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Quantile connectedness among fintech, carbon future, and energy markets: Implications for hedging and investment strategies

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ABSTRACT

This study proposes a novel framework to explore the quantile connectedness among fintech, carbon future, and energy markets with implications for hedging and investment strategies. We aim to construct portfolio strategies for extreme market conditions based on the results of quantile connectedness to address the complex price fluctuations in the energy markets. Using the daily data from January 4, 2017, to March 6, 2023, we find that (i) carbon future and crude oil are the net receivers, while fintech and clean energy are the net contributors. However, the net spillover direction of fintech, carbon futures, and energy markets change frequently under extreme market conditions; (ii) the COVID-19 pandemic and Russia-Ukraine conflict significantly enhance connectedness across all quantile levels; (iii) the sample period is dominated by the lower quantile connectedness, indicating that investors react more strongly to bad news. Furthermore, the result of portfolios shows that, compared to normal market conditions, the dynamic investment weights of minimum connectedness (MCOP) exhibit greater volatility under extreme market conditions. This highlights the differences in portfolio adjustments across different market conditions. In addition, the result shows that the minimum connectedness and minimum correlation portfolio have a greater cumulative return than the minimum variance portfolio. The analysis based on the Sharpe ratio shows that in extreme market conditions, carbon futures and fintech can serve as effective hedging tools for the energy markets. Robustness tests further confirmed our conclusions. Our results have positive implications for decision-makers and investors about risk management and diversified portfolio selection.

1. Introduction

In recent years, international unexpected events such as the COVID-19 pandemic and the Russia-Ukraine conflict have caused significant fluctuations in energy market prices, with extreme market conditions occurring frequently (Ren et al., 2023). The collapse of the energy markets would severely threaten economic activity and cause significant losses across various industries. For investors, concentrated energy market investments can expose them to greater investment risk. Against the backdrop of digitalization and green transformation of the global economy, fintech stocks and carbon futures are increasingly being included in investors' portfolios. Data shows that global fintech investment transactions reached a new high in 2021, with a total investment amount of 2.1 trillion US dollars. In addition, since the launch of the EU carbon market in 2005, both trading volume and trading value have increased significantly. In 2022, the EU trading volume reached 9.277 billion tons. Therefore, in the context of strong demand for hedging risks, it is necessary to analyze the hedging capabilities of carbon futures and fintech in the energy markets. More importantly, the potential connectedness between fintech, carbon futures, and energy markets should be analyzed involving extreme market conditions rather than simply under average conditions. The research by Hernandez et al. (2019) mentions that under extreme market conditions, investors are more likely to suffer losses and seek potential portfolio strategies to deal with risks.

However, there is currently a scarcity of research focusing on the connectedness between fintech, carbon futures, and energy markets, as well as hedging and investment strategies, especially under extreme

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market conditions. On the one hand, in terms of the energy markets, compared to these two types of emerging assets: fintech and carbon futures, most researchers pay more attention to its connectedness with traditional assets, including equity markets (Hamdi et al., 2019; Dai et al., 2022), bond markets (Nguyen et al., 2021; Umar et al., 2023), nonenergy commodity markets (Khalfaoui et al., 2021a), and metals (Uddin et al., 2018; Ghosh et al., 2023). Obviously, the connectedness between fintech, carbon futures, and the energy markets is not clear. On the other hand, previous studies have largely utilized the DY model (Elsayed et al., 2022), TVP-VAR model (Dogan et al., 2022), GARCH family models (Zhang and Sun, 2016), and so on, to investigate the spillover effects between markets under normal market conditions. In other words, most methods use ordinary least squares to estimate VAR models, inferring only the average shocks and their propagation within the connectedness system. In fact, the energy markets may exhibit different trends under extreme market conditions. As Bouri et al. (2021) said, systemic shocks are not necessarily equal to average shocks but can be much larger, necessitating further consideration of the potential heterogeneous effects of the shock size distribution.

