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Borsa İstanbul Review

Borsa İstanbul Review 23-4 (2023) 953–979
http://www.elsevier.com/journals/borsa-istanbul-review/2214-8450

Full Length Article

Multidimensional connectedness among the fourth industrial revolution assets

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Received 26 October 2022; revised 18 April 2023; accepted 18 April 2023
Available online 27 April 2023

Abstract

This study investigates the multidimensional connectedness between various Fourth Industrial Revolution assets and global commodities to analyze their role in portfolio diversification. Using dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC-GARCH), Baruník and Křehlík (BK) frequency connectedness, and quantile connectedness, we estimate the time-frequency connectedness involved in the transmission mechanism at the upper, middle, and lower quantiles, using empirical data from April 30, 2018, to January 9, 2023, which incorporates data before and during the pandemic and consider the impact of the Russia-Ukraine conflict. Our findings reveal that Fourth Industrial Revolution assets are highly correlated, especially during periods of stress and crisis, which necessitates portfolio diversification during such periods. We also find that holding these assets over the long run is better than holding them in the short run. Our results indicate that the connectedness network assessed at the conditional median quantile is not reflective of the level of connectedness associated with substantial positive or negative shocks. This study is of high importance to investors in Fourth Industrial Revolution assets.

JEL classification: C59; G11; G19; G32

Keywords: Artificial intelligence; Blockchain index; Connectedness; Cybersecurity; Disruptive technologies; Fintech; Fourth industrial revolution; Robotics index; Spillover

1. Introduction

The integration of financial markets has increased the need for portfolio diversification. Recently, periods of stress and turbulence have renewed the role of crises in fueling further integration, making it important for investors to consider the correlation, spillover, and connectedness dynamics over various time horizons and between different asset classes (BenSaïda & Litimi, 2021; Cagliesi & Guidi, 2021).

The Fourth Industrial Revolution (FIR) is fundamentally changing every aspect of our lives, with the emergence of many alternative investment opportunities for achieving portfolio diversification and hedging, such as artificial intelligence (AI) and robotics companies, financial (fintech) technology stocks, and technology, blockchain, and cybersecurity companies. At present, AI and robotics are being adopted all over the world, with industrial robots infiltrating not only manufacturing but also other economic activities, including trading on financial markets, transportation via autonomous vehicles, customer relationship management via chatbots, legal services, and medical diagnostics and operations (Webster & Ivanov, 2020). Intuitively, AI and robotics technology businesses have grown in prominence, making them an appealing investment alternative for portfolio diversification. Blockchain

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Peer review under responsibility of Borsa İstanbul Anonim Şirketi.

https://doi.org/10.1016/j.bir.2023.04.002

and cryptocurrencies have also grown in popularity as investment vehicles and are sometimes regarded as superior currencies or even digital gold (Selmi et al., 2018). The application of blockchain technology has been viewed as a significant financial disruptor and manifestation of the FIR (White et al., 2020).

In this study, we examine the multidimensional connectedness between FIR assets and global commodities, with a specific focus on their potential role in portfolio diversification. The FIR assets investigated have emerged because of technological advancements in areas such as AI, blockchain, and the Internet of Things. We employ various methods, including dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC-GARCH), BK frequency connectedness, and quantile connectedness to estimate the time-frequency connectedness and transmission mechanisms. Our empirical sample is from April 30, 2018, to January 9, 2023, and incorporates the periods before and during the COVID-19 pandemic, as well as the impact of the Russia-Ukraine conflict. By analyzing the connectedness between these assets and global commodities, we offer insights into the potential benefit of including these assets in diversified portfolios. Our insights are valuable for investors seeking to manage risk and maximize returns in the context of the rapidly changing global economic landscape.

We find that, first, because of the increase in connectedness, constructing a portfolio comprising FIR assets is not prudent, especially during periods of stress, which is in line with Le, Abakah, and Tiwari (2021), and thus investors should modify their portfolios during crises. Second, the high connectedness between these asset classes, especially in the short run, suggests that holding them is more likely to reduce risk over the long run. Third, the interlinkages between these assets are time and frequency dependent, suggesting that the diversification benefits vary with frequency. Thus, it is important to consider the level of volatility spillovers among the assets in the short, medium, and long term for diversification strategies. Importantly, the impact of level of connectedness due to the pandemic differs from that of the Russia-Ukraine conflict. The war in Ukraine is a transitory factor, but the pandemic significantly altered fundamental factors. Finally, total spillover is greater at the extremes than at the median quantile, suggesting the use of the tail connectedness approach, instead of concentrating only on median-/average-based connectedness.

This study makes several important contributions to the existing literature. First, it is the first study to specifically investigate the role of FIR assets in portfolio diversification. Previous studies have only considered technology-intensive companies in general (Ahmad & Rais, 2018; Kumar et al., 2012a, 2012b) or clean energy technologies (Jawadi et al., 2013; Ortas et al., 2013) or have examined only the connection between one of these assets and other asset classes (Adekoya et al., 2022; Chen et al., 2021; Huynh, Hille, & Nasir, 2020). This study builds on the existing literature by examining a similar set of assets over different time periods. Second, as blockchain technology has been called a major financial disruptor, this study supplements the rapidly growing empirical literature on cryptocurrency (Bouri et al., 2018; Lundgren et al., 2018) by including the Blockchain index. This adds an important dimension to the study of FIR assets. Lastly, this study employs three distinct methodologies—DCC-GARCH, BK frequency connectedness, and quantile connectedness—to assess the time, frequency, and tail connectedness between FIR assets and global commodities. This offers significant advantages over traditional linear and Granger-causality tests and offers a more comprehensive understanding of the dynamics among these assets.

The paper is organized as follows. Section 2 presents the theoretical framework and relevant literature that inform the research questions. Section 3 provides an overview of the data, while Section 4 describes the econometric models. Section 5 presents the study's key findings, and in Section 6, we conduct robustness tests to confirm the reliability of our results. Finally, Section 7 concludes the paper by summarizing our main contributions and discussing their implications for future research and practice.

2. Theoretical framework and literature review

2.1. Theoretical framework exploring the spillover phenomenon among financial markets

In recent years, the globalization, financial liberalization, and increasing international integration of financial markets have intensified information transmission and caused spillover effects (Patel et al., 2022). Financial market integration has broken down regional boundaries and promoted the integration of economies around the world, deepening the interdependence of international financial markets while also exacerbating their vulnerability and risk contagion effect.

Spillovers are associated with two main theories: the economic fundamentals–based hypothesis and the risk contagion hypothesis. The economic fundamentals–based hypothesis posits that macroeconomic variables that are common across countries can affect financial markets in other countries. Because of interconnection of economic fundamentals, asset prices tend to move in a consistent trend, and interdependence gradually increases among financial markets. Common macroeconomic variables include the degree of openness of the stock market, bilateral trade volume, foreign direct investment (FDI), macroeconomic policies, and exchange rate fluctuations. For example, the degree of openness of the stock market reflects the extent to which a country's economy is integrated into that of the global economy, and a higher degree of openness can lead to greater spillover effects. Similarly, an increase in FDI can increase the spillover effects due to the greater integration of the global financial system. Baek et al. (2005) find that standard economic fundamentals are important determinants of market-assessed sovereign risk. Kaminsky and Reinhart (2000) determine that economic crises in one country can affect the economies of countries with which they trade, suggesting that trade channels play a crucial role in the linkage and spillover effects between the financial markets of various countries (regions). Similarly, the literature on financial contagion suggests that the degree of financial integration and trade ties between countries can increase the likelihood of contagion (Forbes & Rigobon, 2002). However, the economic fundamentals–based hypothesis does not explain sudden drops in financial markets, which occur over short periods. Therefore, King and Wadhwani (1990) propose the market contagion hypothesis to explain risk linkage and spillover effects caused by extreme risk events, such as the global financial crisis. This hypothesis posits that extreme risk events can significantly affect the returns and risks of global financial markets, which can drive investors to change their investment strategies for global asset allocation. As a result, the risk linkage among financial markets is enhanced, and irrational trading behavior can lead to transmission of negative impacts to other financial markets. For example, during the 2008 financial crisis, the collapse of Lehman Brothers triggered a chain reaction of financial distress, which spread rapidly across the financial system, causing widespread market panic and financial instability. Investors are heterogeneous in their investment preferences, risk acceptance, and ability to accept and process market information. As a result, many investors may not make rational judgments about the information obtained and are inclined to follow the trend by referring to the trading operations of others in the market when making decisions. This phenomenon, known as herding, is a type of irrational trading behavior. Herding can have risk contagion effects, as many investors follow the same investment strategies and cause asset prices to deviate from their fundamental value.

Several studies have found that herding behavior is a significant source of risk contagion effects (Boyer et al., 2006). In addition to herding, other irrational trading behaviors, such as momentum trading and overconfidence, can also contribute to risk contagion effects. In addition, technological advancements have led to the emergence of a Fourth Industrial Revolution (FIR), which introduced a new era of digitization, automation, and interconnectivity among various assets. The integration of these FIR assets has created new challenges and opportunities for financial markets, including spillover effects. For instance, the integration of artificial intelligence (AI) and machine learning (ML) algorithms into financial trading has led to increased efficiency and accuracy in decision-making, but it has also introduced new risks, such as the potential that algorithmic trading will amplify market volatility and exacerbate spillover effects (Gomber et al., 2018).

2.2. Literature review

The performance of technology stocks has been of interest to scholars since the dot-com crisis in the early 2000s (Ahmed & Alhadab, 2020). Whereas some studies suggest greater potential for future earnings in technology stocks, others indicate almost equivalent returns with nontechnology companies (Mason & Harrison, 2004). One stream of the literature notes the higher volatility of high-tech stock returns compared to non-tech equities, which might indicate that investors perceive uncertainty in the profitability of high-tech companies because of the complexity of implementing innovative technologies (Jiang et al., 2011).

In the era of the FIR, the foundation of blockchain technologies paved the way for cryptocurrency, leading to a new economic order and disruption of standard financial transactions. Cryptocurrency facilitates the application of blockchain technologies, closing the gap between technological advancements and payment procedures. A huge number of papers has investigated the connectedness of cryptocurrency (especially Bitcoin) by revealing its intra-connectedness using different methods and time frames (Balli et al., 2020; Bouri et al., 2021; Fousekis & Tzaferi, 2021; Hasan et al., 2021; Ji et al., 2019; Koutmos, 2018; Kumar et al., 2022; Polat & Kabakçı Günay, 2021; Xu et al., 2021), its connectedness with various asset classes, such as traditional currencies (Andrada-Félix et al., 2020; Hsu et al., 2021), commodities (Fasanya et al., 2022; Ha & Nham, 2022; Hassan et al., 2022; Mo et al., 2022), major equities and financial markets (Cao & Xie, 2022; Hanif et al., 2022; Milunovich, 2018), decentralised finance (Defis), non-fungible tokens, or technology sector (Charfeddine et al., 2022; Karim et al., 2022; Umar et al., 2021), or other asset classes. Considerably fewer papers investigate other technological indexes despite the irrefutable evidence on the importance of AI, blockchain, and other industrial revolution assets in different aspects of the economy and financial sector, and their use in portfolio diversification as hedges is underexplored (Demiralay et al., 2021; Huynh, Hille, & Nasir, 2020).

Some studies have investigated fintech's connectedness with various asset classes, primarily with traditional finance (Adekoya et al., 2022; Chen et al., 2021; Le et al., 2021a, 2021b; Li et al., 2020). Among those studies, Le, Abakah, and Tiwari (2021) provide evidence on the poor hedging benefits of fintech company shares in a portfolio with common stocks, as they note the high connectedness between technology stocks and traditional equities. Furthermore, the relationship between technology stocks and energy prices has been studied, confirming linkages in returns and volatility (Bondia et al., 2016; Kumar et al., 2012a, 2012b). Huynh, Nasir, et al. (2020) find that portfolios consisting of AI, robotics stocks, and green bonds exhibit heavy tail dependence, implying a high probability of large joint losses in times of economic turbulence. Demiralay et al. (2021) investigate the interdependence between AI and robotics stocks and traditional (including stocks and bonds) and alternative (commodities and cryptocurrency) assets and find that co-movements significantly depend on the wavelet decomposition levels, suggesting time-scale-dependent investment benefits. However, they also observed substantially higher co-movements of AI stocks with the composite stock index, corporate bonds, and commodities at all scales after

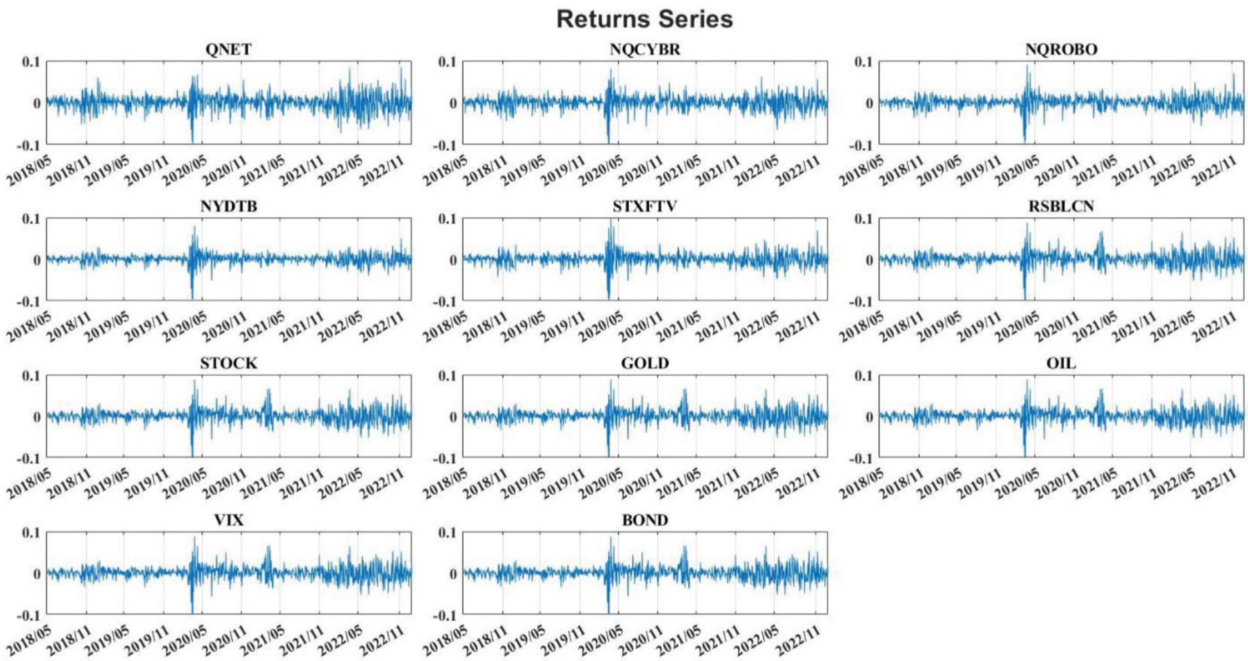


Fig. 1. Return series.

March 2020, implying that the inclusion of these assets in AI and robotics stock portfolios may not enhance risk-adjusted portfolio performance in times of market turbulence. These studies highlight the importance of considering various FIR assets when diversifying portfolios and carefully considering the risks associated with heavy tail dependence and the time-varying nature of co-movements (Demiralay et al., 2021; Huynh, Hille, & Nasir, 2020).

