\tau_1,\tau_2)\right)_{j1,j2=1,\ \ldots,d} \tag{A.18}$$

So, the quantile coherence estimator is written as:

$$\widehat{\Re}_{n,R}^{j1,j2}(\omega;\tau_1,\tau_2)\ :=\ \frac{\widehat{G}_{n,R}^{j1,j2}(\omega;\tau_1,\tau_2)}{\left(\widehat{G}_{n,R}^{j1,j1}(\omega;\tau_1,\tau_1)\widehat{G}_{n,R}^{j2,j2}(\omega;\tau_2,\tau_2)\right)1\Big/2}. \tag{A.19}$$

Data availability

Data will be made available on request.

References

Abdulkarim, F.M., Akinlaso, M.I., Hamid, B.A., Ali, H.S., 2020. The nexus between oil price and islamic stock markets in Africa: a wavelet and Multivariate-GARCH approach. Borsa Istanb. Rev. 20 (2), 108–120.

Adekoya, O.B., Oliyide, J.A., 2021. How COVID-19 drives connectedness among commodity and financial markets: evidence from TVP-VAR and causality-in-quantiles techniques. Resour. Policy 70.

Ahmed, F., Gurdgiev, C., Sohag, K., Islam, M.M., Zeqiraj, V., 2024. Global, local, or glocal? Unravelling the interplay of geopolitical risks and financial stress. J. Multinatl. Financ. Manag. 75, 100871.

Akkoc, U., Civcir, I., 2019. Dynamic linkages between strategic commodities and stock market in Turkey: evidence from SVAR-DCC-GARCH model. Resour. Policy 62, 231–239.

Aloui, C., Jammazi, R., 2009. The effects of crude oil shocks on stock market shifts behaviour: a regime switching approach. Energy Econ. 31 (5), 789–799.

Alshater, M.M., Hanif, W., El Khoury, R., Mensi, W., 2024. Interplay of crises: unpacking intraday spillovers in oil and european equities in the shadow of the COVID-19 and the Ukraine-Russia war. Borsa Istanb. Rev. 24 (4), 747–771.

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

Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J. Risk Financ. Manag. 13 (4), 84.

Arouri, M.E.H., Lahiani, A., Nguyen, D.K., 2015. World gold prices and stock returns in China: insights for hedging and diversification strategies. Econ. Model. 44, 273–282.

Arshanapalli, B., Doukas, J., 1993. International stock market linkages: evidence from the pre-and post-October 1987 period. J. Bank. Financ. 17 (1), 193–208.

Barunik, J., Kley, T., 2015. Quantile cross-spectral measures of dependence between economic variables. ArXiv Preprint 235–247. *ArXiv:1510.06946*.

Baruník, J., Kley, T., 2019. Quantile coherency: A general measure for dependence between cyclical economic variables. The Econometrics Journal 22 (2), 131–152.

Basher, S.A., Sadorsky, P., 2006. Oil price risk and emerging stock markets. Glob. Financ. J. 17 (2), 224–251.

Basher, S.A., Sadorsky, P., 2016. Hedging emerging market stock prices with oil, gold, VIX, and bonds: a comparison between DCC, ADCC and GO-GARCH. Energy Econ. 54, 235–247.

Baumöhl, E., Kočenda, E., Lyócsa, Š., V\`yrost, T., 2018. Networks of volatility spillovers among stock markets. Physica A Statistical Mechanics Applications 490, 1555–1574.

Baur, D.G., McDermott, T.K., 2010. Is gold a safe haven? International evidence. J. Bank. Financ. 34 (8), 1886–1898.

Beber, A., Brandt, M.W., 2010. When it cannot get better or worse: the asymmetric impact of good and bad news on bond returns in expansions and recessions. Rev. Financ. 14 (1), 119–155.

Becker, K.G., Finnerty, J.E., Gupta, M., 1990. The intertemporal relation between the US and Japanese stock markets. J. Financ. 45 (4), 1297–1306.

Beckmann, J., Czudaj, R., 2013. Gold as an inflation hedge in a time-varying coefficient framework. The North American Journal of Economics and Finance 24, 208–222.

Beine, M., Cosma, A., Vermeulen, R., 2010. The dark side of global integration: Increasing tail dependence. Journal of Banking & Finance 34 (1), 184–192.

Bouri, E., Lei, X., Jalkh, N., Xu, Y., Zhang, H., 2021. Spillovers in higher moments and jumps across US stock and strategic commodity markets. Resour. Policy 72, 102060.