Secondly, most studies have already recognized that one of the purposes of studying risk spillovers between markets is to provide investors with insightful investment strategies. If the correlation between markets is low, a portfolio can be constructed to diversify risk (Le, 2023). However, few papers have conducted diversified portfolio assessments based on this. We believe that portfolio construction is a substantial extension of related research, especially under extreme market conditions. This is because, in such conditions, investors may face greater risks and have a stronger desire to hedge those risks. At this time, diversified and flexible adjustments to the portfolio are of great significance to investors. In previous studies, Broadstock et al. (2022) innovatively utilized the minimum connectedness approach to construct portfolios of green and black bonds in the United States, Europe, and China. They found that in the "minimum connectedness portfolio", the representation of green bonds from the United States, Europe, and China is more balanced. Unfortunately, they only consider investor portfolio construction under normal market conditions and ignore different market conditions. On this basis, Adekoya et al. (2022) investigated the asymmetric transmission of return spillovers between the price of oil and the price of Islamic stocks using asymmetric TVP-VAR, and undertook dynamic diversification exercises based on three portfolio methods. They further distinguished market conditions and found that the minimum connectedness (MCOP) successfully measured the asymmetry between upward and downward markets, providing important insights for portfolio management. Abdullah et al. (2023) also came to the same conclusion. However, the current research still has limitations. According to the assumptions of the Markowitz portfolio theory, the distribution of asset returns follows a multivariate normal distribution. However, the distribution of financial asset returns is often asymmetric and heavy-tailed. In extreme market conditions, the portfolio returns can be severely affected. Therefore, it is necessary to consider the tail risk of the asset portfolio (Goode et al., 2015).

According to herd behavior (Demirer and Kutan, 2006) and contagion risk theory (Masson, 1998), when investors face incomplete information, the risk spillover effect between markets increases. This phenomenon often leads investors to rely more on the actions of others and market sentiment when making decisions, thereby amplifying price volatility. In extreme market conditions, the degree of correlation may differ from what is observed under normal market conditions (Cunado et al., 2023). In other words, the level of connectedness during this period is likely to be higher than under calm financial market conditions. This also presents new requirements for portfolio construction in extreme market circumstances. Therefore, we need a unified framework that comprehensively captures the connectedness between fintech, carbon futures, and energy markets and provides valuable insights for risk hedging and investment strategies during extreme market conditions.

To address the above gap, this paper proposes a framework for hedging and investment strategy analysis based on quantile connectedness. This framework not only helps us comprehensively capture spillover effects among fintech, carbon futures, and energy markets but also further assesses portfolio performance under extreme market conditions, thereby providing valuable predictive information for investors. In previous studies, Yousaf et al. (2022) used the quantile approach to study the return correlation between renewable energy tokens and the fossil fuel markets, aiming to explore the existing dependence structure under different market conditions. However, they did not further discuss hedging and investment strategies. Khan et al. (2023) used the quantile connectedness approach to study the relationship between global financial uncertainty and emerging market sector indices. However, in portfolio analysis, they still relied on the TVP-VAR model, which makes it difficult to distinguish between different market conditions. The hedge and investment strategy framework based on quantile connectedness proposed in this paper captures the comprehensive behavior of all extreme and normal market fluctuations, evaluating hedging efficiency and portfolio performance under different market conditions. As Sheikh et al. (2024) stated, QVAR offers an appropriate framework for studying the dependencies between different quantiles. In other words, we not only focus on spillover effects among markets under normal conditions but also differentiate between different quantiles (upper and lower) to study the direction and magnitude of spillover effects under extreme market scenarios, aiming to capture tail risks between markets. Furthermore, building upon the connectedness analysis, we further evaluated portfolios under different market conditions to assist investors in flexibly adjusting investment strategies to navigate complex and dynamic price trends.

The key conclusions of this paper are as follows: Our research finds that under normal market conditions, carbon futures and crude oil are the main receivers, while fintech and clean energy are the main contributors. However, under extreme market conditions, the net spillover roles of fintech, carbon futures, and energy markets are unstable. We also captured the event dependency of quantile connectedness; specifically, the COVID-19 pandemic and the Russia-Ukraine conflict significantly enhanced connectedness across all quantile levels. Furthermore, we find that the sample period is dominated by lower quantile connectedness, indicating that investors react more strongly to bad news. Additionally, the portfolio results show that under extreme market conditions, the minimum connectedness (MCOP) dynamic investment weights exhibit greater volatility compared to normal market conditions. The cumulative return results indicate that portfolios with minimum connectedness and minimum correlation have higher cumulative returns than those with minimum variance. An analysis based on the Sharpe ratio suggests that under extreme market conditions, carbon futures and fintech can serve as effective hedging tools for the energy market. Robustness tests further confirmed our conclusions. Our findings have positive implications for policymakers and investors in terms of risk management and diversified portfolio selection.