This study fills this gap by analyzing the spillover effect among several FIR indexes to understand their role in portfolio diversification (Demiralay et al., 2021; Huynh, Hille, & Nasir, 2020). Some investors would benefit by understanding the co-movement between the FIR assets and whether it would be wise to invest collectively in those asset classes or diversify the portfolio with other asset classes.

3. Data

To evaluate the connectedness among the FIR innovative assets, this study considers six global indexes: the Internet Index (QNET), Cybersecurity Index (NQCYBR), Artificial Intelligence and Robotics Index (NQROBO), Disruptive Technologies Index (NYDTB), FinTech (STXFTV) and Blockchain Index (RSBLCN). Appendix Table A1 describes all the indexes selected and their abbreviations. Most of the indexes selected are used for the first time. Our dataset is obtained from the DataStream database and covers the period from April 30, 2018, to January 9, 2023 (the time of writing). For this purpose, we obtain daily closing prices on all the indexes and calculate the continuously compounded daily returns by taking the difference in the log value of two consecutive prices. The dataset is divided into pre-COVID, during COVID, and since the Russian invasion of Ukraine. The cutoff dates are January 23, 2020,[1] when COVID-19 broke out, and February 24, 2022, when Russia invaded Ukraine. Fig. 1 illustrates the time-varying returns of all the series, showing similar patterns and trends. Large declines were observed at the end of December and the beginning of January, coinciding with the outbreak of the pandemic. The impact of RUI is not immediately apparent. Fig. 2, which illustrates the volatility series,[2] shows similar results. A jump is seen in volatility, coinciding with the pandemic. Therefore, investors are advised to keep an eye on major global events.

Table 1 presents the summary statistics of the volatility series for the FIR assets in Panel A and global factors in Panel B. The mean volatility of all the indexes is positive during the sample period. In Panel A, the highest and lowest average daily volatility is observed for QNET (0.014%) and NYDTB (0.008%), respectively. QNET has not only the highest average but also the highest standard deviation. NYDTB, however, has the lowest average with the lowest risk, which is suitable for risk-averse investors. In Panel B, VIX has the highest return (0.058%) and the highest standard deviation (0.056%), whereas Bond has the lowest average and the lowest risk. All volatility series depart from the Gaussian distribution, with a high level of kurtosis and nonzero skewness. The skewness is positive in all markets, while kurtosis is much higher than 3. The significant Jarque-Bera statistics reveal the nonnormal distributed series in these markets.

The results of the augmented Dickey-Fuller (ADF) unit-root stationarity tests provide evidence of stationarity in all series. Finally, the results of the Ljung-Box test for the autocorrelation

[1] Following Ashraf (2020), we assume that the period of COVID-19 begins on January 23, 2020, when it first came to public attention and databases started to report COVID-19-related information.

[2] Volatility is calculated based on the GARCH (1,1) model.

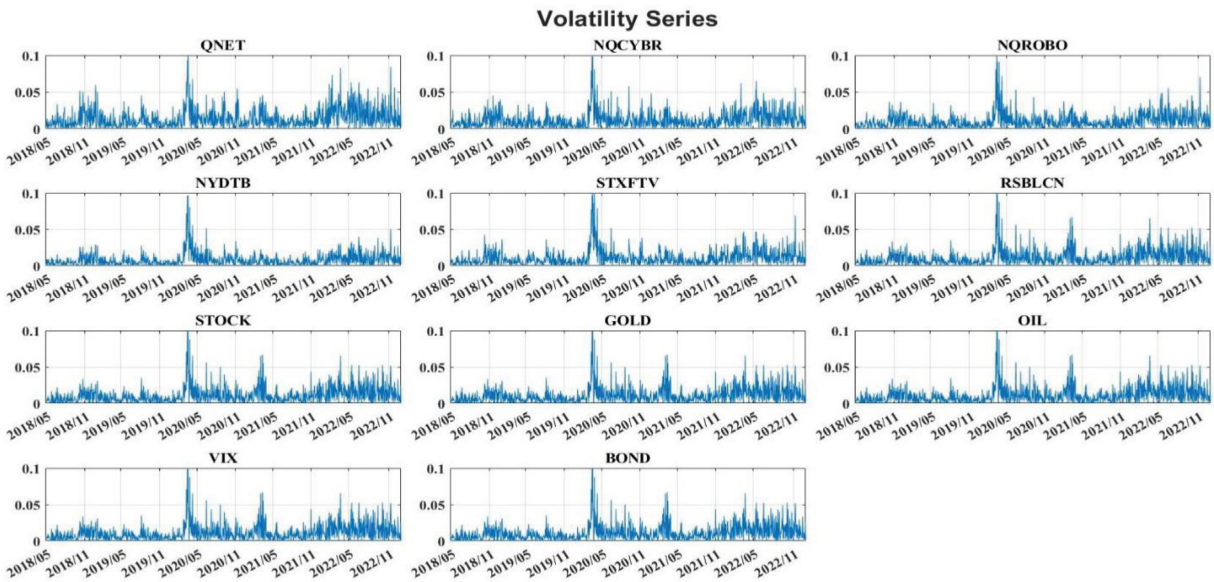


Fig. 2. Volatility series.

of the residual returns series reject the null hypothesis of no autocorrelation. The combination of a leptokurtic distribution and stationarity makes the series ideal candidates for quantile-based interconnectedness analysis.

4. Econometric models

To investigate the existence of spillovers among different segments of the FIR market, we first estimate the time connectedness using DCC-GARCH connectedness and the frequency connectedness by Baruník and Křehlík (2018). The next step is to investigate asymmetrical connectedness by running the quantile connectedness.

4.1. DCC-GARCH connectedness

This paper employs the DCC-GARCH connectedness approach developed by Gabauer (2020), which is based on the volatility impulse response function (VIRF), representing the impact of a shock in variable i on variable j's conditional volatility. This approach offers several key advantages over traditional methods. First, it allows us to overcome the limitations of rolling-window analysis, such as the arbitrary choice of window size and loss of observations. Second, it enables us to examine the time-varying nature of the propagation mechanism between financial markets. This study represents a significant contribution to the field as it is the first to use Gabauer's DCC-GARCH connectedness approach in investigating the connectedness between the FIR assets, while controlling for global variables. The VIRF can be written as:

$$\Psi^g = VIRF\left(J, \delta_{j,t}, F_{t-1}\right) = E\left(H_{t+J} \middle| \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}\right) - E\left(H_{t+J} \middle| \varepsilon_{j,t} = 0, F_{t-1}\right) \tag{1}$$

where $\delta_{j,t}$ is a selection vector with a 1 in the jth position and 0 otherwise.

An important step in VIRF is the forecasting of the conditional variance-covariance, in three steps. In the first step, the conditional volatilities $(D_{t+h}|F_t)$ are predicted using GARCH (1,1):

$$E(h_{ii,t+1}|F_t) = \omega + \alpha\delta^2_{1,t} + \beta h_{ii,t} h = 1 \tag{2}$$

$$E(h_{ii,t+h}|F_t) = \sum_{i=0}^{h-1} \omega(\alpha+\beta)^i + (\alpha+\beta)^{h-1} E(h_{ii,t+h}|F_t) h > 1 \tag{3}$$

In the second step, $E(Q_{t+1}|F_t)$ is predicted according to:

$$E(Q_{t+1}|F_t) = (1-a-b)\overline{Q} + au_t u_t^{'} + bQ_t h = 1 \tag{4}$$

$$E(Q_{t+1}|F_t) = (1-a-b)\overline{Q} + aE\left(u_{t+h-1}u_{t+h-1}^{'}|F_t\right) + bE(Q_{t+h-1}|F_t) h > 1 \tag{5}$$

where $E(u_{t+h-1}u_{t+h-1}^{'}|F_t) \approx E(Q_{t+h-1}|F_t)$ helps in forecasting the dynamic conditional correlations (Engle & Sheppard, 2001), and finally the conditional variance-covariances.

In the third step, the dynamic conditional variance-covariances are estimated by:

$$E(R_{t+h}\backslash F_t) \approx diag\left[E\left(q_{iit+h}^{-1/2}\right)|F_t, \ldots, E\left(q_{iit+h}^{-1/2}\right) \times |F_t\right] E(Q_{t+h}) diag\left[E\left(q_{iit+h}^{-1/2}\right)|F_t, \ldots, E\left(q_{iit+h}^{-1/2}\right)|F_t\right] \tag{6}$$

$$E(H_{t+h}|F_t) \approx E(D_{t+h}|F_t)E(R_{t+h}|F_t)E(D_{t+h}|F_t) \tag{7}$$

Subsequently, the generalized forecast error variance decomposition (GFEVD) is calculated using the VIRF:

Table 1
Descriptive statistics of daily volatility (%).

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	STOCK	GOLD	OIL	VIX	BOND
Mean	0.014	0.012	0.011	0.008	0.011	0.011	0.011	0.007	0.019	0.058	0.004
Median	0.01	0.009	0.008	0.006	0.007	0.008	0.008	0.005	0.013	0.044	0.003
Maximum	0.116	0.104	0.105	0.096	0.133	0.103	0.131	0.056	0.336	0.48	0.026
Minimum	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.013	0.011	0.011	0.009	0.011	0.011	0.012	0.007	0.025	0.056	0.003
Skewness	1.956	2.321	2.844	3.638	3.633	2.548	2.9	2.482	5.239	2.434	2.317
Kurtosis	9.136	12.724	18.122	26.9	27.168	14.175	19.015	12.57	48.796	12.403	11.515
JB test	2.57E+03***	5.64E+03***	1.27E+04***	3.03E+04***	3.09E+04***	7.32E+03***	1.41E+04***	5.64E+03***	1.07E+05***	5.44E+03***	4.56E+03***
ADF test	−7.55***	−7.49***	−6.22***	−6.59***	−6.15***	−6.02***	−6.84***	−19.58***	−7.09***	−14.73***	−7.90***
LB test	632.60***	630.80***	693.15***	1394.00***	1409.30***	713.18***	1099.20***	152.05***	633.81***	178.23***	598.85***
Observations	1177	1177	1177	1177	1177	1177	1177	1177	1177	1177	1177

Notes: ***, **, * denotes the null hypothesis rejection at the 1%, 5% and 10%, respectively. JB test indicates the Jarque-Bera test. ADF denotes Augmented Dickey–Fuller test. LB test denotes the Ljung-Box test.

$$\begin{cases} GIRF_t(h,\delta_{j,t},F_{t-1}) = E(Y_{t+h}|\varepsilon_{j,t}=\delta_{j,t},F_{t-1}) - E(Y_{t+h}|F_{t-1}) \\ \Psi^g_{j,t}(h) = \dfrac{A_{h,t}S_t\varepsilon_{j,t}}{\sqrt{S_{jj,t}}}\dfrac{\delta_{j,t}}{\sqrt{S_{jj,t}}} \\ \delta_{j,t} = \sqrt{S_{jj,t}} \\ \Psi^g_{j,t}(h) = S_{jj,t}^{-\frac{1}{2}}A_{h,t}S_t\varepsilon_{j,t} \end{cases} \tag{8}$$

In GFEVD, several connectedness measures can be constructed, such as the total connectedness index (*TCI*), which measures the overall degree of network connectedness.

$$C^g_t(h) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\varphi}^g_{ij,t}(h)}{\sum_{i,j=1}^{N} \tilde{\varphi}^g_{ij,t}(h)} * 100 \tag{9}$$

The directional connectedness, *TO*, represents the impact of variable i on all other variables j.

$$C^g_{i\to j,t}(h) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\varphi}^g_{ji,t}(h)}{\sum_{j=1}^{N} \tilde{\varphi}^g_{ji,t}(h)} * 100 \tag{10}$$

The directional connectedness, *FROM*, measures the impact of other variables j on variable i.

$$C^g_{i\leftarrow j,t}(h) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\varphi}^g_{ij,t}(h)}{\sum_{i=1}^{N} \tilde{\varphi}^g_{ij,t}(h)} * 100 \tag{11}$$

The *NET* connectedness is the difference between *TO* and *FROM*, in which a positive (negative) value indicates the role of a transmitter (receiver):

$$C^g_{i,t} = C^g_{i\to j,t}(h) - C^g_{i\leftarrow j,t}(h) \tag{12}$$

4.3. BK frequency connectedness

Baruník and Křehlík (BK; 2018) developed a technique that measures connectedness in the frequency domain framework, such as long-, medium-, and short-term cycles. Their contribution is the identification of aggregate connectedness at various frequency domains to ascertain the frequency at which spillover is the highest. By determining this frequency, investors can decide whether to invest in the long or short run, considering that investors have different investment horizons. More specifically, the BK method decomposes spillover at several frequencies. The formulation is based on the use of a spectral formulation of the decomposition variance. In other words, the significant characteristic of the BK method is that it can measure the dynamics of connectedness among a set of variables over time and across various frequencies simultaneously. In this way, the BK framework transforms connectedness into different components that in turn yield the original connectedness measure.

Specifically, the scaled GFEVD on a frequency band $d = (a, b) : a, b \in (-\pi, \pi), a < b$ can be defined as:

$$\begin{cases} (\tilde{\theta}_d)_{j,k} = (\theta_d)_{j,k} \Big/ \sum_k (\theta_\infty)_{j,k} \\ (\theta_d)_{j,k} = \dfrac{1}{2\pi} \displaystyle\int_d \Gamma_j(\omega)(f(\omega))_{j,k} d\omega \\ (\theta_\infty)_{j,k} = \displaystyle\sum_{d_s} (\theta_{d_s})_{j,k} \end{cases} \tag{13}$$

where $(\theta_d)_{j,k}$ denotes generalized variance decompositions on frequency band d; $\Gamma_j(\omega)$ denotes the frequency share of the variance of the jth variable; $(f(\omega))_{j,k}$ represents the portion of the spectrum of the jth variable at frequency ω due to shocks to the kth variable; d_s denotes an interval in the real line from the set of intervals D.

The frequency connectedness on the frequency band d can be obtained by:

$$C_d^F = 100 \times \left(\frac{\sum \tilde{\theta}_d}{\sum \tilde{\theta}_\infty} - \frac{Tr\{\tilde{\theta}_d\}}{\sum \tilde{\theta}_\infty} \right) \tag{14}$$

where $Tr(\cdot)$ is the trace operator. This frequency connectedness framework enables us to identify the short-, medium-, and long-term connectedness when frequency band d is set at different intervals.

4.4. Quantile connectedness

To examine the quantile transmission mechanism among these assets at upper, middle, and lower quantiles, we employ the quantile connectedness approach proposed by Ando et al. (2018).