Bredin, D., Conlon, T., Pot`i, V., 2017. The price of shelter-downside risk reduction with precious metals. Int. Rev. Financ. Anal. 49, 48–58.

Calvo, G.A., 2004. Contagion in emerging markets: when wall street is a carrier. Springer.

Chang, K.-L., 2021. Do US and Japanese uncertainty shocks play important roles in affecting transition mechanisms of Japanese stock market? North Am. J. Econ. Financ. 58, 101494.

Chatziantoniou, I., Gabauer, D., 2021. EMU risk-synchronisation and financil fragility through the prism of dynamic connectedness. Q. Rev. Econ. Financ. 79, 1–14.

Chen, K., Wang, M., 2019. Is gold a hedge and safe haven for stock market? Appl. Econ. Lett. 26 (13), 1080–1086.

Chkili, W., 2016. Dynamic correlations and hedging effectiveness between gold and stock markets: evidence for BRICS countries. Res. Int. Bus. Financ. 38, 22–34.

Ciner, C., Gurdgiev, C., Lucey, B.M., 2013. Hedges and safe havens: an examination of stocks, bonds, gold, oil and exchange rates. Int. Rev. Financ. Anal. 29, 202–211.

Cui, J., Goh, M., Li, B., Zou, H., 2021. Dynamic dependence and risk connectedness among oil and stock markets: new evidence from time-frequency domain perspectives. Energy 216, 119302.

Dai, Z., Zhu, H., 2022. Time-varying spillover effects and investment strategies between WTI crude oil, natural gas and Chinese stock markets related to belt and road initiative. Energy Econ. 108, 105883.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American statistical association 74 (366a), 427–431.

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

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.

Disli, M., Nagayev, R., Salim, K., Rizkiah, S.K., Aysan, A.F., 2021. In search of safe haven assets during COVID-19 pandemic: an empirical analysis of different investor types. Res. Int. Bus. Financ. 58, 101461.

Donadelli, M., Paradiso, A., 2014. Is there heterogeneity in financial integration dynamics? Evidence from country and industry emerging market equity indexes. J. Int. Financ. Mark. Inst. Money 32, 184–218.

Ederington, L.H., Lee, J.H., 1993. How markets process information: news releases and volatility. J. Financ. 48 (4), 1161–1191.

El Khoury, R., Mensi, W., Alshater, M.M., Kang, S., 2025. Extreme risk spillovers and hedging strategies between Indonesia sectorial stocks and commodity markets. Int. J. Emerg. Mark. 20 (1), 428–467.

Elsayed, A., Billah, M.A., Goodell, J.W., Hadhri, S., 2024. Examining connections between the fourth industrial revolution and energy markets. Energy Econ. 133, 107476.

Elsayed, A.H., Nasreen, S., Tiwari, A.K., 2020. Time-varying co-movements between energy market and global financial markets: implication for portfolio diversification and hedging strategies. Energy Econ. 90, 104847.

Enwereuzoh, P.A., Odei-Mensah, J., Junior, P.O., 2021. Crude oil shocks and African stock markets. Res. Int. Bus. Financ. 55, 101346.

Fang, Y., Jing, Z., Shi, Y., Zhao, Y., 2021. Financial spillovers and spillbacks: new evidence from China and G7 countries. Econ. Model. 94, 184–200. https://doi.org/10.1016/j.econmod.2020.09.022.

Fetais, A.H., Aysan, A.F., Nagayev, R., 2024. Navigating the complexities of GCC real state markets: an analysis of interlinkages amidst shocks and oil effects. J. Multinatl. Financ. Manag. 74, 100859.

Filis, G., 2010. Macro economy, stock market and oil prices: do meaningful relationships exist among their cyclical fluctuations? Energy Econ. 32 (4), 877–886.

Fisher, I. (1930). The theory of interest. New York, 43, 1–19.

Gabauer, D., Chatziantoniou, I., Stenfors, A., 2023. Model-free connectedness measures. Financ. Res. Lett. 54, 103804.

Gao, R., Zhao, Y., Zhang, B., 2021. The spillover effects of economic policy uncertainty on the oil, gold, and stock markets: evidence from China. Int. J. Financ. Econ. 26 (2), 2134–2141.