The research contribution of this paper has the following three aspects. **First**, this paper comprehensively explores the connectedness among fintech, carbon futures, and energy markets from a systemic perspective under different market conditions (normal and extreme). To our knowledge, this is the first empirical study to place fintech, carbon futures, and energy markets under the same risk spillover framework. The study of Tiwari et al. (2023) is relevant to our paper, but it studies the pair dependence between fintech and a single energy market through non-parametric quantile causality and CQ methods. Additionally, given the importance of the current development of the carbon market, this study includes carbon futures in the research framework. Our research extends the existing literature on financial market risk spillover and provides a new perspective for cross-market spillover research. **Second**, this paper evaluates hedging and multivariate portfolio strategies across different quantiles. We considered the impact of the asymmetry in the distribution of financial asset returns on portfolio

performance, enabling investors to make informed decisions even in complex and volatile market conditions. **Third**, this paper innovatively constructs a hedging and investment strategy analysis framework based on quantile connectedness, making it possible to evaluate hedging properties and portfolio performance within a unified quantile connectedness framework. Most previous studies have investigated these two parts using unrelated methods (Ali et al., 2023; Khan et al., 2023; Yousfi et al., 2024). The empirical section of this paper further demonstrates the broad applicability of this framework, enriching the literature on quantile connectedness and portfolio optimization in theory, while also providing valuable tools and methods for practical application.

The rest of the paper is structured as follows: Section 2 provides a literature review, Section 3 elaborates the methodology and Section 4 describes the data, Section 5 discusses the empirical findings, and Section 6 concludes the study with policy implications.

2. Literature review

Given the importance of energy markets in socioeconomic activities, price fluctuations in energy markets can significantly impact other markets (Xie et al., 2024). Currently, an increasing number of scholars are focusing on the risk spillover effects of energy markets to identify the risk transmission mechanisms between energy markets and other markets. El Hedi Arouri et al. (2011) used a generalized VAR-GARCH approach to study volatility spillovers between European and the U.S. oil and equity markets and found that in Europe such spillovers are usually one-way, but in U.S. are two-way. According to Broadstock et al. (2012), during the 2008 financial crisis, there was a notable strengthening of the correlation between global oil prices and Chinese energy-related equities. This reflects the sensitivity of investors in China's energy-related stocks to shocks in international crude oil. Khalfaoui et al. (2021b) used wavelet coherence and quantile cross-spectral analysis to empirically examine the correlation between the oil market and major precious and base metals. The study found that gold and platinum are closely related to oil, influencing oil prices, especially during periods of global market turmoil. Lorente et al. (2023) studied the correlation between climate change indices, green financial assets, renewable energy markets, and the geopolitical risk index. The findings reveal that green bonds and the clean energy market are negatively correlated with the geopolitical risk index. It is evident that these studies have greatly enriched the literature on energy market risk spillovers, providing new perspectives for risk management in energy markets.

Furthermore, to address the risks brought by energy market fluctuations, many scholars have conducted further research from the perspective of hedging and portfolio strategies. Akhtaruzzaman et al. (2021) examined the safe-haven properties of gold during the pandemic and found that gold was a good hedging strategy against WTI crude oil during the first phase of the COVID-19 pandemic. Naeem et al. (2021) examined the asymmetric connectivity of green bonds and commodities in the time and frequency domains through the overflow framework of DY and BK. They found that because the correlation between green bonds and crude oil is weak in the short term, the sensible investment strategy is to include green bonds and crude oil assets in the portfolio. Arfaoui et al. (2023) explored the asymmetric return and volatility correlations between gold and multiple energy markets across three subperiods before and after the COVID-19 pandemic. The study found that after vaccination, investors should increase their investments in energy commodities rather than gold. These studies have explored the positive significance of different markets for energy market risk hedging strategies; however, few have focused on fintech and carbon futures.

With the arrival of the fourth Industrial Revolution, fintech has developed rapidly. As a subversive change in the financial field, its related assets have also attracted the attention of many investors. The development of fintech could bring a turnaround to the energy market, which strengthens the linkages between related markets. In previous studies, most scholars focused on the spillover effect of the technology market. Ahmad (2017) found tech stocks play a crucial role in the return and volatility spillover of renewables and crude oil. Their results suggest that the combination of clean energy indices and crude oil futures offers more profitable hedging opportunities than technology stocks. Nasreen et al. (2020) examined the dynamic correlation between oil prices, clean energy, and tech stock returns and found that the correlation between oil prices and tech stock returns is weak in terms of time and frequency. At present, there is little research literature on the spillover effects between fintech assets and energy markets, but some academics have also focused on the connections between fintech assets and other markets. Le (2023) proved that fintech and common stock are not good hedging tools in the same portfolio. Chen et al. (2023) captured the correlation between fintech and traditional financial institutions in China. In addition, some scholars have paid attention to the role of fintech in promoting energy transition. Croutzet and Dabbous (2021) highlighted the importance of fintech as a factor influencing the use of renewable energy. They found a significant positive correlation between fintech development and renewable energy use. This conclusion provides support for measures to encourage the development of fintech to facilitate the development of energy transition. Tao et al. (2022) also further confirmed that the development of fintech can help reduce greenhouse gas emissions.