First, we define the quantile vector autoregression, QVAR(p):

$$y_t = \gamma(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) y_{t-j} + \mu(\tau) \tag{15}$$

where $\tau \in (0, 1)$ denotes the quantile index, y_t and y_{t-j} are n-vectors of endogenous variables, p denotes the lag length of the QVAR model, $\gamma(\tau)$ and $\mu(\tau)$ represent the n-vector of intercepts and residuals at quantile τ, respectively, and $\Phi_j(\tau)$ is the parameter matrix of the jth lagged coefficients at quantile τ. Next, the population $\tau - th$ conditional quantile of response y is as follows:

$$Q_\tau(y_t) = \gamma(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) y_{t-j} \tag{16}$$

Second, QVAR(p) is transformed into an infinite order vector moving average representation (QVMA (∞)) using Wold's theorem:

$$y_t = \kappa(\tau) + \sum_{i=1}^{\infty} A_j(\tau) \mu_{t-1} \tag{17}$$

where

$$\kappa(\tau) = \left(I_n + \Phi_1(\tau) + \ldots + \Phi_p(\tau)\right)^{-1} \gamma(\tau) \tag{18}$$

$$A_j(\tau) = \begin{cases} 0, j < 0 \\ I_n, j = 0 \\ \Phi_1(\tau) A_{j-1} + \ldots + \Phi_p(\tau) A_{p-1}, j > 0 \end{cases} \tag{19}$$

Third, the GFEVD with a forecast horizon H is calculated following Koop et al. (1996) and Pesaran and Shin (1998). It illustrates the impact that a shock to variable j has on variable i. Following Diebold and Yilmaz (2012, 2014), we calculate the five connectedness measures at each quantile τ based on normalized GFEVD, which comprises $TCI(\tau)$, $TO(\tau)$, $FROM(\tau)$, $NET(\tau)$, and $NPDC(\tau)$.

5. Results

To thoroughly examine the role of these assets in a portfolio, we take a three-pronged approach. First, we consider time connectedness using the DCC-GARCH connectedness approach, which analyzes the degree to which these assets in a portfolio comove over time. The DCC-GARCH approach is particularly useful in capturing the dynamic and time-varying nature of connectedness among assets. Second, we focus on the BK frequency connectedness, as it is critical to evaluate the level of volatility spillovers between assets in the short, medium, and long term when considering diversification strategies. This helps to clarify how different frequencies of financial market movements can affect the performance of a portfolio. Third, we examine quantile connectedness, which assesses the presence of asymmetric spillovers and tail dependence. The quantile connectedness approach is particularly useful in capturing the asymmetrical nature of connectedness among assets, which is important for understanding how the relationship between assets changes under different market conditions, including economic downturns and upturns. The purpose of this multifaceted approach is to provide a comprehensive understanding of the volatility connectedness and portfolio diversification opportunities across FIR assets. This information can then be used to make informed decisions about diversification strategies, which are crucial for managing risk and maximizing portfolio returns.

5.1. Time connectedness

5.1.1. Static connectedness

Table 2 shows the average connectedness measures among the six indexes studied in the time domain. The elements on the main diagonal of Table 2 correspond to own-variable (i.e., idiosyncratic) shocks whereas off-diagonal elements represent interaction among the variables in the network. The sum of off-diagonal elements in the columns denoted “contribution to” measures the volatility spillovers transmitted from a specific market to all other markets, whereas the sum of off-row

Table 2
Volatility spillovers in the time domain.

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	CONTRIBUTION FROM
QNET	25.94	13.55	15.31	15.76	15.15	14.29	74.06
NQCYBR	15.28	28.43	14.82	14.1	14.73	12.63	71.57
NQROBO	13.28	11.37	25.24	18.42	15.14	16.55	74.76
NYDTB	13.07	10.07	17.71	25.62	17.28	16.24	74.38
STXFTV	13.53	11.54	15.86	18.46	25.74	14.86	74.26
RSBLCN	13	9.98	17.21	17.69	15.06	27.05	72.95
CONTRIBUTION TO	68.17	56.51	80.91	84.44	77.36	74.58	441.98
NET	−5.89	−15.05	6.15	10.06	3.1	1.63	TCI = 73.66

Notes: This table presents the volatility spillover results among six FIR indexes using DCC-GARCH Connectedness approach. Values in the *i-th* row of the *j-th* column indicate the strength of the spill-over effect from the *i-th* market to the *j-th* market. Net denotes the net spillover for each individual market.

elements denoted "contribution from" measures the volatility spillovers received from a given market. Finally, the sum of off-row elements divided by the sum of columns (off-diagonal and main diagonal) yields the TC index, and the difference between the sum of each off-diagonal column and the sum of each off-diagonal row demonstrates net connectedness.

The results show that the TCI is 73.66%, indicating that the indexes studied are highly interconnected. More specifically, 74% of the total variance of forecast errors is explained by spillover shocks across the indexes studied, while only 26% is explained by idiosyncratic industry-specific shocks. Looking at "contribution to," we find that disruptive technologies are the highest transmitters of spillover (84.44%) followed by AI and robotics (80.91%). The transmitter of the fewest shocks is cybersecurity with 56.51%. In the "from" column, fintech and AI and robotics are the largest recipients of spillover from the other markets in the system, 74.26%, and the recipient of the least spillover is cybersecurity, with 71.57%. The net spillovers (last line of Table 2) are positive for all indexes, except QNET and NQCYBR, suggesting that these two indexes are net receivers of spillovers, being influenced more than they influence other markets, whereas the rest are net transmitters of spillovers. NYDTB is the major net transmitter (10.06%), transmitting spillovers to all indexes, followed by NQROBO (6.15%), while NQCYBR is a major net receiver (−15.05%). Interestingly, fintech is a transmitter whereas blockchain plays only a minor role (1.63%).

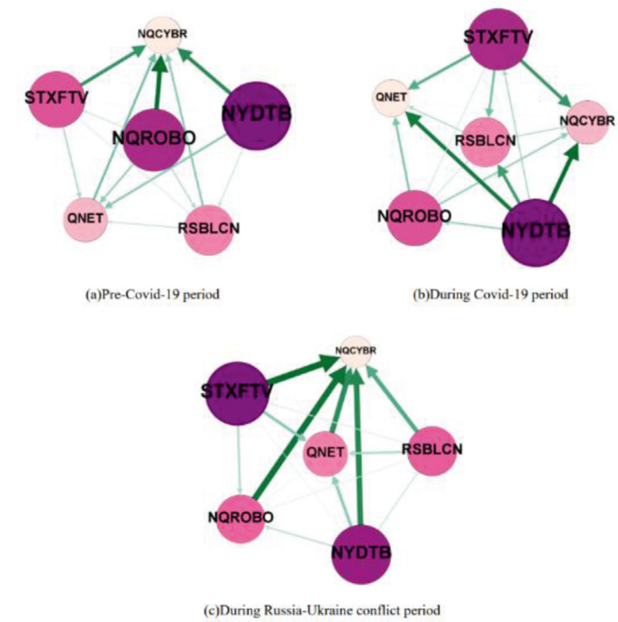


Fig. 3. Net pairwise directional network of volatility spillovers in the time domain.
Notes: This figure presents the net pairwise directional volatility spillovers among six FIR indices during different periods in the time domain. The node size reflects the overall magnitude of transmission/reception for each product. The edge size indicates the magnitude of the net pairwise volatility spillovers between two products. Besides, the magnitude is also reflected by whether the color of node/edges is dark (strong) or light (weak). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

5.1.2. Network visualization

To understand the impact of turbulent events and how a market can play different roles in Vto account for the pandemic, and February 24, 2022, to account for the Russia-Ukraine conflict). Thus, the sample is divided into periods before COVID, during COVID, and during the conflict in Ukraine. In the network plot, the direction and thickness of the arrows represent spillover direction and strength, respectively. Fig. 3 shows that, in the pre-COVID period, NYDTB, NQROBO, and STXFTV are the main transmitters of shocks, mainly to NQCYBR. The latter receives shocks from all indexes. During the pandemic, NYDTB maintains its main role as a transmitter mainly to NQCYBR, QNET, and RSBLCN. The role of TXFTV as a transmitter increases during the pandemic, whereas NQROBO's role declines. However, all three indexes transmit shocks to NQCYBR, QNET, and RSBLCN. During the Russian-Ukraine conflict, network connectedness is different. Although NYDTB remains the main transmitter, the role of STXTV increases and that of RSBLCN reverses, becoming a main transmitter during the war in Ukraine. Moreover, the war creates a strong pairwise connection between QNET and NQCYBR.

The results show that during stressful periods the role of the disruptive technologies index (NYDTB) and cybersecurity index (NQCYBR) remains the same, but other relationships changed. However, the pandemic and the war have different impacts on connectedness, indicating that connectedness depends not only on the crisis but on the nature of the crisis. Whereas the pandemic was a health crisis before turning into an unprecedented economic crisis, which created higher uncertainty and ambiguity and increased dependence on technology, the war in Ukraine is mainly a geopolitical risk, presenting a unique challenge. The conflict could have a more pronounced effect on energy and global financial markets, given Russia's significant role in the energy market and the global economy.

5.1.3. Dynamic connectedness

The average connectedness results can obscure the impact of a single incident or a big shock on connectedness. As a result, it is important to employ dynamic or time-variant total connectedness to investigate the development of TCI over time, as shown in Fig. 4. The figures for TCI between 2018 and the end of 2019 can be regarded as relatively stable. A slightly changing trend appeared when TCI was between approximately 65% and 78%. After the pandemic began, the index trended upward at the end of 2019, hitting its apex (80%) around March 2020, indicating that the pandemic significantly affected connectedness between those indexes. The index started to rapidly decline until the end of 2021, falling below 65%. These results are consistent with previous studies by Chemka et al. (2021), Disli et al. (2021), and Guo et al. (2021), which also find evidence of increased volatility in times of crisis followed by a decline in volatility over time. However, the Russian invasion of Ukraine led to another increase in connectedness of approximately 75% at the end of the period. Thus, the results support the crisis effect and are consistent with market contagion, in which crisis generates large connectedness.

5.2. Net connectedness

Next, we investigate the dynamic patterns of net connectedness in the markets studied, in order to determine whether a market's role as a net transmitter or receiver of shocks changes over time in comparison to other markets. The findings are presented in Fig. 5, and the main results are as follows. First, the cybersecurity index remains a receiver of shocks from the five indexes throughout the full period studied. This suggests that the cybersecurity index is more reactive than proactive in responding to external shocks. Second, the disruptive technologies index is a transmitter of shocks throughout the period. This implies that the disruptive technologies index is not only affected by external shocks but also capable of transmitting shocks to other markets, possibly due to its innovative nature. The internet index is mostly a net receiver, except for a few instances in which it is a net transmitter. However, during the Russian-Ukraine war, it becomes a net transmitter perhaps due to the potential impact of the war on the online and digital industries, which are closely related to the internet index. The AI and robotics index is a net transmitter during most of the period. This could be because AI and robotics are rapidly growing industries that may be disrupting other markets or because the index represents companies with high-tech capabilities so they can adapt quickly to changes in the market. The fintech index plays an alternating role, switching between net transmitter and net receiver in several instances. This may be due to the relatively new and evolving nature of the fintech industry, which is still adapting to changes in the market and may not have a well-defined role as a transmitter or receiver of shocks. Finally, the blockchain index shows no persistent role as a transmitter or receiver of shocks, but in recent years it has become a net transmitter, especially during the Russian-Ukraine war. This may be due to the potential impact of the war on digital currency and the use of blockchain technology in financial transactions. Overall, our analysis suggests that the role of a market as a net transmitter or receiver of shocks in the system is not fixed but, rather, depends on the time interval and the nature of the market. Our findings may be useful for investors and policy makers in understanding the interconnectedness of markets and potential risks and opportunities for investment.

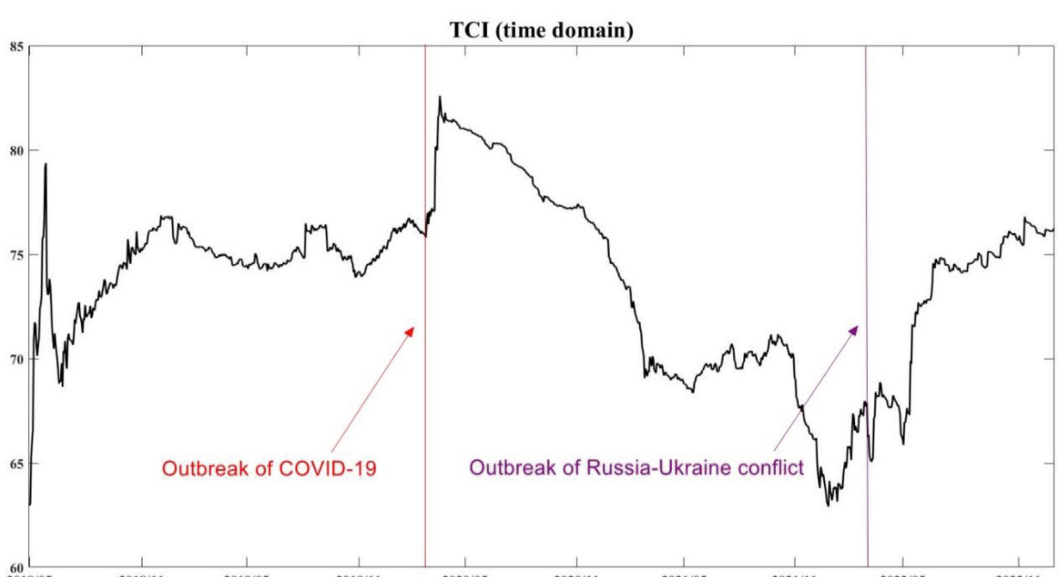


Fig. 4. Dynamic total spillovers in the time domain.
Notes: This figure displays dynamic volatility connectedness among six FIR indices using DCC-GARCH approach.

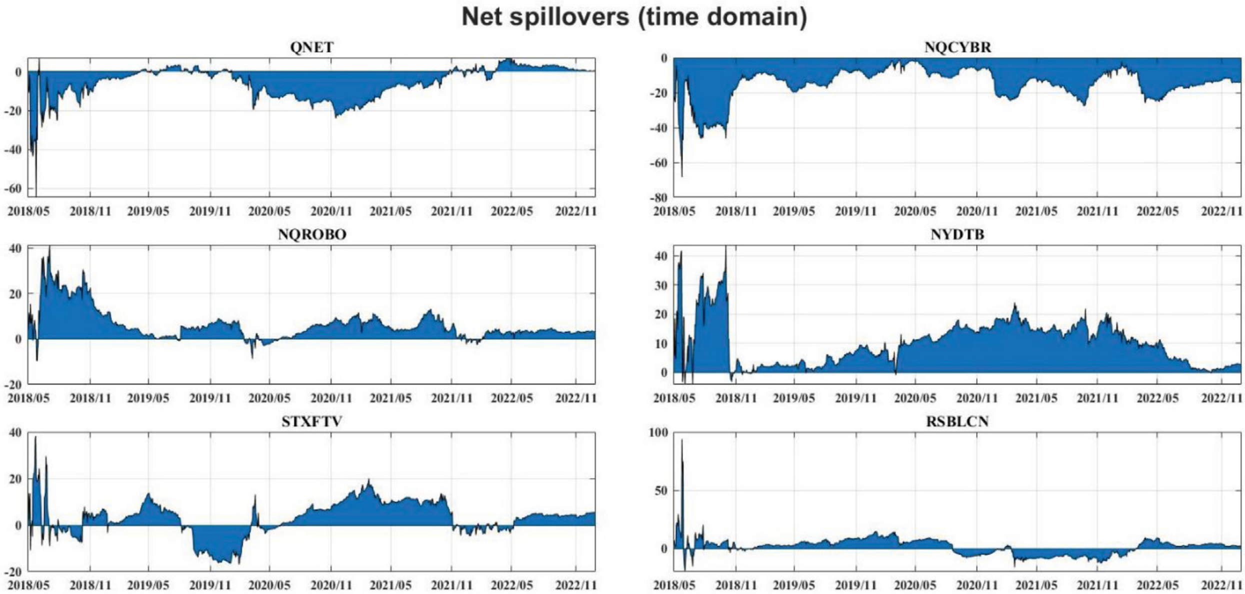


Fig. 5. Net spillovers in the time domain.
Notes: This figure illustrates the dynamic net spillovers for each FIR index over time, with positive values indicating net transmitters and negative values indicating net receivers.