Ghorbel, A., Fakhfekh, M., Jeribi, A., Lahiani, A., 2022. Extreme dependence and risk spillover across G7 and China stock markets before and during the COVID-19 period. J. Risk Financ.
Gilmore, C.G., McManus, G.M., 2002. International portfolio diversification: US and central european equity markets. Emerg. Mark. Rev. 3 (1), 69–83.
Gkillas, K., Gupta, R., Pierdzioch, C., 2020. Forecasting realized gold volatility: is there a role of geopolitical risks? Financ. Res. Lett. 35, 101280.
Gkillas, K., Tsagkanos, A., Vortelinos, D.I., 2019. Integration and risk contagion in financial crises: evidence from international stock markets. J. Bus. Res. 104, 350–365.
Gong, C., Kim, S., 2018. Regional business cycle synchronization in emerging and developing countries: regional or global integration? Trade or financial integration? J. Int. Money Financ. 84, 42–57.
Gorton, G., Rouwenhorst, K, Geert, 2006. Facts and fantasies about commodity futures. Financ. Anal. J. 62 (2), 47–68. https://doi.org/10.2469/faj.v62.n2.4083.
Gubareva, M., Shafiullah, M., Teplova, T., 2025. Cross-quantile risk assessment: the interplay of crude oil, artificial intelligence, clean tech, and other markets. Energy Econ. 141, 108085.
Hamao, Y., Masulis, R.W., Ng, V., 1990. Correlations in price changes and volatility across international stock markets. Rev. Financ. Stud. 3 (2), 281–307.
Hamilton, J.D., 2003. What is an oil shock? J. Econ. 113 (2), 363–398.
Hanif, W., Hadhri, S., Elkhoury, R., 2024. Quantile spillover and connectedness between oil shocks and the stock markets of the largest oil producers and consumers. J. Commod. Mark. 34, 100404.
Hao, X., Ma, Y., Pan, D., 2024. Geopolitical risk and the predictability of spillovers between exchange, commodity and stock markets. J. Multinatl. Financ. Manag. 73, 100843.
Harnphattananusorn, S., 2024. Spillover effects between oil, gold, stock, and exchange rate returns in Thailand: an extended joint connected TVP-VAR approach. Int. J. Energy Econ. Policy 14 (5), 62–72.
Harvey, C.R., Huang, R.D., 1991. Volatility in the foreign currency futures market. Rev. Financ. Stud. 4 (3), 543–569.
Hsu, C.C., Tsai, W.C., 2025. Exploring the role of crude oil futures in portfolio diversification. J. Multinatl. Financ. Manag. 79, 100917.
Hung, N.T., Vo, X.V., 2021. Directional spillover effects and time-frequency nexus between oil, gold and stock markets: evidence from pre and during COVID-19 outbreak. Int. Rev. Financ. Anal. 76, 101730.
Jain, P., Maitra, D., McIver, R.P., Kang, S.H., 2022. Quantile dependencies and connectedness between stock and precious metals markets. J. Commod. Mark., 100284
Jiang, Y., Fu, Y., Ruan, W., 2019. Risk spillovers and portfolio management between precious metal and BRICS stock markets. Phys. A Statist. Mech. Appl. 534, 120993.
Jiang, K., Ye, W., 2022. Does the asymmetric dependence volatility affect risk spillovers between the crude oil market and BRICS stock markets? Econ. Model. 117, 106046.
Junttila, J., Pesonen, J., Raatikainen, J., 2018. Commodity market based hedging against stock market risk in times of financial crisis: the case of crude oil and gold. J. Int. Financ. Mark. Inst. Money 56, 255–280.
Kollias, C., Kyrtsou, C., Papadamou, S., 2013. The effects of terrorism and war on the oil price–stock index relationship. Energy Econ. 40, 743–752.
Kyle, A.S., Xiong, W., 2001. Contagion as a wealth effect. J. Financ. 56 (4), 1401–1440.
Kyriazis, N., Papadamou, S., Tzeremes, P., Corbet, S., 2024. Quantifying spillovers and connectedness among commodities and cryptocurrencies: evidence from a Quantile-VAR analysis. J. Commod. Mark. 33, 100385.
Li, X., Guo, Q., Liang, C., Umar, M., 2023. Forecasting gold volatility with geopolitical risk indices. Res. Int. Bus. Financ. 64, 101857.
Liao, J., Zhu, X., Chen, J., 2021. Dynamic spillovers across oil, gold and stock markets in the presence of major public health emergencies. Int. Rev. Financ. Anal. 77.
Lin, L., Kuang, Y., Jiang, Y., Su, X., 2019. Assessing risk contagion among the brent crude oil market, London gold market and stock markets: evidence based on a new wavelet decomposition approach. North Am. J. Econ. Financ. 50, 101035.