The trading mechanism of the carbon markets provides market-oriented solutions for energy conservation and emission reduction, and is also an important means to promote energy transition (Zhang et al., 2020). The connectedness between the price of energy and the price of carbon has drawn increasing attention as carbon trading has spread quickly throughout the world. Zhang and Sun (2016) examined the correlation between carbon pricing and the prices of fossil energy. They found that the coal market has a significant relationship with the carbon market, followed by the natural gas market and Brent oil. Ma et al. (2020) built the linkage mechanism model of the Chinese capital market, energy market, and carbon emission trading markets. The result shows that each price of market variation in the product return series exhibits clustering, and the dynamic correlation exhibits the characteristics of time-varying and persistence. To investigate the frequency volatility spillovers, connectivity, and the nonlinear link between the price of the European Emission Allowance (EUA) and the renewable energy index, Hanif et al. (2021) used different Copula functions to discover that the short-term spillover intensity between the carbon price and the S & P clean energy and wind energy index is higher. In addition, Su et al. (2023) captured the extreme risk spillover between the carbon markets and the energy markets.

In fact, the hedging properties of fintech and carbon futures have already been discussed in the literature. Rabbani et al. (2023) examined spillover effects and hedging strategies between fintech, sukuk, and Islamic equity markets and found that fintech plays a significant role in fixed-income Islamic portfolios. Tiwari et al. (2023) pointed out that fintech and green financial instruments not only help investors diversify their portfolios to hedge risks and enhance returns but also contribute to reducing the negative impacts of climate change. Pham et al. (2022) found that during periods of low volatility, carbon prices are decoupled from cryptocurrencies. This study highlights the diversified returns of carbon, green, and non-green cryptocurrencies over time. Suleman et al. (2023) studied the time-frequency spillovers and connectedness network between the European ETS and sustainable development markets, finding that the carbon market can reduce portfolio risk in both the short and long term. Through the above literature, we find that the relative hedging properties of fintech and carbon futures, as representative assets of the digital and green economy, have been supported by some studies. In recent years, significant fluctuations in energy markets have led to an increased demand for hedging, making it necessary to analyze the hedging capabilities of carbon futures and fintech in the energy markets.

Additionally, whether considering market connectedness or hedging

and portfolio strategies, the existing literature mostly focuses on the average effects between markets, emphasizing risk transmission and hedging strategies under normal market conditions while neglecting extreme market situations. In studies concerning connectedness, Sadorsky (2012) used the multivariate GARCH model to analyze the volatility spillover effects among the stock prices of oil, clean energy companies, and technology companies. The findings indicate that there is a stronger correlation between the stock prices of clean energy and technology stock prices than there is with oil prices. Dogan et al. (2022) employed the TVP-VAR method to study the correlation and spillover effects between green finance and renewable energy, noting that the dynamic correlation is heterogeneous over time and influenced by unexpected events. Akyildirim et al. (2022) used the same method to explore the correlation between the energy stock indices of major oil-exporting and oil-importing countries, finding that oil-exporting countries primarily transmit shocks, while oil-importing countries primarily absorb shocks. Liu et al. (2023) employed the DCC-MVGARCH model and spillover index method to study the volatility link between the European carbon emissions market and the energy markets. Their results indicate that there is indeed volatility correlation and bidirectional spillover effects between the two markets. Although these studies have well complemented the literature related to risk spillovers in energy markets, most of them have captured spillover effects between markets only from the perspective of average shocks. However, the risk spillover effects in extreme market conditions need further attention, as they often result in greater losses for investors.