5.3. Frequency connectedness

5.3.1. Static connectedness

We advance our analysis by investigating the spillover effects between the FIR assets at various frequencies. This decomposition accounts for market participants' diverse expectations and desires across different time horizons. To achieve this, we divide our analysis into three different timeframes. First, we define the timeframe of short-term analysis as one to five trading days. This timeframe is selected because conventional trading typically takes place five days a week, which is a reasonable time needed for investors to restructure or rebalance their portfolios. By analyzing the short-term dynamics, we can observe how the FIR assets are affected by shocks in the market occur over several days. Second, we examine the medium-term analysis, which covers a period from 5 to 20 trading days, corresponding to approximately one month, and can be used to capture medium-term fluctuations in the market. Finally, we examine the long-term analysis, which covers a period of 20 or more trading days. This timeframe corresponds to more than one month and can be used to capture long-term trends in the market. By analyzing the long-term dynamics, we can observe how the FIR assets are affected by fundamental changes in the market, such as changes in government policy or major technological advancements. Table 3 shows the volatility connectedness for the short-, medium-, and long-term horizons, respectively, following BK. By examining the spillover effects between the FIR assets at different frequencies, we provide investors and policy makers with a more complete understanding of the dynamics of the market and potential risks and opportunities for investment.

The highest total volatility transmission is 37.68%. The results suggest that the FIR assets are not highly interconnected, with limited transmission of volatility among them. This is contrary to expectations, given significant technological overlap among assets. However, the lower level of interconnectivity is consistent with the notion that the assets have different value drivers and market dynamics. Moreover, the spillover effects among the FIR assets are not uniform across the different time horizons. Specifically, volatility transmission is higher in the short term than in the medium and long term, which indicates that market participants' expectations and desires vary across different time frames. For instance, volatility spillover in the first band is 37.68%, which falls to 16.66% and 19.40% in the second and third bands, respectively. Another key finding is that the proportion of contribution or receipt of spillover declines in the long term than in the short term. This indicates that shocks are quickly absorbed into the market, and their effects tend to dissipate over time. These results are consistent with the efficient market hypothesis such that asset prices fully reflect all information in the short term (Fama, 1998). Overall, our findings highlight the importance of considering the time horizon in monitoring market spillovers and optimizing portfolio allocation and risk management strategies. The multihorizon approach can offer a more comprehensive understanding of market dynamics, which can help investors and policy makers make more informed decisions about asset allocation, risk management, and regulatory policies.

A closer look shows that certain indexes play a more dominant role in terms of transmitting or receiving volatility across different time horizons. In the short term, the disruptive technologies and fintech indexes are net transmitters of volatility, whereas the internet and cybersecurity indexes are net receivers. The blockchain and AI and robotics indexes have a relatively neutral role, transmitting and receiving a similar number of shocks. However, we observe some changes in the interconnection of indexes over time. For instance, the disruptive technology index continues to be the main transmitter at all

Table 3
Volatility spillovers in the frequency domain.

Panel A: Short term

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	FROM
QNET	16.34	7.56	7.76	7.85	7.95	7.13	38.25
NQCYBR	8.35	19.1	7.47	6.43	7.44	5.92	35.61
NQROBO	7.34	6.31	15.08	9.79	8.15	8.65	40.23
NYDTB	6.93	5.03	9.15	14.18	8.98	8.6	38.69
STXFTV	6.88	5.86	7.47	8.72	14.31	7.06	35.99
RSBLCN	6.81	4.98	8.7	9.13	7.66	15.56	37.29
TO	36.31	29.74	40.55	41.93	40.18	37.36	226.06
Net	−1.94	−5.87	0.31	3.23	4.19	0.07	TCI = 37.68

Panel B: Medium term

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	FROM
QNET	4.92	2.75	3.49	3.68	3.43	3.35	16.69
NQCYBR	3.4	4.67	3.38	3.57	3.44	3.07	16.85
NQROBO	2.92	2.33	4.88	4.04	3.26	3.64	16.19
NYDTB	2.93	2.22	3.84	5.39	3.83	3.44	16.25
STXFTV	3.13	2.55	3.75	4.45	5.46	3.47	17.35
RSBLCN	3.07	2.23	3.88	3.95	3.49	5.59	16.62
TO	15.44	12.08	18.33	19.68	17.45	16.96	99.95
Net	−1.25	−4.77	2.15	3.43	0.1	0.35	TCI = 16.66

Panel C: Long term

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	FROM
QNET	4.58	3.04	4.06	4.39	3.9	3.83	19.22
NQCYBR	3.49	4.4	3.99	4.32	3.97	3.6	19.37
NQROBO	3.05	2.65	5.25	4.74	3.76	4.18	18.37
NYDTB	3.27	2.75	4.61	6.15	4.57	4.13	19.33
STXFTV	3.47	3.1	4.65	5.47	5.94	4.26	20.95
RSBLCN	3.21	2.63	4.58	4.75	3.97	5.81	19.14
TO	16.48	14.17	21.89	23.67	20.17	20	116.38
Net	−2.74	−5.2	3.52	4.34	−0.78	0.87	TCI = 19.4

Notes: This table presents the results of static volatility spillovers among six FIR indexes in the frequency domain using Baruník and Křehlík's methodology (2018), with three panels labeled A, B, and C. Panel A represents the short term (1–5 days), panel B represents the medium term (5–20 days), and panel C represents the long term (20 days or more).

frequencies, and its transmission increases in the long term from 3.23% to 4.34%. Disruptive technologies are typically characterized by the potential to radically transform existing industries and create new ones. These technologies often have the potential to create significant volatility in the markets as investors assess their potential impact on companies and industries. As a result, the disruptive technology index is likely to continue to transmit volatility to other assets in the short- and long-term investment horizons. Additionally, as the underlying technologies and industries continue to evolve and mature, the potential for volatility transmission may continue to increase, reinforcing the index's role as a main transmitter of spillover. Similarly, blockchain maintains its role as a minor transmitter at all frequencies. Its impact on the overall transmission of volatility is smaller than that of other assets, confirming the role of Bitcoin as a hedging instrument (Arouri et al., 2015; Baur & Lucey, 2010; Selmi et al., 2018; Urquhart & Zhang, 2019). However, fintech's role as the main transmitter declines over time because the shocks transmitted by fintech tend to diminish, so in the long run it becomes a net receiver, and the effects become less significant as the market becomes more efficient and stable. This result is somewhat consistent with the findings of Le, Yarovaya, and Nasir (2021), which suggests that fintech assets consistently transmit shocks to other assets. In addition, the fintech industry is highly dynamic and innovative, with frequent changes in its market structure, regulations, and technological advancements. As a result, short-term spillovers from fintech may be more pronounced, as market participants adjust to new information and market developments. Additionally, as other sectors of the economy, such as disruptive technologies, continue to evolve and drive market dynamics, the relative importance of fintech may decline, and it may become more of a net receiver of spillovers.

Meanwhile, the role of the internet and cybersecurity as main receivers remains consistent across all frequencies, suggesting that they tend to be influenced by external factors and events that can trigger uncertainty and risk in the market. For example, cyberattacks and data breaches can affect the performance and reputation of companies in the cybersecurity sector, leading to a decline in their stock prices. Similarly, changes in consumer behavior, such as increased online activity or shifts in online shopping habits, can affect the performance of companies in the internet sector. As a result, these sectors tend to be more reactive to market shocks and are more likely to receive spillover effects from other assets. However, the importance of AI and robotics changes from a roughly neutral role in the short term to a net transmitter in the medium and long term. In particular, its net transmission increases from 0.31% in the short term to 2.15% and 3.52% in the medium and long term, respectively. As AI and robotics become more prevalent and integrated into various industries, their impact on the broader market may become more pronounced, leading to greater transmission of volatility over time. Moreover, in the short term, although market participants may be more focused on near-term factors, such as earnings reports and other company-specific news, they may begin to pay more attention to the broader macroeconomic and technological trends as the time horizon lengthens.

These results suggest that investors and policy makers should pay close attention to the specific characteristics of each index, as they can significantly impact market dynamics and transmission of volatility across different time horizons. Additionally, it is important to regularly monitor and reassess the role of each index, as it can change over time and affect investment decisions and risk management strategies.

5.4. Network visualization

Appendix Figure A1 reports the network connectedness of the sample by dividing it into three periods: pre-COVID, during COVID, and the Russian-Ukraine war. In the pre-COVID period, fintech was the main transmitter in the short term, while disruptive technologies and AI and robotics were the main transmitters in the medium and long term. During the pandemic, the network connectedness slightly changes in the short term with the disruptive technologies (AI and robotics) index playing the role of the main transmitter in the short term (medium and long term). However, during the Russian-Ukraine war, network connectedness changed: fintech was the main short-term transmitter, whereas internet and blockchain were the main medium- and long-term transmitters. The results suggest that connectedness is frequency dependent and support the previous findings, showing that the pandemic and the Russian-Ukraine war did not have the same impact on network connectedness, indicating that the network's response to different events can vary significantly.

The reasons for these findings include the changing business and economic conditions associated with different events. For example, before the COVID-19 pandemic, the fintech sector was the main transmitter in the short term because it was experiencing rapid growth and investment, and this led to increased interconnectedness. Similarly, the disruptive technologies and AI and robotics sectors were the main transmitters in the medium and long term because they were seen as having long-term growth potential, and investors were willing to invest in these areas. During the pandemic, short-term network connectedness changed, so the disruptive technologies index becomes the main transmitter. This could be because the pandemic accelerated the adoption and development of technologies that could help people work and live remotely, such as virtual meeting platforms and online collaboration tools. Then, during the Russian-Ukraine war, network connectedness changed again and in a different way. This is probably because the war disrupted global trade and supply chains, which led to greater emphasis on digital and online technologies to facilitate cross-border transactions and communication.

5.5. Dynamic frequency connectedness

Fig. 6 displays the frequency-based time-varying connectedness results, showing a high level of connectedness in the short-run horizon but long-run connectedness for the majority of the period. This observation reinforces our observation regarding a higher level of connectedness in the short-run horizon in our network-based connectedness analysis (Table 3). This is in line with previous research that suggests that market shocks tend to have a more immediate and significant impact on financial markets than on the longer term. This could be due to the fact that market participants are more focused on short-term horizons and react quickly to market news and events. However, there are variations in the spillover, with a spike in long-term connectedness to more than 70% during the pandemic, suggesting an increase in market connectedness in periods of market stress. The market conditions were particularly turbulent during this period, which significantly changed the fundamental factors that affect long-term connectedness. This could be due to panicked decisions by investors, leading to a broader market sell-off and higher volatility. However, the outbreak of the war in Ukraine created a transitory factor, increasing connectedness in the short term, consistent with Akhtaruzzaman et al. (2021), Fassas (2020), Haddad et al. (2020), and Papadamou et al. (2021), who found an upsurge in short-term connectedness during periods of market stress. This suggests that the impact of the conflict is more limited in scope and duration and does not fundamentally alter the underlying factors that determine long-term connectedness, indicating that the nature of volatility spillovers is both time varying and frequency dependent, which is consistent with the heterogeneous market hypothesis (Müller et al., 1993). This hypothesis suggests that different market participants have different trading strategies and time horizons, which can result in heterogeneous responses to market shocks and varying levels of connectedness over different time horizons. Overall, the findings show that different events can create both long-lasting and short-term effects on connectedness, and the frequency of these events can impact the level of connectedness in the short and long run.

To further explain the spillover results, we estimate net spillovers at various frequency levels (see Appendix Figure A2). The spillover results show that the net transmission and reception of volatility in the sample is highly dependent on the frequency of the analysis. NYDTB (NQCYB) is found to be a net transmitter (receiver) of volatility at all frequencies, indicating consistent behavior across time horizons. At the same time, STXFTX appears to be the primary transmitter of volatility at shorter frequencies (1–4 days), but its role varies at medium- and long-term frequencies. The NQROBO index, however, is a net transmitter of volatility in the medium and long term, but it becomes a net receiver after the Russian invasion of Ukraine. These findings highlight the time- and frequency-dependent role of each index in

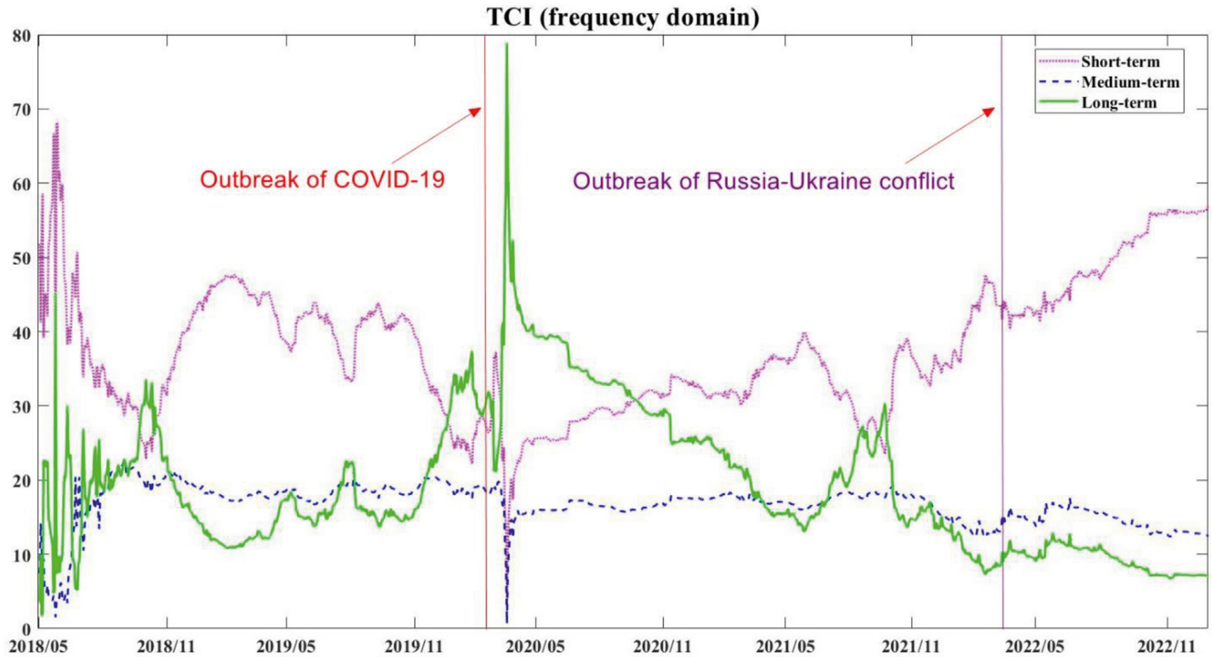


Fig. 6. Dynamic total spillovers in the frequency domain.
Notes: This figure displays the dynamic TCI among six FIR indices in the frequency domain using Baruník and Křehlík's methodology (2018). The pink line represents TCI at the short-term, and the blue and green lines represent TCI at the medium-term and long-term, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

transmitting volatility and indicate that the behavior of the indexes is not uniform across different frequencies. The finding that the role of each index is time and frequency dependent is consistent with that of previous studies (Le, Abakah, & Tiwari, 2021). Thus, market participants need to be aware of the changing nature of volatility spillovers and adjust their investment strategies accordingly. For example, during periods of high short-term connectedness, it may be beneficial to focus on high-frequency trading strategies that take advantage of short-term price movements. Policy makers may implement measures to reduce volatility and prevent panic selling. At the same time, during periods of high long-term connectedness, it may be more important to focus on long-term investment strategies that take into account fundamental factors that affect asset prices. Policy makers may need to focus on promoting market transparency and ensuring that investors have access to reliable information that allows them to make informed investment decisions.