Liow, K.H., 2015. Volatility spillover dynamics and relationship across G7 financial markets. North Am. J. Econ. Financ. 33, 328–365.
Maghyereh, A.I., Abdoh, H., Awartani, B., 2019. Connectedness and hedging between gold and islamic securities: a new evidence from time-frequency domain approaches. Pac. Basin Financ. J. 54, 13–28.
Malik, F., Umar, Z., 2019. Dynamic connectedness of oil price shocks and exchange rates. Energy Econ. 84.
Mazur, M., Dang, M., Vega, M., 2021. COVID-19 and the March 2020 stock market crash: evidence from S&P500. Financ. Res. Lett. 38, 101690.
Mensi, W., Aslan, A., Vo, X.V., Kang, S.H., 2023. Time-frequency spillovers and connectedness between precious metals, oil futures and financial markets: hedge and safe haven implications. Int. Rev. Econ. Financ. 83, 219–232.
Mensi, W., Hammoudeh, S., Shahzad, S.J.H., Shahbaz, M., 2017. Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. J. Bank. Financ. 75, 258–279.
Mensi, W., Hkiri, B., Al-Yahyaee, K.H., Kang, S.H., 2018. Analyzing time–frequency co-movements across gold and oil prices with BRICS stock markets: a VaR based on wavelet approach. Int. Rev. Econ. \ Financ. 54, 74–102.
Mensi, W., Mishra, T., Ko, H.-U., Vo, X.V., Kang, S.H., 2024. Quantile dependence and portfolio management between oil, gold, silver, and MENA stock markets. Res. Int. Bus. Financ. 70, 102296.
Mensi, W., Naeem, M.A., Vo, X.V., Kang, S.H., 2022. Dynamic and frequency spillovers between Green bonds, oil and G7 stock markets: implications for risk management. Econ. Anal. Policy 73, 331–344.
Mensi, W., Rehman, M.U., Hammoudeh, S., Vo, X.V., 2021. Spillovers between natural gas, gasoline, oil, and stock markets: evidence from MENA countries. Resour. Policy 71, 101983.
Mensi, W., Shafiullah, M., Vo, X.V., Kang, S.H., 2021. Volatility spillovers between strategic commodity futures and stock markets and portfolio implications: evidence from developed and emerging economies. Resour. Policy 71.
Mensi, W., Vo, X.V., Kang, S.H., 2021. Time and frequency connectedness and network across the precious metal and stock markets: evidence from top precious metal importers and exporters. Resour. Policy 72.
Mensi, W., Vo, X.V., Kang, S.H., 2022. COVID-19 pandemic's impact on intraday volatility spillover between oil, gold, and stock markets. Econ. Anal. Policy 74, 702–715.
Mensi, W., Yousaf, I., Vo, X.V., Kang, S.H., 2022. Asymmetric spillover and network connectedness between gold, BRENT oil and EU subsector markets. J. Int. Financ. Mark. Inst. Money 76, 101487.
Mensi, W., Ziadat, S.A., Rababa'a, A.R. Al, Vo, X.V., Kang, S.H., 2024. Oil, gold and international stock markets: extreme spillovers, connectedness and its determinants. Q. Rev. Econ. Financ. 95, 1–17.
Ming, L., Shen, Y., Yang, S., Zhu, S., Zhu, H., 2020. Does gold serve as a hedge for the stock market in China? Evidence from a Time-Frequency analysis. Emerg. Mark. Financ. Trade 56 (3), 659–672.
Mohanty, S.K., Nandha, M., Turkistani, A.Q., Alaitani, M.Y., 2011. Oil price movements and stock market returns: evidence from gulf cooperation council (GCC) countries. Glob. Financ. J. 22 (1), 42–55.
Morana, C., 2013. Oil price dynamics, macro-finance interactions and the role of financial speculation. J. Bank. \ Financ. 37 (1), 206–226.
Morana, C., Beltratti, A., 2008. Comovements in international stock markets. J. Int. Financ. Mark. Inst. Money 18 (1), 31–45.
Naeem, M.A., Hasan, M., Arif, M., Balli, F., Shahzad, S.J.H., 2020. Time and frequency domain quantile coherence of emerging stock markets with gold and oil prices. Physica A Statistical Mechanics Applications 553, 124235.
Narayan, P.K., Narayan, S., Zheng, X., 2010. Gold and oil futures markets: are markets efficient? Appl. Energy 87 (10), 3299–3303.
Niu, Z., Ma, F., Zhang, H., 2022. The role of uncertainty measures in volatility forecasting of the crude oil futures market before and during the COVID-19 pandemic. Energy Econ. 112, 106120.
Ozcelebi, O., Pérez-Montiel, J., Kang, S.H., 2025. Extreme time–frequency connectedness between oil shocks and sectoral markets in the United States. Financ. Innov. 11, 65.
Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Economics letters 58 (1), 17–29.