From the perspective of hedging characteristics and portfolios, most of the previous literature has analyzed this under average or specific market conditions. Arif et al. (2022) explores the hedging and safe-haven potential of green bonds in relation to traditional stocks, fixed income, commodities, and foreign exchange investments, finding that green bond indices can serve as a diversification asset for medium- to long-term equity investors. Chen et al. (2023) studied the time-varying correlation and hedging effectiveness of 12 green economy sector stocks against natural gas futures. They conducted a hedging effectiveness analysis for each asset, demonstrating that under average market conditions, green economy sector stocks can provide a satisfactory hedging effect against natural gas futures market risks. However, Gao et al. (2024) pointed out that investors need to make additional adjustments to their portfolios during special events, especially under extreme market conditions. It is worth noting that many scholars have recognized the advantages of quantiles in analyzing extreme market conditions (Yousaf et al., 2022). Currently, the academic community has not proposed a unified framework for hedging and investment strategy analysis based on the quantile connectedness approach.

Based on the above review, we find that there are still gaps in the current literature. This paper proposes a hedging and investment strategy analysis framework based on quantile connectedness, which not only captures the risk transmission mechanisms among fintech, carbon futures, and energy markets under extreme market conditions but also provides investors with portfolio analysis to address complex and dynamic market scenarios. This serves as a valuable addition to the existing literature.

3. Methodology

3.1. Quantile connectedness approach

As the cornerstone of our methodology, we use the quantile connectedness approach (Chatziantoniou et al., 2021) to study the connectivity across the fintech, carbon future, and energy markets. We first build a quantile vector using a quantile vector autoregression (QVAR), and then we use this model to compute all connectedness metrics:

$$Z_t = \boldsymbol{\mu}_t(\tau) + \boldsymbol{d}_1(\tau)Z_{t-1} + \boldsymbol{d}_2(\tau)Z_{t-2} + \ldots + \boldsymbol{d}_p(\tau)Z_{t-p} + \boldsymbol{u}_t(\tau) \quad (1)$$

In the top Eq. (1), Z_t represents a vector of the internal variables, τ takes values within [0,1] and characterizes a value of the indicator's quantile. The variable p represents the QVAR model's lag period, $\boldsymbol{\mu}_t(\tau)$ means a conditional mean vector, $\boldsymbol{d}_j(\tau)$ refers to the QVAR coefficient matrix, and $\boldsymbol{u}_t$ denotes the error vector. QVAR(p) is transformed into QVMA (∞), and the technique proposed by Wold is utilized:

$$Z_t = \boldsymbol{\mu}_t(\tau) + \sum_{j=i}^{p} \boldsymbol{d}_j(\tau)Z_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}_t(\tau) + \sum_{i=0}^{\infty} \boldsymbol{Z}_i(\tau)\boldsymbol{u}_{t-i} \quad (2)$$

The generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998) is employed to establish the impact of a disturbance in series j has on variable i by means of the variability of its predicted error. This can be said in the form shown below:

$$\theta_{ij}(H) = \frac{\left(\sum(\tau)\right)_{jj}^{-1} \sum_{h=0}^{H} \left(\left(\boldsymbol{Z}_h(\tau) \sum(\tau)\right)_{ij}\right)^2}{\sum_{h=0}^{H} \left(\boldsymbol{Z}_h(\tau) \sum(\tau) \boldsymbol{Z}_h'(\tau)\right)_{ii}} \quad (3)$$

$$\widetilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{K=1}^{N} \theta_{ij}(H)} \quad (4)$$

After normalization, the following equations hold true: $\sum_{i=1}^{N} \widetilde{\theta}_{ij}(H) = 1$and $\sum_{j=1}^{N} \sum_{i=1}^{N} \widetilde{\theta}_{ij}(H) = N$. This indicates that each row sum equals to unity, representing the effect of a shock in series i on both itself and the remaining series j. Eq. (3) shows how the *ith* variables affect the variance of the *jth* variables' forecast error at horizon H, represented by $\widetilde{\theta}_{ij}(H)$.

The following formula can be used to determine the shock of one variable i on all other variables j:

$$TO_i(H) = \sum_{i=1\ i \neq j}^{N} \widetilde{\theta}_{ji}(H) \quad (5)$$

Similarly, if we want to calculate the shock of one variable i from all other variables j, we can use the following formula:

$$FROM_i(H) = \sum_{i=1\ i \neq j}^{N} \widetilde{\theta}_{ij}(H) \quad (6)$$

The difference between the total directional connectivity from others and the total directional connectedness towards others is shown by the overall directional connectedness net total. This can be thought of as series i's net effect on the per-established network:

$$NET_i(H) = TO_i(H) - FROM_i(H) \quad (7)$$

The total connectedness index (TCI) can be calculated using the following formulas:

$$TCI_i(H) = N^{-1} \sum_{i=1}^{N} TO_i(H) = N^{-1} \sum_{i=1}^{N} FROM_i(H) \quad (8)$$

3.2. Portfolio allocation methods

We examine several methods for building portfolios, including traditional methods and more contemporary methods involving connectedness-focused portfolios. Please take note that we only provide summaries of the strategies we employ.