5.6. Quantile connectedness

5.6.1. Average connectedness

Table 4 gives the results of the quantile vector autoregression (VAR)- based spillovers between the six indexes. It reports the results for the transmissions for the median quantile ($\tau = 0.5$) in Panel A, which is used as a reference for comparing the results of connectedness at the lower ($\tau = 0.05$) and upper ($\tau = 0.95$) tails in Panels B and C, respectively.

The TCI at the median quantile, 77.76%, indicates significant connectedness among the FIR assets. Disruptive technologies (81.06%) and AI and robotics (79.66%) indexes are the highest spillover transmitters, while cybersecurity (69.82%) is the lowest. The "from" column shows high and close connectedness between these assets, ranging from 77.17% to 79.16%. Disruptive technologies (81.82%) is the highest receiver, while cybersecurity (75.42%) is the lowest. NQCYBR, NYDTB, QNET, and RSBLCN are net recipients of spillovers, while NQROBO and STXFTV are net transmitters of spillovers. These findings suggest that fintech and AI and robotics can be used to forecast other assets in the system. This analysis aligns with previous studies that also find evidence of connectedness among technology-related assets {Formatting Citation}. Our finding that fintech and AI and robotics are net transmitters of spillovers is consistent with previous research that identifies these sectors as sources of systemic risk. The use of advanced technologies in the financial sector, including fintech and AI, could lead to increased interconnectedness and systemic risk (Li et al., 2020). The finding that cybersecurity is a net receiver of spillovers is also consistent with previous research that identifies this sector as vulnerable to systemic risk.

In Panels B and C, TCI is higher at extreme upper (81.69%) and extreme lower (80.31%) tails that at the median (77.76%), indicating a higher level of connectedness during extreme market conditions. This highlights the importance of studying connectedness at the tails for portfolio diversification. The "to" connectedness varies across the extreme quantiles, and AI and robotics (cybersecurity) have the highest (lowest) connectedness in the extreme lowest quantile, at 82.84% (77.78%), and cybersecurity (blockchain) has the highest (lowest) connectedness in the extreme highest quantile, at 83.35% (79.66%). The "from" connectedness also varies across the extreme quantiles, in which cybersecurity has the lowest connectedness in the extreme highest quantile (78.90%), and AI and robotics

Table 4
Volatility spillovers based on the quantile VAR.

Panel A: Median quantile τ = 0.5							
	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	FROM
QNET	22.94	15.41	15.34	15.6	15.86	14.85	77.06
NQCYBR	16.3	24.58	15.3	14.35	15.84	13.63	75.42
NQROBO	14.96	14.04	22.25	17.18	15.45	16.13	77.75
NYDTB	14.94	16.97	16.92	22.18	16.25	16.74	81.82
STXFTV	15.51	14.62	15.56	16.62	22.47	15.23	77.53
RSBLCN	14.82	12.8	16.54	17.31	15.49	23.05	76.95
TO	76.52	69.82	79.66	81.06	78.89	76.59	466.53
NET	−0.54	−1.6	1.9	−1.23	1.36	−0.36	TCI = 77.76
Panel B: Extreme lower quantile τ = 0.05							
	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	FROM
QNET	20	15.89	15.67	15.97	16.16	16.31	80
NQCYBR	16.45	19.44	15.8	15.84	16.25	16.22	80.56
NQROBO	14.54	15.55	18.63	16.36	16.13	16.79	79.37
NYDTB	16.17	15.36	16.38	18.92	16.05	17.12	81.08
STXFTV	16.24	15.6	18.85	16.33	19.28	12.7	79.72
RSBLCN	16.65	15.37	16.13	16.8	16.2	18.85	81.15
TO	80.04	77.78	82.84	81.3	80.79	79.14	481.88
NET	0.04	−2.79	3.46	0.21	1.08	−2.01	TCI = 80.31
Panel C: Extreme upper quantile τ = 0.95							
	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	FROM
QNET	19.66	16.87	14.97	16.46	16.17	15.88	80.34
NQCYBR	16.41	21.1	15.1	16.09	16.18	15.12	78.9
NQROBO	15.98	16.7	18.29	16.49	16.23	16.31	81.71
NYDTB	18.9	16.44	15.58	19.29	16.52	16.26	83.71
STXFTV	15.69	17.06	15.05	16.67	19.43	16.09	80.57
RSBLCN	15.9	16.28	19.41	16.8	16.52	19.08	84.92
TO	82.89	83.35	80.12	82.51	81.62	79.66	490.15
NET	2.55	4.45	−1.59	−2.79	1.05	−5.25	TCI = 81.69

Notes: This table presents the results of static volatility spillovers among six FIR indexes based on the quantile VAR, with three panels labeled A, B, and C. Panel A represents the median quantile (τ = 0.5), panel B represents the extreme lower quantile (τ = 0.05), and panel represents the extreme upper quantile (τ = 0.95).

have the lowest connectedness in the extreme lowest quantile (79.37%). The net transmitters and receivers also vary across the extreme quantiles, and fintech and internet are net transmitters in both quantiles, AI and robotics and disruptive technologies in the lowest quantile, and cybersecurity in the highest quantile. The net receivers are blockchain in both quantiles, cybersecurity in the lowest quantile, and AI and robotics and disruptive technologies in the highest quantile. Our study suggests that the internet (fintech) has a more significant role as a net transmitter in the highest quantile, whereas cybersecurity, AI and robotics, and disruptive technologies change their role depending on the tail distribution. Blockchain is a net receiver with a higher magnitude at the highest quantile.

The finding that fintech is a net transmitter in all markets, and hence an influential asset market, has implications for portfolio management and risk diversification strategies. It suggests that an allocation to fintech could provide a way to hedge against risks in other FIR assets and that changes in fintech market conditions may be a leading indicator of changes in other FIR assets. This is consistent with previous research that highlights the potential benefits of investing in fintech as a way of accessing exposure to technology-driven innovation and disruption (Feng et al., 2019; Li et al., 2020).

Furthermore, the finding that net recipients and transmitters differ across quantiles highlights the importance of studying connectedness at different levels of market stress, such as extreme upper and lower tails, to provide a more nuanced view of risk and diversification (Baur & Lucey, 2010). This is particularly relevant in the context of FIR assets, which are likely to be subject to significant volatility and uncertainty as a result of ongoing technological change and disruption.

The findings highlight the importance of considering tail risk when analyzing market interconnectedness, consistent with previous research {Formatting Citation}, who found that tail risk, or risk associated with extreme market movements, could be an important indicator of systemic risk. This suggests that focusing only on conditional mean-based estimators is not sufficient for understanding spillovers associated with extreme events. Moreover, the time-varying nature of the connectedness measures in the tails is different from that observed at the conditional mean or median. Investors should consider the unique characteristics and interconnectedness of FIR assets when constructing portfolios and managing risks. By understanding the net spillovers and transmission patterns among these assets, investors can better diversify their portfolios and potentially identify leading indicators of changes in market conditions.

5.6.2. Dynamic connectedness

Given that the average connectedness findings are "static" and may fail to portray the underlying dynamics and the impact of some political, economic, or other events on network connectedness, we turn to the "dynamic" total connectedness results. Fig. 7 shows the evolution of TCI over time and in response to events. The results demonstrate that TCI fluctuates widely, ranging from 55% to almost 90%, and is time varying and event dependent. Thus, significant events may have a significant impact on the network's volatility dynamics and the evolution of connectedness over time. The peaks in TCI are at the end of 2018, the end of 2019, and May 2020, and the troughs are in October 2019, December 2020, June 2021, and November 2021. These fluctuations may be influenced by significant events, such as the trade war between China and the US in 2018, the COVID-19 pandemic in early 2020, and the Russia's invasion of Ukraine in February 2022. Regardless of the circumstances, the primary goal is to depict the extent to which these six markets comove over time. Dynamic connectedness appears to be rather high, showing that these markets move in proximity. In this context, there is a high likelihood that contagion dynamics will develop in various markets.

An important finding can be obtained by comparing the dynamic connectedness across various quantiles. First, the dynamic total connectedness values are typically higher in the middle quartile (50%) than in the first and third quartiles, indicating that assets in this range tend to comove more closely over time. Second, the green and pink lines do not move in equal magnitude, suggesting the presence of an asymmetric relationship. Thus, the impact of volatility shocks on total connectedness depends on the type of shocks and the time interval. For example, after the outbreak of the pandemic, the green line shows higher levels of connectedness, whereas after Russia initiated the war in Ukraine, the pink line is at a higher level. The results support the findings by Bouri et al. (2021a, 2021b) that the time variation in TCI between the lower and upper tails demonstrates asymmetric behavior. Overall, the findings suggest a high likelihood that contagion dynamics develop across various markets. Our results align with those in other studies (Abakah et al., 2022; Adekoya et al., 2022; Bouri et al., 2021a, 2021b), highlighting the importance of considering asymmetric relationships among markets when analyzing market connectedness and spillover effects.

The net directional dynamic connectedness findings are reported in Appendix Figure A3. As in the previous analysis, our findings are presented for all three quantiles: the 5th quantile (pink line), the 50th quantile (blue line), and the 95th quantile (green line). Furthermore, positive values correspond to net transmitters, whereas negative values correspond to net recipients of volatility shocks. Two points are important to analyze: (1) whether the role of assets shifts between net transmitters and net receivers depending on the time interval; and (2) whether the assets transmit (receive) more in some quantiles than others and may switch roles across quantiles. Our results show that at higher quantiles, the net transmission mechanism is more pronounced. Irrespective of the quantile under investigation, the results indicate a volatile transmission mechanism. All indexes play both roles during this period. The net connectedness of these indexes are dynamics (i.e., across time and quantiles).

5.6.3. Network visualization

Network diagrams in the middle, lower, and upper quantiles are used to determine the intensity, direction, and structure of

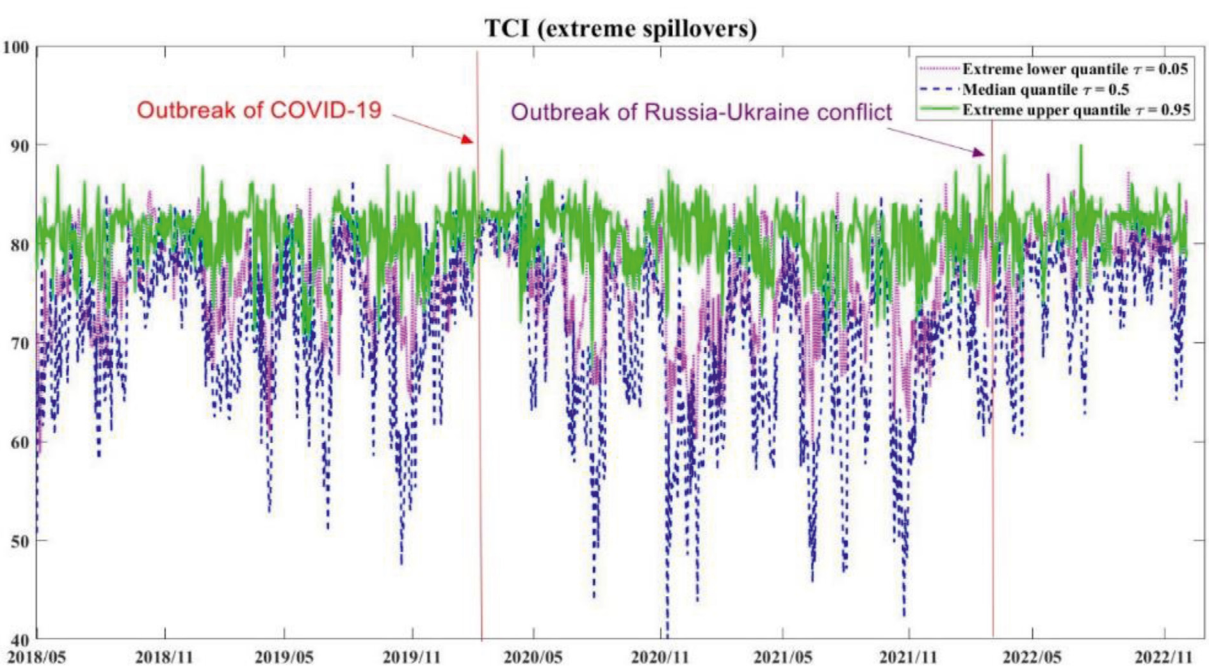


Fig. 7. Dynamic Extreme Total Spillovers

Notes: This figure displays the dynamic extreme TCI. The blue line represents TCI at the median, and the pink and green lines represent TCI at the 5th and 95th quantiles, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the information spillover across the FIR assets (Appendix Figure A4). They show the intensity and direction of information spillover between the transmitters and receivers. At the lowest quantile, the results show that the largest information transmitters are AI and robotics and fintech, with a strong connection from fintech to blockchain. At the highest quantile, the main transmitters are AI and robotics at the lowest quantile and cybersecurity, with a strong connection from AI and robotics to blockchain. The results for spillovers at the middle quantile are similar to those at the highest quantile, and cybersecurity and AI and robotics are the main transmitters. However, cybersecurity is strongly connected with disruptive technologies.

The results of the study demonstrate asymmetrical spillover dependence on quantiles, suggesting a structural change in the network topology, with different behavior for positive and negative shocks. The study also highlights the unsuitability of using the conditional median quantile to assess the level of connectedness associated with substantial positive or negative shocks, which is consistent with prior research; Baumöhl (2019) and Bouri et al. (2020) also emphasize the need for regulatory surveillance to consider tail-based dependence.

6. Robustness tests

To confirm the robustness of our findings, we estimate connectedness for different forecast horizons. Specifically, we use a 20-day-ahead forecast error, instead of 10 days. The results, presented in Appendix Figures A5 and A.6, show that the same findings regarding dynamic and net connectedness under the three models (time, frequency, and quantile) still hold under this alternative forecast horizon. This suggests that the results are not sensitive to the choice of forecast horizon and are robust.

Moreover, it is important to include global factors in a connectedness study as a robustness test because financial markets are highly interconnected and global in nature. The transmission of shocks and risks across borders can have significant impacts on asset returns and financial stability. Therefore, the inclusion of global factors, such as overall stock markets, commodity prices, and global risk indexes, makes our examination of how shocks and risks are transmitted across various asset classes and regions more comprehensive. Therefore, we add five global variables: a stock index proxied by Nasdaq, bonds, gold, oil, and the Volatility Index. Appendix Table A2, A3, and A4 provide robust results using the time, frequency, and quantile models, even with the inclusion of global variables. The transmission of volatility is greater in the short term than the medium and long term, and the TCI is higher during extreme market conditions than at the median. Notably, all global variables, except for the stock index, are primary receivers, and NQROB, NYDTB, STXFTV, and RSBLCN have positive net spillovers. Additionally, Appendix Figure A7 confirms the robustness of our dynamic connectedness findings under the three models (time, frequency, and quantile) with the inclusion of global variables.