Petmezas, D., Santamaria, D., 2014. Investor induced contagion during the banking and european sovereign debt crisis of 2007–2012: wealth effect or portfolio rebalancing? J. Int. Money Financ. 49, 401–424.

Reboredo, J.C., 2013. Is gold a safe haven or a hedge for the US dollar? Implications for risk management. J. Bank. Financ. 37 (8), 2665–2676.

Sakurai, Y., Kurosaki, T., 2020. How has the relationship between oil and the US stock market changed after the Covid-19 crisis? Financ. Res. Lett. 37, 101773.

Salisu, A.A., Vo, X.V., Lawal, A., 2021. Hedging oil price risk with gold during COVID-19 pandemic. Resour. Policy 70, 101897.

Serrano, P., Vaello-Sebastia, A., Vich-Llompart, M.M., 2024. The international linkages of market risk perception. J. Multinatl. Financ. Manag. 72, 100826.

Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., 2020. Safe haven, hedge and diversification for G7 stock markets: gold versus bitcoin. Econ. Model. 87, 212–224.

Shahzad, S.J.H., Ameer, S., Shahbaz, M., 2016. Disaggregating the correlation under bearish and bullish markets: A Quantile-quantile approach. Economics Bulletin 36 (4), 2465–2473.

Tahai, A., Rutledge, R.W., Karim, K.E., 2004. An examination of financial integration for the group of seven (G7) industrialized countries using an I cointegration model. Appl. Financ. Econ. 14 (5), 327–335.

Tian, M., Alshater, M.M., Yoon, S.-M., 2022. Dynamic risk spillovers from oil to stock markets: fresh evidence from GARCH copula quantile regression-based CoVaR model. Energy Econ., 106341

Tiwari, A.K., Raheem, I.D., Bozoklu, S., Hammoudeh, S., 2022. The oil Price-Macroeconomic fundamentals nexus for emerging market economies: evidence from a wavelet analysis. Int. J. Financ. Econ. 27 (1), 1569–1590.

Tiwari, A.K., Trabelsi, N., Alqahtani, F., Hammoudeh, S., 2019. Analysing systemic risk and time-frequency quantile dependence between crude oil prices and BRICS equity markets indices: a new look. Energy Econ. 83, 445–466.

Uddin, G.S., Hernandez, J.A., Shahzad, S.J.H., Kang, S.H., 2020. Characteristics of spillovers between the US stock market and precious metals and oil. Resour. Policy 66, 101601.

Umar, Z., Trabelsi, N., Zaremba, A., 2021. Oil shocks and equity markets: the case of GCC and BRICS economies. Energy Econ. 96.

Wen, D., Wang, Y., Ma, C., Zhang, Y., 2020. Information transmission between gold and financial assets: mean, volatility, or risk spillovers? Resour. Policy 69.

Williams, J.B., 1938. Theory Invest. Value.

Wu, K., Zhu, J., Xu, M., Yang, L., 2020. Can crude oil drive the co-movement in the international stock market? Evidence from partial wavelet coherence analysis. North Am. J. Econ. Financ. 53, 101194.

Xiong, W., 2001. Convergence trading with wealth effects: an amplification mechanism in financial markets. J. Financ. Econ. 62 (2), 247–292.

Younis, I., Naeem, M.A., Shah, W.U., Tang, X., 2025. Inter- and intra-connectedness between energy, gold, bitcoin, and gulf cooperation council stock markets: new evidence from various financial crises. Res. Int. Bus. Financ. 73, 102548.

Yu, L., Zha, R., Stafylas, D., He, K., Liu, J., 2020. Dependences and volatility spillovers between the oil and stock markets: new evidence from the copula and VAR-BEKK-GARCH models. Int. Rev. Financ. Anal. 68, 101280.

Zaremba, A., Aharon, D.Y., Demir, E., Kizys, R., Zawadka, D., 2021. COVID-19, government policy responses, and stock market liquidity around the world: a note. Res. Int. Bus. Financ. 56, 101359.

Zhang, Y., Wang, M., Xiong, X., Zou, G., 2021. Volatility spillovers between stock, bond, oil, and gold with portfolio implications: evidence from China. Financ. Res. Lett. 40, 101786.