The MVP approach, which finds the portfolio with the least volatility given a selection of financial assets, is one widely used technique in multivariate portfolio analysis (Markovitz, 1959). The following formula is used to estimate the weights of the portfolios:

$$\omega_{Ht} = \frac{\boldsymbol{H}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{H}_t^{-1}\boldsymbol{I}} \quad (9)$$

The $\boldsymbol{I}$ is a multidimensional vector of ones with dimensions m, $\boldsymbol{H}_t$ is a conditional variance-covariance matrix with dimensions $m*m$ for period

Table 1
Brief description of data.

Sector	Index	Abbreviation
Energy markets	Crude Oil WTI	OIL
	S&P/TSX Renewable Energy & Clean Technology Index	RECT
	MAC Global Solar Energy Index	SOLAR
	ISE Global Wind Energy Index	WIND
Metal markets	Gold	GOLD
	Silver	SILVER
Fintech market	Global X FinTech ETF	FINTECH
Carbon futures market	Carbon Emissions Futures	CRN

t, and ω_{Ht} is a portfolio weight vector with dimensions $m*1$.

The MCP is a different newly created and well-liked portfolio construction strategy (Christo et al., 2024). This is where the technique deviates from the MVP: the portfolio weights are established by reducing the conditional correlations. The following is an explanation of how the portfolio weights are calculated:

$$R_t = diag(H_t)^{-0.5} H_t diag(H_t)^{-0.5} \tag{10}$$

Where R_t is a matrix with dimensions of $m*m$. With this, the weights for the Minimum Correlation Portfolio (MCP) are provided by:

$$\omega_{Rt} = \frac{\boldsymbol{R_t}^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{R_t}^{-1}\boldsymbol{I}} \tag{11}$$

Finally, we use pairwise connectedness indices to construct the MCOP (Broadstock et al., 2022). Network shocks can be reduced by using a portfolio strategy that reduces bilateral connectedness. Consequently, in the final portfolio, assets that neither influence nor are influenced by others are assigned a higher weight. This has the following mathematical expression:

$$\omega_{Ct} = \frac{\boldsymbol{PCI_t}^{-1}\boldsymbol{I}}{\boldsymbol{IPCI_t}^{-1}\boldsymbol{I}} \tag{12}$$

Where $\boldsymbol{PCI_t}$ stands for the bilateral connectivity indicator matrix.

3.3. Portfolio evaluation approaches

To evaluate the performance of the portfolios, two measures are used: the hedging efficacy (Ederington, 1979) and the Sharpe ratio (Sharpe, 1963).

The Sharpe ratio (SR), also referred to as the reward to volatility ratio, can be computed using the following formula:

$$SR = \frac{\bar{r}_p}{\sqrt{var(r_p)}} \tag{13}$$

Where the portfolio returns, assuming a zero risk-free rate, are denoted by the symbol r_p. The higher the SR in relation to portfolio risk, the better the returns. The SR makes it possible to compare different portfolios because it provides information on the highest portfolio return for a particular level of volatility.

The hedge-effectiveness is given by:

$$HE_i = 1 - \frac{var(r_p)}{var(r_i)} \tag{14}$$

Where the volatility of asset I is denoted by var. (r_i), the portfolio variance is indicated by var. (r_p), and the percentage decrease in the variance of the asset I 's unhedged position is denoted by HE_i. A high (low) risk decrease is indicated by a high (low) HE indexes.