7. Conclusion and implications

This paper builds on the existing literature on volatility spillovers across financial markets and examines the degree of connectedness across the FIR assets using time, frequency, and quantile connectedness. In doing so, this groundbreaking study adds to the rapidly expanding body of knowledge regarding AI, fintech, and blockchain.

Our results show that, using DCC-GARCH, there is a high degree of connectedness and increased contagion during crises. In a turbulent period, these assets have a high probability of suffering substantial losses, implying a lack of diversification among them.

The analysis of frequency-based connectedness reveals two main findings: first, connectedness is stronger at higher frequencies, supporting the efficient market theory, and, second, the net transmitter of volatility depends on the frequency. Interlinkages are thus dependent on time and frequency, consistent with the heterogeneous market concept (Müller et al., 1993). These results suggest that diversification benefits differ across frequencies, with less diversification at higher frequencies, meaning that holding these assets for a long time may reduce risk, whereas trading them in the short term may increase it because of their rising volatility. Moreover, the results show that whereas the Russian-Ukraine conflict is a transient factor, the pandemic significantly altered the fundamental factors.

Using the quantile connectedness method by Ando et al. (2022), total connectedness is found to be stronger during extreme (bearish or bullish) market conditions than normal market conditions. Fintech is a net transmitter in all markets, suggesting that investors should keep an eye on its movements to forecast the behavior of other FIR assets. Our analysis also suggests that spillovers vary significantly over time, and tail-based connectedness should be considered in addition to median-based connectedness.

Our results offer potential implications and insights for investors, portfolio managers, and policy makers regarding portfolio allocation, forecasting, and risk management in different market conditions. Investors and portfolio managers are advised not to combine these assets because of the prevalence of some risks. Such a portfolio is particularly vulnerable to large joint losses during market turbulence. The existence of time and frequency-dependent interactions between the FIR assets emphasizes the significance of dynamic portfolio changes based on calendar time and investment horizons. Investors considering these assets should be aware that the increased interconnectedness in the wake of the outbreak of COVID-19 will reduce the benefits of hedging and diversification. Contagion theory, which holds that asset values experience sudden shifts when unexpected exogenous shocks occur, is supported by increased cross-market correlations during periods of turmoil. Therefore, investors should modify their portfolios during crises because connectedness rises, and the diversification benefits decline. Our findings recommend a buy-and-hold investment approach to reduce risks related to volatility spillovers because long-term volatility transmission is lower. Investors who are aware of tail spillovers should also keep an eye on them during bull and bear markets to develop the best possible investment plans.

By understanding the interrelationship, policy makers and regulators should develop policy measures to avoid contagion risk in markets. They should take the necessary steps to reduce the danger of market contagion. Market authorities could implement measures to reduce shocks from other markets using our findings on the propagation, intensity, and directions of spillover during bearish and bullish market scenarios.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgements

This paper was supported by grants from the National Natural Science Foundation of China (Grant No. 71971048, 72271135), Liaoning Provincial Social Science Foundation (Grant No. L22CJY014), and Basic Research Project of Liaoning Provincial Department of Education (Grant No. LJKQR20222505).

Appendix

Table A.1
Description of Indices.

Index	Abbr.	Coverage
Internet Index	QNET	The Nasdaq Internet Index is a modified market capitalization-weighted index designed to track the performance of the largest and most liquid US-listed companies engaged in internet-related businesses and that are listed on the Nasdaq Stock Market, the New York Stock Exchange (NYSE), or the NYSE Amex. It includes companies engaged in a broad range of internet-related services, including internet software, internet access providers, internet search engines, web hosting, website design, and internet retail commerce.
Cybersecurity Index	NQCYBR	The Nasdaq CTA Cybersecurity IndexSM is designed to track the performance of companies engaged in the cybersecurity segment of the technology and industrial sectors. The index includes companies primarily involved in building, implementing, and managing security protocols applied to private and public networks, computers and mobile devices to protect data integrity and network operations.
Artificial Intelligence (AI) and Robotics Index	NQROBO	The Nasdaq CTA Artificial Intelligence and Robotics Index is designed to track the performance of companies engaged in the artificial intelligence and robotics segment of the technology, industrial, medical, and other economic sectors. The index includes companies in artificial intelligence or robotics that are classified as either enablers, engagers, or enhancers.
Disruptive Technologies Index	NYDTB	The Disruptive Technologies Index is designed to track the performance of companies that are likely to disrupt an existing market and value network.
FinTech	STXFTV	The Global Fintech Index consists of companies associated with financial technology (fintech). These businesses use technology to change how financial services are offered to end customers, and/or to boost the competitive edge of traditional financial services providers by improving efficiencies and driving new products and solutions. As the evolution of fintech progresses, and its support from governments and regulators increases, these companies are well positioned to benefit from the long-term trend toward fintech, which may have a substantial impact on their revenues in the future.
Blockchain Index	RSBLCN	The Nasdaq Blockchain Economy Index is designed to measure the returns of companies that are committing material resources to developing, researching, supporting, innovating, or using blockchain technology for their proprietary use or for use by others.

Table A.2
Volatility spillovers in the time domain among FIR assets and global variables.

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	STOCK	GOLD	OIL	VIX	BOND	*FROM*
QNET	19.94	9.42	11.87	11.82	11.38	10.75	15.29	1.07	1.38	5.14	1.94	80.06
NQCYBR	11.85	22.68	11.94	11.15	11.5	9.45	12.59	1.17	1.82	3.93	1.91	77.32
NQROBO	10.77	8.61	20.17	14.42	11.78	12.55	12.26	1.11	1.63	4.68	2.02	79.83
NYDTB	10.01	7.1	13.15	18.86	12.56	11.77	14.25	1.5	1.97	6.47	2.38	81.14
STXFTV	10.95	8.39	12.37	13.92	19.95	11.28	12.07	1.46	1.73	5.45	2.44	80.05
RSBLCN	10.71	7.39	13.21	13.43	11.5	21.16	11.45	1.43	1.6	5.01	3.1	78.84
STOCK	13.54	8.7	11.97	14.71	11.6	10.43	18.12	1.31	1.58	6.22	1.82	81.88
GOLD	3.9	3.63	4.51	5.62	5.4	4.82	4.55	58.49	2.94	1.91	4.23	41.51
OIL	3.67	3.47	5.72	6.48	5.29	4.8	4.8	2.32	56.16	2.43	4.85	43.84
VIX	7.8	5.56	7.51	11.64	8.75	7.77	11.2	0.68	1.86	33.32	3.91	66.68
BOND	4.46	3.73	4.89	6.24	5.79	7.28	4.79	3.02	4.14	5.59	50.06	49.94
TO	87.67	66.01	97.13	109.42	95.55	90.9	103.25	15.08	20.65	46.83	28.6	761.1
NET	7.61	−11.32	17.3	28.28	15.5	12.06	21.37	−26.43	−23.18	−19.85	−21.33	TCI = 69.19

Notes: This table presents the volatility spillover results among six FIR indices and five global variables, including stock, gold, oil, bond and VIX, using DCC-GARCH Connectedness approach. Values in the *i-th* row of the *j-th* column indicate the strength of the spill-over effect from the *i-th* market to the *j-th* market. Net denotes the net spillover for each individual market.

Table A.3
Volatility spillovers in the frequency domain among FIR assets and global variables.

Panel A: Short-term

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	STOCK	GOLD	OIL	VIX	BOND	*FROM*
QNET	12.45	5.22	6.09	5.96	5.94	5.53	8.9	0.61	0.72	2.8	0.75	42.5
NQCYBR	6.16	15.29	5.99	5.02	5.61	4.3	6.36	0.61	1.02	2.02	0.78	37.85
NQROBO	5.89	4.85	12.18	7.83	6.34	6.76	6.77	0.52	0.86	2.71	0.76	43.28
NYDTB	5.3	3.6	7.04	10.68	6.56	6.45	8.01	0.81	1.04	3.92	1	43.73
STXFTV	5.41	4.3	5.93	6.73	11.23	5.51	6.03	0.72	0.9	2.85	0.95	39.33
RSBLCN	5.64	3.76	7	7.32	6.16	12.66	6.14	0.68	0.97	2.96	1.64	42.29
STOCK	7.75	4.73	6.16	7.8	5.86	5.29	10.94	0.75	0.83	3.67	0.69	43.53
GOLD	2.09	1.95	2.14	2.76	2.46	1.88	2.57	44.46	1.78	1.19	2.48	21.29
OIL	1.19	1.13	1.86	2.13	1.77	1.43	1.58	1.41	41.93	1.33	2.5	16.31
VIX	5.35	3.59	5.14	8.16	6.17	5.72	8.07	0.5	1.2	23.63	2.57	46.48
BOND	1.81	1.58	2.1	2.69	2.47	3.72	1.98	2	2.41	3.42	35.07	24.18
TO	46.59	34.73	49.46	56.4	49.33	46.58	56.41	8.59	11.73	26.86	14.11	400.78
NET	4.09	−3.13	6.17	12.67	10	4.29	12.88	−12.71	−4.58	−19.62	−10.07	TCI = 36.43

Panel B: Medium-term

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	STOCK	GOLD	OIL	VIX	BOND	*FROM*
QNET	3.75	1.88	2.66	2.67	2.47	2.33	3.03	0.2	0.32	1.14	0.52	17.22
NQCYBR	2.6	3.54	2.8	2.87	2.7	2.22	2.88	0.24	0.43	0.9	0.54	18.17
NQROBO	2.27	1.66	3.89	3.09	2.44	2.55	2.52	0.24	0.37	1	0.56	16.71
NYDTB	2.13	1.48	2.73	3.8	2.68	2.23	2.85	0.31	0.47	1.22	0.56	16.67
STXFTV	2.52	1.79	2.89	3.25	4	2.45	2.67	0.32	0.4	1.24	0.63	18.15
RSBLCN	2.33	1.54	2.77	2.71	2.37	3.91	2.37	0.32	0.3	0.96	0.56	16.22
STOCK	2.72	1.73	2.59	3.15	2.53	2.23	3.37	0.25	0.37	1.24	0.5	17.31
GOLD	0.77	0.72	1.03	1.24	1.27	1.15	0.85	7.65	0.63	0.27	0.73	8.66
OIL	1.04	1	1.73	1.85	1.42	1.35	1.32	0.41	8.03	0.55	1.2	11.9
VIX	1.37	1.04	1.26	1.93	1.4	1.12	1.73	0.09	0.43	5.92	0.76	11.13
BOND	1.08	0.94	1.16	1.47	1.35	1.44	1.14	0.42	0.87	1.05	7.63	10.91
TO	18.84	13.78	21.63	24.23	20.62	19.06	21.37	2.81	4.58	9.56	6.57	163.05
NET	1.61	−4.39	4.92	7.56	2.47	2.84	4.07	−5.85	−7.32	−1.57	−4.35	TCI = 14.82

Panel C: Long-term

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	STOCK	GOLD	OIL	VIX	BOND	*FROM*
QNET	3.72	2.19	3.16	3.25	3.04	2.8	3.36	0.3	0.4	1.12	0.74	20.36
NQCYBR	3.02	3.49	3.25	3.44	3.33	2.88	3.34	0.36	0.44	0.96	0.65	21.66
NQROBO	2.63	2	4.1	3.58	3.01	3.13	2.94	0.36	0.45	0.99	0.73	19.83
NYDTB	2.64	1.98	3.31	4.35	3.36	2.95	3.39	0.43	0.57	1.28	0.87	20.77
STXFTV	3.03	2.29	3.57	4.01	4.61	3.22	3.33	0.46	0.52	1.3	0.93	22.67
RSBLCN	2.85	1.97	3.41	3.43	3.02	4.43	2.94	0.46	0.41	1.07	0.92	20.49
STOCK	3.06	2.16	3.2	3.81	3.23	2.81	3.76	0.38	0.48	1.25	0.73	21.1
GOLD	1.22	1.01	1.54	1.84	1.86	1.93	1.35	5.09	0.64	0.38	1.06	12.85
OIL	1.55	1.39	2.22	2.5	2.13	2.04	1.91	0.48	5.6	0.62	1.4	16.24
VIX	1.04	0.88	1.04	1.56	1.18	0.88	1.38	0.09	0.31	3.78	0.72	9.07
BOND	1.71	1.29	1.78	2.26	2.12	2.19	1.85	0.45	0.86	1.24	6.45	15.76
TO	22.75	17.18	26.48	29.68	26.28	24.82	25.79	3.78	5.07	10.21	8.75	200.8
NET	2.39	−4.49	6.65	8.92	3.61	4.34	4.69	−9.07	−11.17	1.13	−7.01	TCI = 18.25

Notes: This table presents the results of static volatility spillovers among six FIR indexes and five global variables, including stock, gold, oil, bond and VIX in the frequency domain using Baruník and Křehlík's methodology (2018), with three panels labeled A, B, and C. Panel A represents the short term (1–5 days), panel B represents the medium term (5–20 days), and panel C represents the long term (20 days or more).

Table A.4
Volatility spillovers based on the quantile VAR among FIR assets and global variables.