4. Data

A brief description of the data is presented in Table 1. This paper focuses on three markets, namely fintech, carbon futures, and energy markets. We choose Global X FinTech ETF (FINTECH) to represent the fintech market, which is a basket of stocks of fintech-related companies that are revolutionizing mature industries including insurance, investment, fundraising, and third-party lending through cutting-edge mobile and digital technologies.[2] The carbon market is mainly represented by the price of carbon emission futures in the EU (CRN). As far as we know, the EU carbon futures market is currently the largest and longest-running carbon futures trading market in the world (Yuan et al., 2023). Within the energy market, we include the widely followed crude oil market, and the clean energy markets made up of wind, solar, and clean energy technologies, which are represented by WTI Crude Oil price (OIL), ISE Global Wind Energy Index (WIND), MAC Global Solar Energy Index (SOLAR), and S&P/TSX Renewable Energy & Clean Technology Index (RECT) respectively. Additionally, to better illustrate the effectiveness of hedging, we include gold (GOLD) and silver (SILVER), two traditional safe-haven assets, whose hedging benefits have been studied by scholars (Akhtaruzzaman et al., 2021). The data selected in this paper span from January 4, 2017, to March 6, 2023, with a total of 1448 observations. Our data period includes the outbreak of COVID-19 and the Russia-Ukraine conflict, which makes it possible to observe the impact of unexpected events on the overall spillover level. All series are obtained from Bloomberg and https://www.investing.com.

By using the first-order difference of the logarithm prices, all the price data are transformed into logarithm returns. Fig.1 depicts the time series plots of returns for the fintech, carbon futures, and energy markets. It shows that returns were more volatile during the COVID-19 pandemic and the Russia-Ukraine conflict, two significant economic events. This increased volatility indicates that the market's sensitivity to uncertainty and risk rises during major events. Such fluctuations may reflect investors' concerns about future economic conditions, sharp changes in market sentiment, and the potential impact of external shocks on corporate profits and the overall economy.

The descriptive statistics of all returns are shown in Table 2. First, all average return rates are positive, indicating that investments in these markets are profitable. Among them, the average return rate of CRN is the highest at 0.179, while the average return rate of RECT is the lowest, nearly equal to 0. Second, the standard deviations of OIL and CRN are greater than those of other assets, indicating that OIL and CRN carry higher market risk. Third, the skewness, kurtosis, and Jarque-Bera statistics show that most of these series are not normally distributed and exhibit leptokurtic distributions. Fourth, all asset series are stationary at the 1 % level, according to Elliott, Rothenberg, and Stock's (ERS) modified ADF test. Finally, the Ljung-Box Q statistics indicate that the return data of all assets exhibit autocorrelation. These results provide a good foundation for subsequent model building.

The coefficient matrix for the fintech, carbon futures, and energy markets is shown in Fig.2. First, we can see that there are significant positive correlations among most markets. Notably, the correlation between gold and silver is the highest at 0.79, which may be due to both being viewed as similar safe-haven assets by investors. Additionally, there are significant correlations between fintech and the three clean energy markets, with coefficients ranging from 0.58 to 0.66, while the correlation between fintech and the crude oil market is very low. This variable correlation suggests the potential for diversification effects of fintech in the energy markets. Finally, we find that CRN has a weak positive correlation with other markets, with correlation coefficients ranging from 0 to 0.2. Therefore, this provides preliminary evidence that CRN may serve as a hedging tool for other markets.

[2] https://markets.ft.com/data/etfs/tearsheet/summary?s=FINX:NMQ:USD.