Panel A: Median quantile τ = 0.5

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	STOCK	GOLD	OIL	VIX	BOND	*FROM*
QNET	21.23	9.08	8.97	9.64	9.22	9.04	13.18	4.36	4.16	6.75	4.36	78.77
NQCYBR	10.09	24.85	8.58	7.92	9.28	7.78	10.07	4.68	4.69	7.03	5.02	75.15
NQROBO	9.22	7.99	20.98	11.41	9.04	10.75	10.8	4.36	4.04	6.9	4.49	79.02
NYDTB	8.64	6.56	10.81	19.98	9.28	10.55	12.16	4.41	4.41	8.62	4.58	80.02
STXFTV	9.5	8.3	9.14	10.51	21.34	9.46	10.66	4.47	4.07	7.66	4.88	78.66
RSBLCN	8.85	6.97	10.48	11.19	9.3	22.63	10.1	4.69	4.14	7.06	4.59	77.37
STOCK	11.67	8.27	9.73	12.13	9.21	9.18	19.15	4.17	4.08	8.14	4.27	80.85
GOLD	6.01	5.64	5.66	6.41	5.65	6.39	6.16	39.23	5.95	5.9	7.01	60.77
OIL	5.62	6.05	6.08	6.97	5.68	6.33	6.42	6.14	36.11	7.04	7.58	63.89
VIX	7.56	6.63	7.19	10.51	8.62	7.82	9.94	4.57	4.76	27.24	5.18	72.76
BOND	6.34	6.38	6.25	7.16	6.27	6.62	6.8	6.72	6.97	7.35	33.15	66.85
TO	83.5	71.86	82.89	93.85	81.57	83.92	96.29	48.56	47.27	72.45	51.97	814.13
NET	4.73	−3.29	3.87	13.83	2.9	6.55	15.44	−12.21	−16.62	−0.31	−14.88	TCI = 74.01

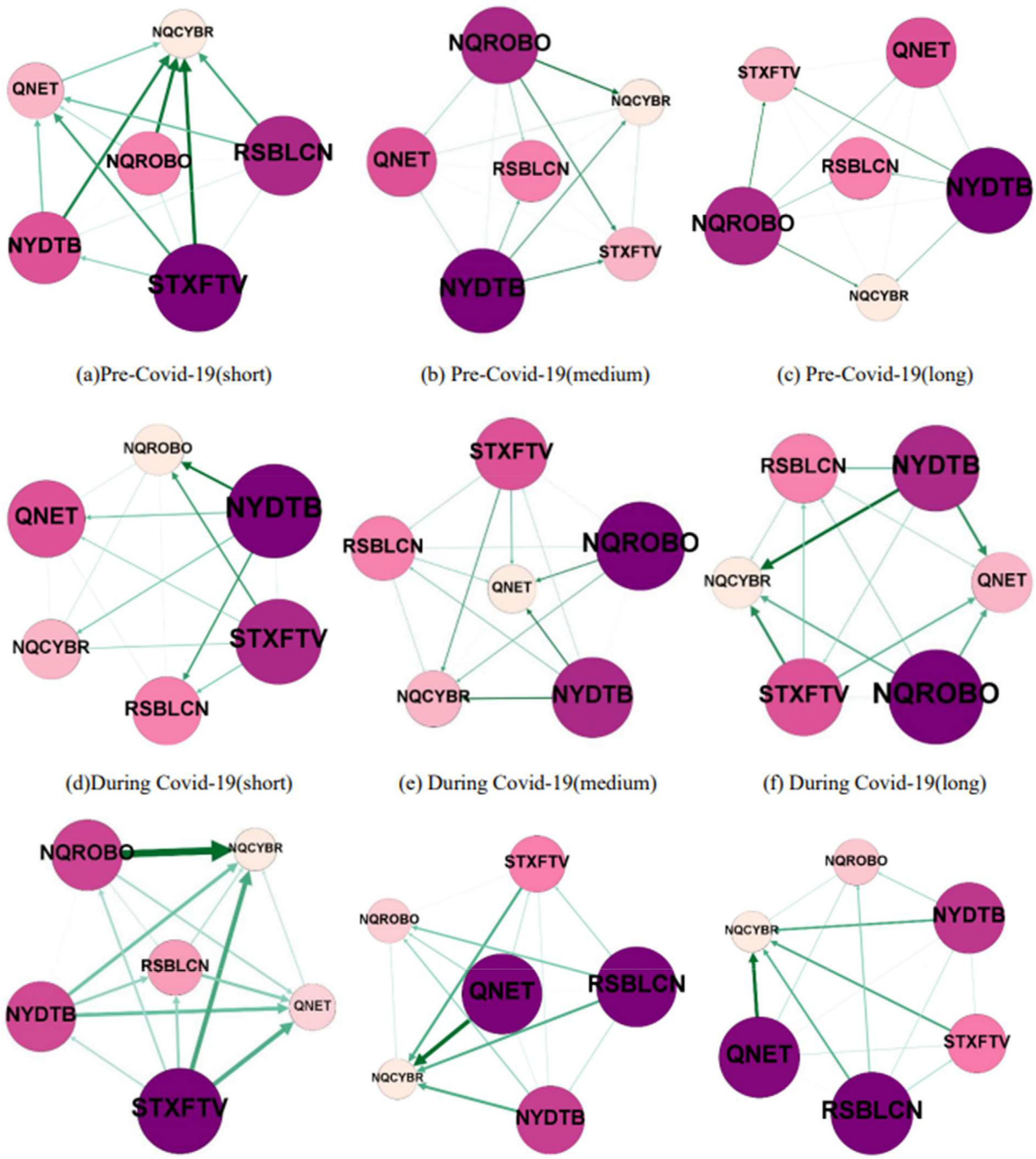
Panel B: Extreme lower quantile τ = 0.05

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	STOCK	GOLD	OIL	VIX	BOND	*FROM*
QNET	14.63	10.37	10.47	10.52	10.25	10	12.26	4.58	4.1	7.4	5.43	85.37
NQCYBR	11	15.69	10.48	10	10.43	9.46	11.32	4.63	4.25	7.31	5.45	84.31
NQROBO	10.22	9.7	14.42	11.6	10.31	10.82	11	4.56	4.66	7.15	5.55	85.58
NYDTB	9.94	8.88	11.16	13.89	10.77	10.57	11.72	4.51	4.91	8.29	5.36	86.11
STXFTV	10.25	9.76	10.51	11.37	14.65	10.05	10.84	4.83	4.39	7.86	5.48	85.35
RSBLCN	10.14	9.06	11.18	11.34	10.23	15.08	10.71	4.73	4.52	7.36	5.64	84.92
STOCK	11.64	10.07	10.62	11.73	10.31	9.99	13.86	4.18	4.3	8.17	5.12	86.14
GOLD	7.64	7.27	7.73	8.01	8.15	7.8	7.37	24.83	6.62	5.33	9.25	75.17
OIL	6.69	6.7	7.89	8.67	7.5	7.44	7.56	6.78	25.29	6.75	8.71	74.71
VIX	9.18	8.47	8.88	10.77	9.63	8.91	10.65	3.92	4.95	18.11	6.54	81.89
BOND	7.87	7.47	8.13	8.26	7.99	7.98	7.84	8.02	7.42	7.72	21.3	78.7
TO	94.58	87.74	97.05	102.27	95.56	93.02	101.28	50.73	50.13	73.34	62.54	908.24
NET	9.21	3.43	11.48	16.16	10.21	8.1	15.14	−24.43	−24.58	−8.55	−16.17	TCI = 82.57

Panel C: Extreme upper quantile τ = 0.95

	QNET	NQCYBR	NQROBO	NYDTB	STXFTV	RSBLCN	STOCK	GOLD	OIL	VIX	BOND	*FROM*
QNET	13.74	9.15	9.36	9.44	9.16	9.09	11.05	6.84	7.19	7.94	7.05	86.26
NQCYBR	9.9	14.63	9.23	9.04	9.35	8.5	10.02	6.92	7.36	8.02	7.04	85.37
NQROBO	9.36	8.8	13.43	10.07	9.01	9.62	10.26	6.83	7.23	8.29	7.09	86.57
NYDTB	9.39	8.24	10.01	13.07	9.02	9.8	10.85	6.84	7.14	8.56	7.07	86.93
STXFTV	9.71	8.93	9.31	9.61	13.54	9.25	10.04	6.83	7.15	8.31	7.3	86.46
RSBLCN	9.52	8.39	9.79	10.19	9.15	13.53	9.85	6.97	7.17	8.17	7.27	86.47
STOCK	10.49	8.81	9.52	10.23	9.14	9.21	13.51	6.82	7.02	8.46	6.8	86.49
GOLD	8.66	7.98	8.03	8.34	8.03	8.14	8.88	18.17	7.88	7.48	8.42	81.83
OIL	8.34	8.09	8.33	8.77	8.12	8.4	8.92	7.8	16.59	8.35	8.29	83.41
VIX	8.71	8.33	8.57	9.67	9.13	8.94	10.01	6.77	7.26	14.73	7.87	85.27
BOND	8.54	8.01	8.34	8.77	8.33	8.39	8.73	8.23	8.21	8.66	15.78	84.22
TO	92.62	84.74	90.52	94.13	88.44	89.35	98.59	70.84	73.61	82.24	74.18	939.28
NET	6.36	−0.63	3.95	7.21	1.98	2.89	12.11	−10.99	−9.81	−3.03	−10.03	TCI = 85.39

Notes: This table presents the results of static volatility spillovers among six FIR indexes and five global variables, including stock, gold, oil, bond and VIX based on the quantile VAR, with three panels labeled A, B, and C. Panel A represents the median quantile (τ = 0.5), panel B represents the extreme lower quantile (τ = 0.05), and panel represents the extreme upper quantile (τ = 0.95).



(a)Pre-Covid-19(short) (b) Pre-Covid-19(medium) (c) Pre-Covid-19(long)

(d)During Covid-19(short) (e) During Covid-19(medium) (f) During Covid-19(long)

(g)During Russia-Ukraine war(short) (h) During Russia-Ukraine war(medium) (i)During Russia-Ukraine war(long)

Fig. A.1. Net pairwise directional network of volatility spillovers in the frequency domain.

Notes: This figure presents the net pairwise directional volatility spillovers among six FIR indices in the frequency domain, by dividing it into three periods: pre-COVID, during COVID, and the Russian-Ukraine war. The node size reflects the overall magnitude of transmission/reception for each product. The edge size indicates the magnitude of the net pairwise volatility spillovers between two products. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors.

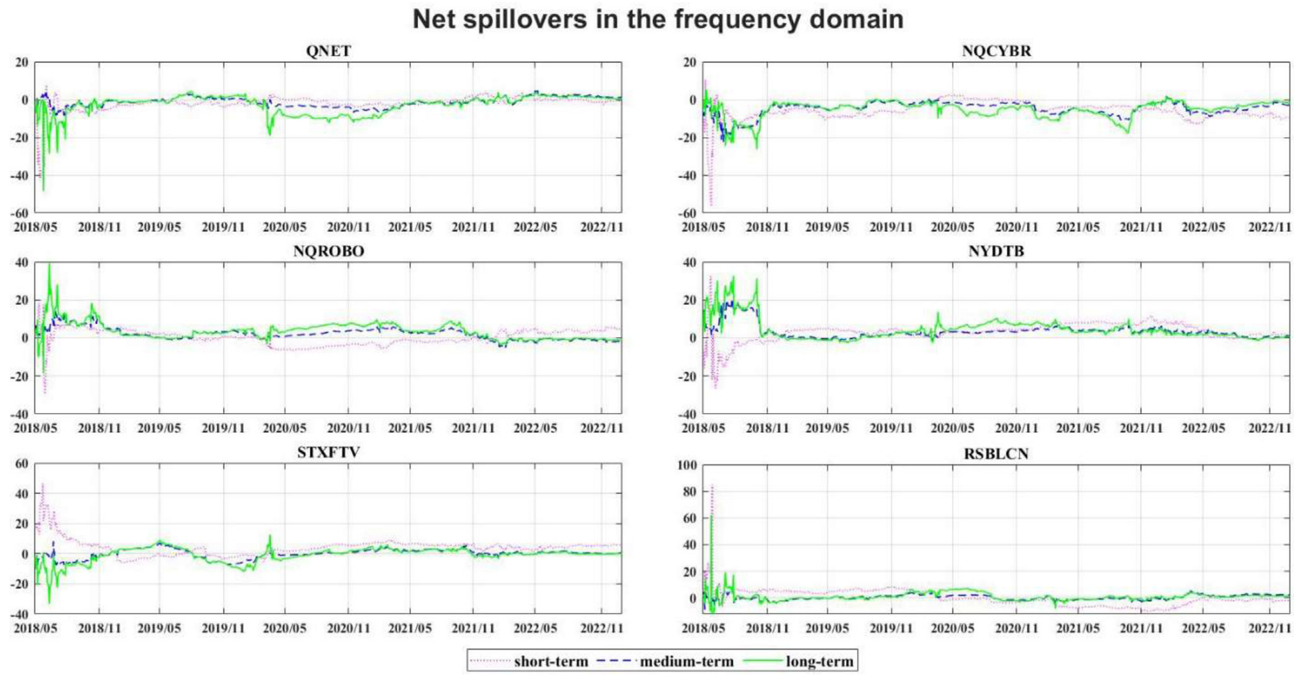


Fig. A.2. Net spillovers in the frequency domain.
Notes: This figure displays dynamic net spillover for each FIR asset over time in the frequency domain using Baruník and Křehlík's methodology (2018), with positive values indicating net transmitters and negative values indicating net receivers. The pink line represents TCI at the short-term, and the blue and green lines represent TCI at the medium-term and long-term, respectively.

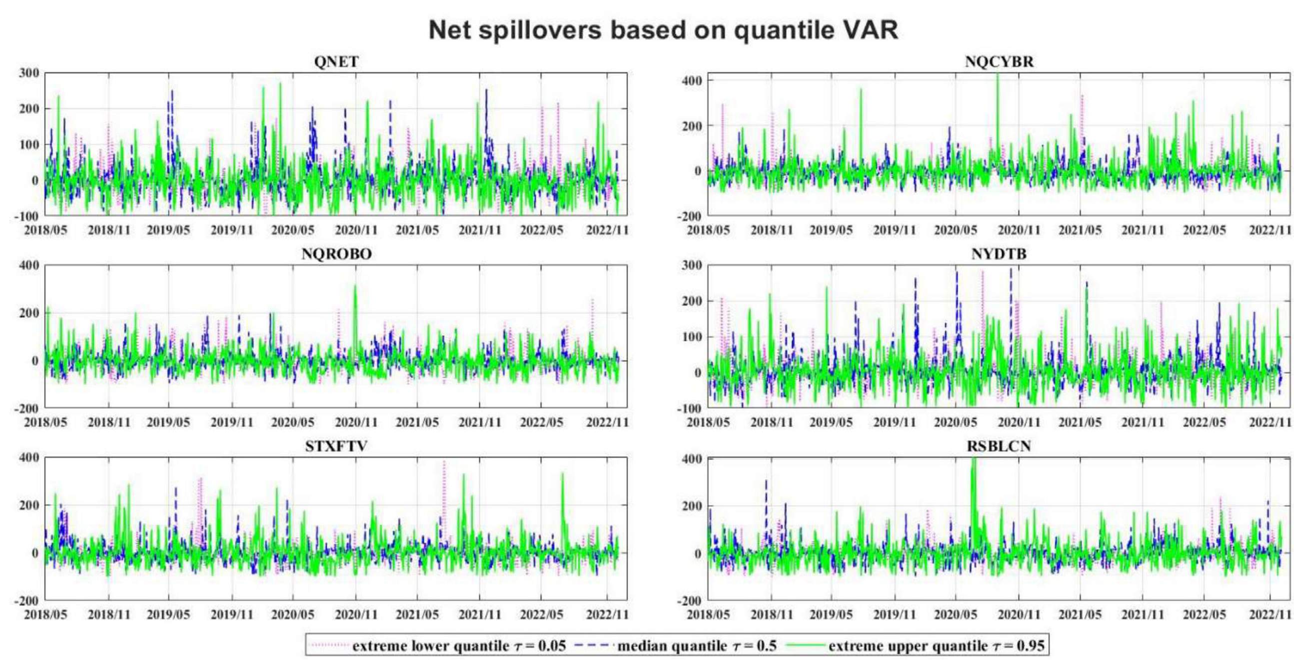


Fig. A.3. Net spillovers Based on Quantile VAR.
Notes: This figure displays dynamic net spillover for each FIR asset over time based on the quantile VAR, with positive values indicating net transmitters and negative values indicating net receivers. The blue line represents TCI at the median, and the pink and green lines represent TCI at the 5th and 95th quantiles, respectively.

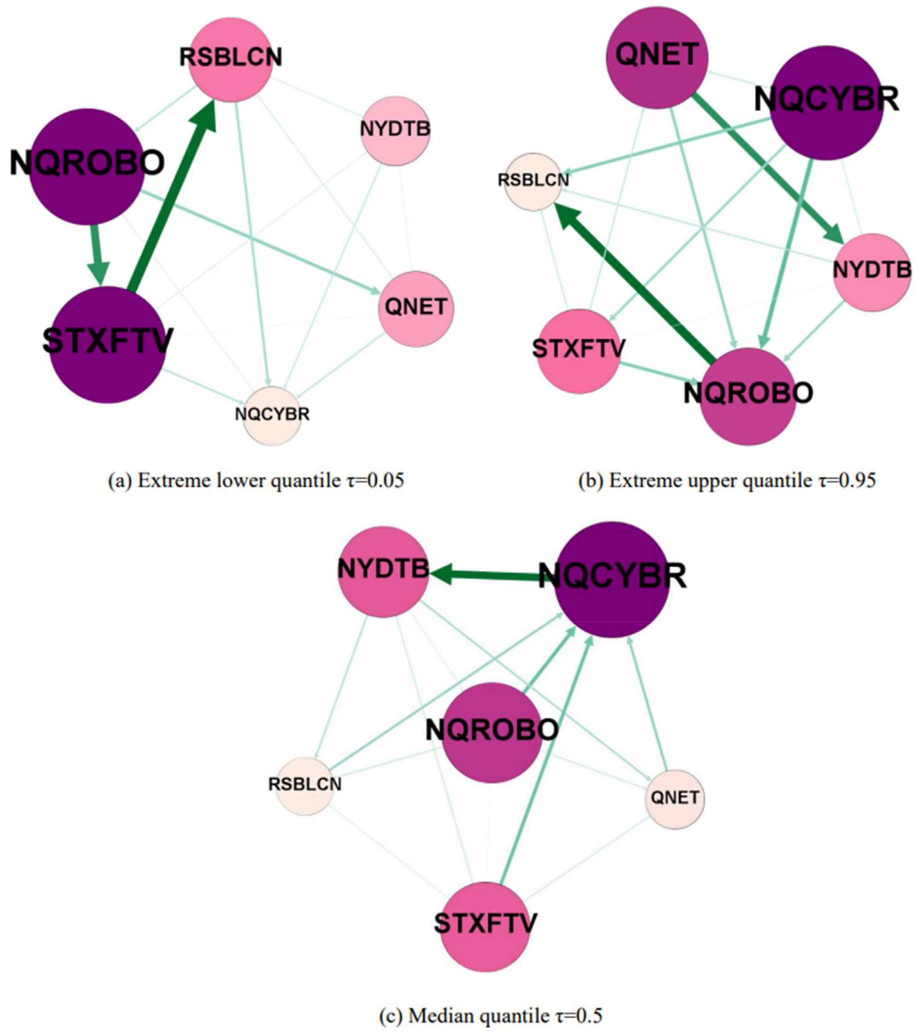
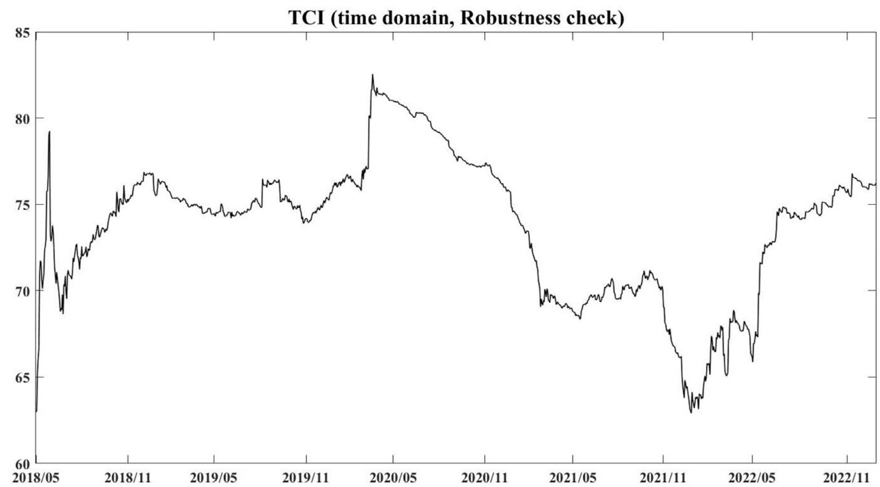


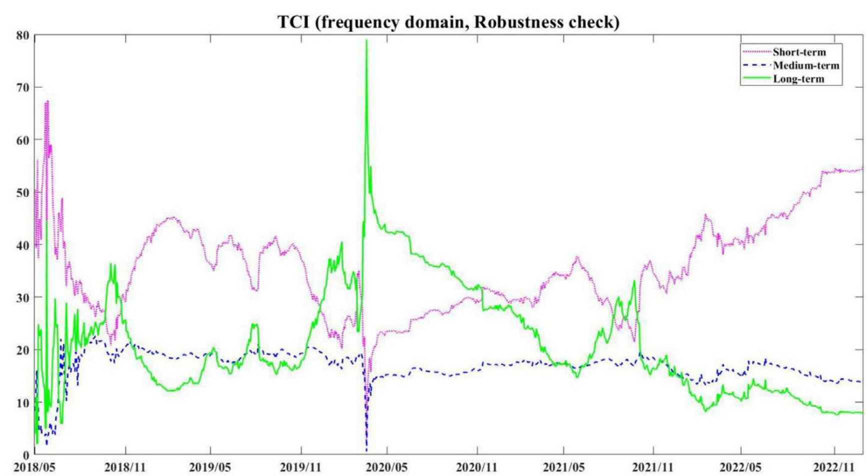
Fig. A.4. Net pairwise directional network of volatility spillovers based on quantile VAR.

Notes: This figure presents the net pairwise directional volatility spillovers among six FIR indices at median, lower, and upper quantiles. The node size reflects the overall magnitude of transmission/reception for each product. The edge size indicates the magnitude of the net pairwise volatility spillovers between two products. The magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors.

Panel A: Time domain



Panel B: Frequency domain



Panel C: Extreme spillovers

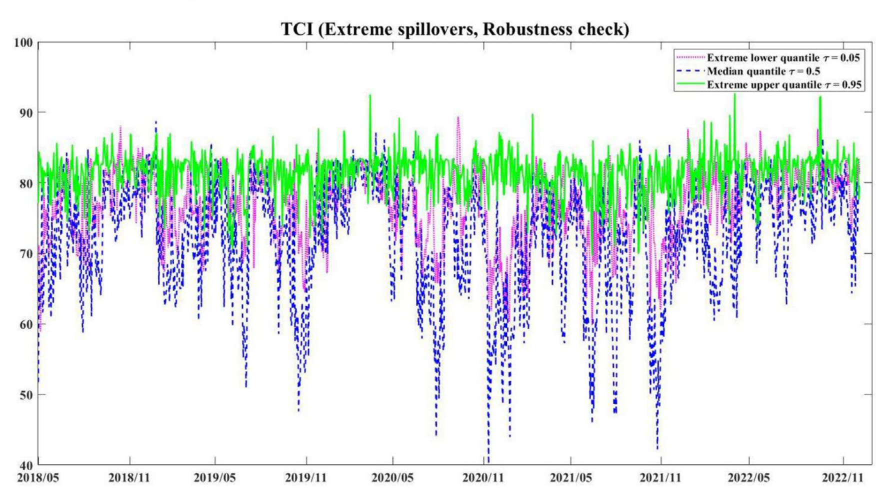
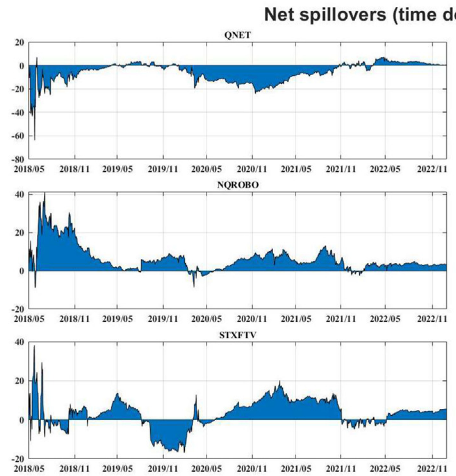


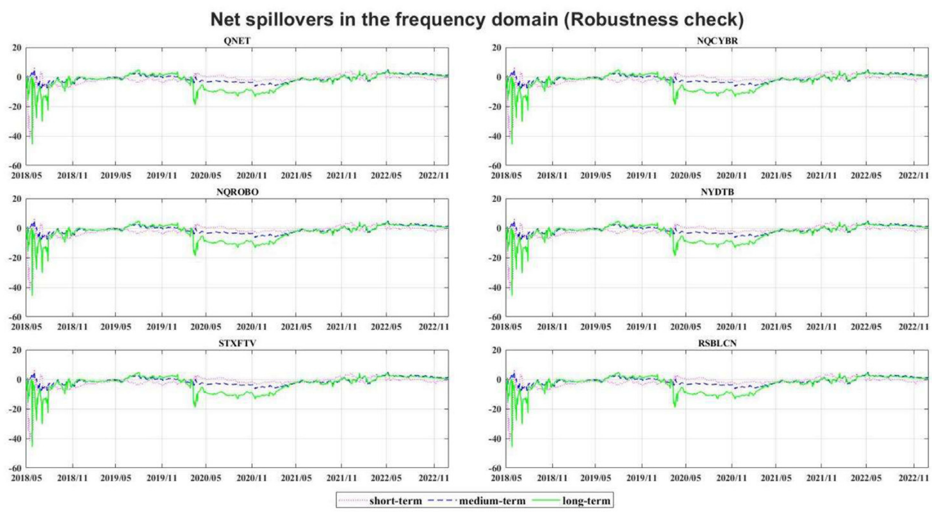
Fig. A.5. Dynamic Connectedness Using a 20-day (Robustness tests).

Notes: This figure displays dynamic volatility connectedness among six FIR indices using a 20-day-ahead forecast error. Panel A reports the dynamic TCI in the time domain, Panel B displays it in the frequency domain using Baruník and Křehlík's methodology (2018), while Panel C reports the dynamic extreme TCI.

Panel A: Time domain



Panel B: Frequency domain



Panel C: Extreme spillovers

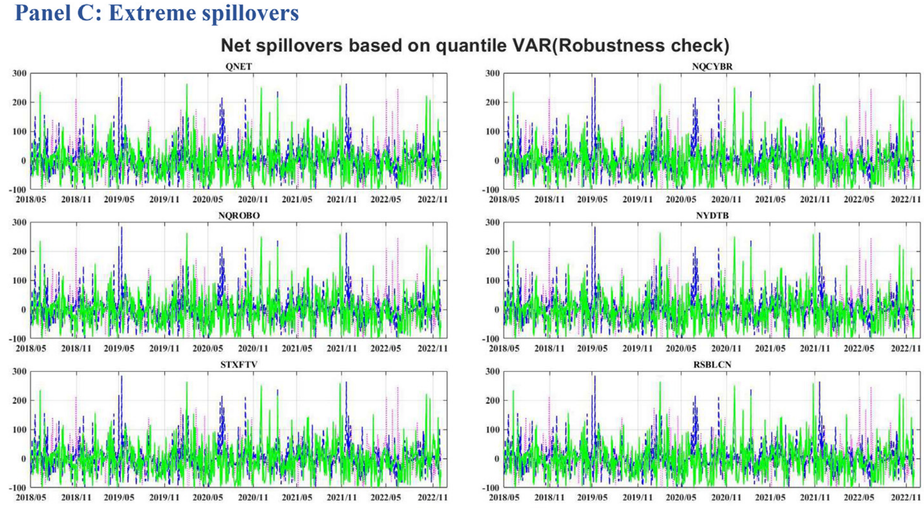
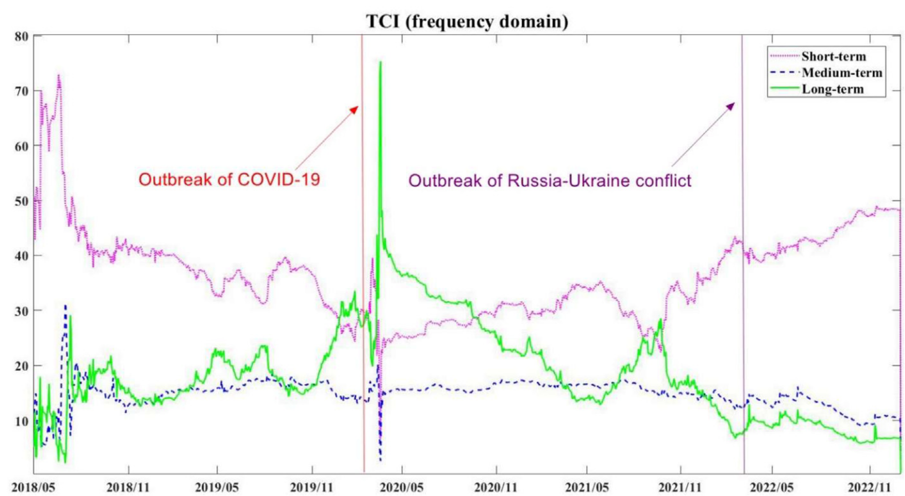


Fig. A.6. Net Connectedness Using a 20-day (Robustness tests).

Notes: This figure displays the dynamic net spillovers for each FIR index over time, with positive values indicating net transmitters and negative values indicating net receivers, using a 20-day-ahead forecast error. Panel A reports the dynamic TCI in the time domain, Panel B displays it in the frequency domain using Baruník and Křehlík's methodology (2018), while Panel C reports the dynamic extreme TCI.

Panel A: Time domain

Panel B: Frequency domain



Panel C: Extreme spillovers

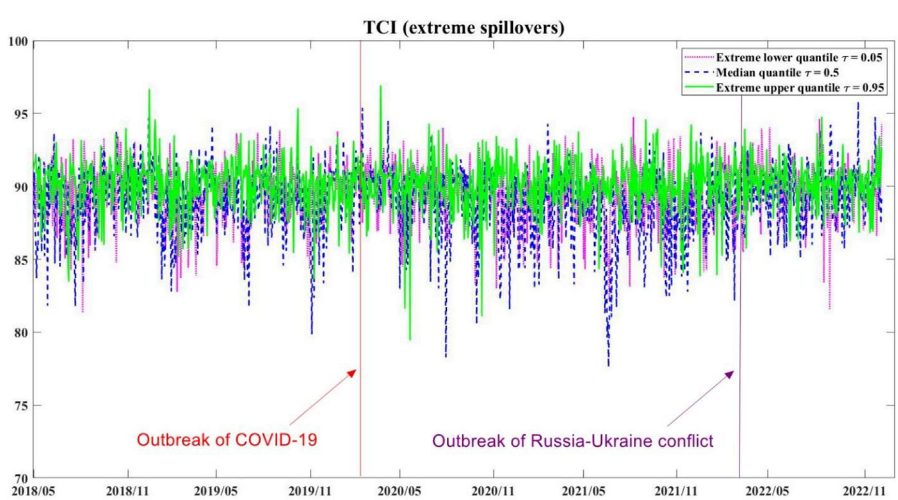


Fig. A.7. Dynamic Connectedness with the Inclusion of Global Variables (Robustness tests).
Notes: This figure displays dynamic volatility connectedness among six FIR indices and five global variables including stock, gold, oil, bond and VIX. Panel A reports the dynamic TCI in the time domain, Panel B displays it in the frequency domain using Baruník and Křehlík's methodology (2018), while Panel C reports the dynamic extreme TCI.

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