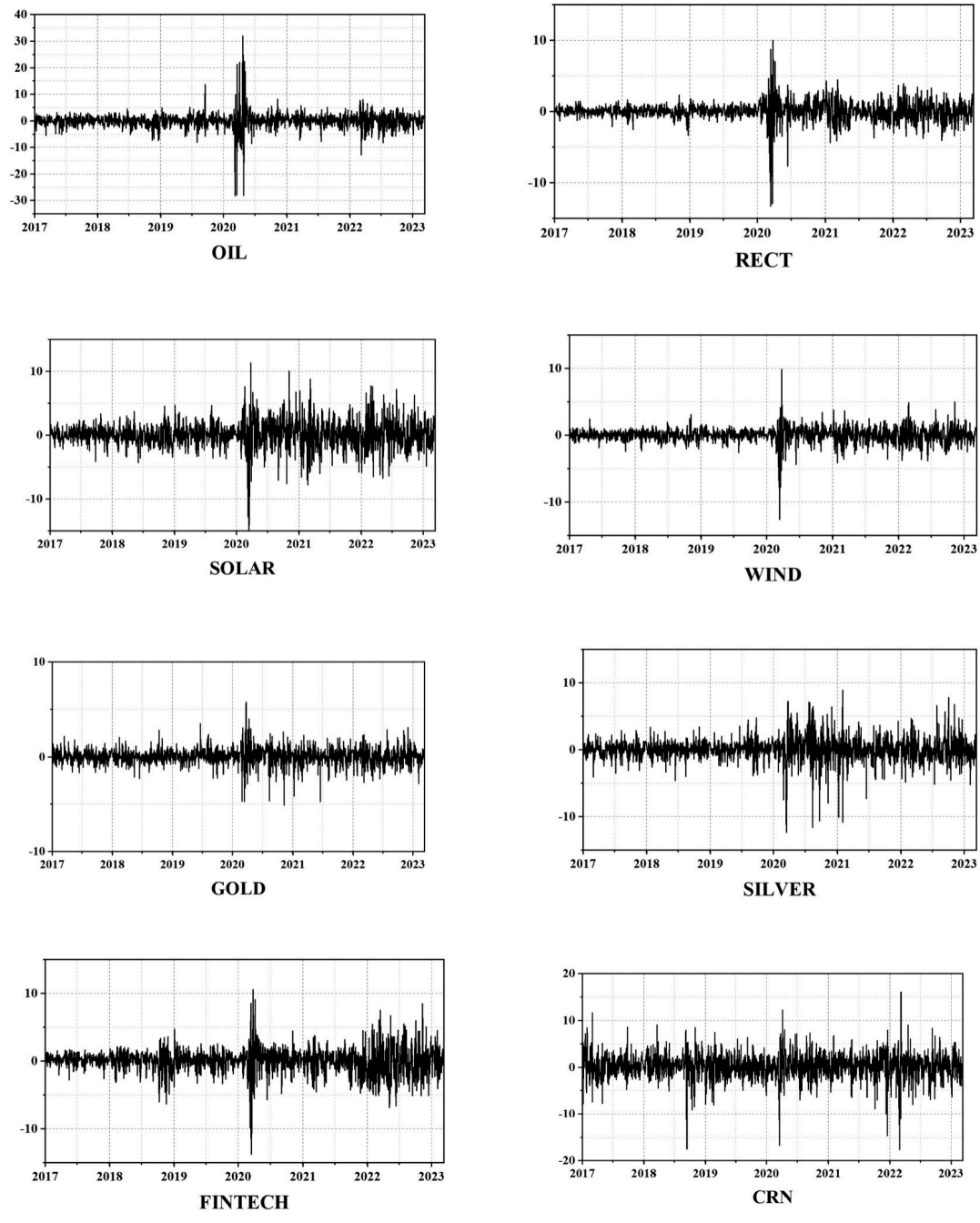


Fig. 1. Time series plots of the fintech, carbon future and energy market returns.

5. Empirical results

5.1. Quantile connectedness

5.1.1. Static quantile connectedness

The static connectedness levels at different quantiles are shown in Tables 3 to 5. The "From" denotes spillover from other markets, "TO" denotes the effect of the spillover to other markets. The "TCI" value represents the total risk spillover strength, while the "NET" value represents the net value of the spillover effect. The market is a recipient if the "NET" value is negative; on the other hand, it is a contributor if the "NET" value is positive.

In Table 3, we can see that the TCI is 44.2 % in the medium ($\tau = 0.5$). This demonstrates that the level of information transmission among the sample variables is approximately 44 %. According to Ahmad (2017), it can be said that the level of system information transfer in the whole system is moderately high, and can be suitable for the analysis of hedging and portfolio diversification. To be specific, the biggest spillover impact is between Gold and Silver, while the least is between Gold and CRN. Our results are consistent with J. Chen et al. (2022). This may be because Gold and Silver have a natural connection as traditional safe-haven assets, while CRN, as an emerging market, possesses a certain degree of independence. In addition, according to the value of "To" in the results of the static spillover analysis, clean energy markets (RECT, Wind, and Solar) are the largest spillover transporter in this system. RECT has the highest spillover for Solar, Wind, and Fintech. Similarly, it is not difficult to see that in addition to the higher spillover among the three clean energy markets, Wind and Solar also have a higher spillover to Fintech. Specifically, the spillover of RECT, Wind, and Solar to Fintech is 19.1 %, 14.7 %, and 17.7 % respectively. For return shocks passed

Table 2
Descriptive statistics of returns.

	OIL	RECT	SOLAR	WIND	GOLD	SILVER	FINTECH	CRN
Mean	0.08	0	0.09	0.009	0.029	0.011	0.029	0.179
	- 0.335	- 0.991	- 0.12	- 0.772	- 0.232	- 0.813	- 0.574	- 0.019
Variance	9.931***	2.027***	4.809***	1.464***	0.845***	3.355***	3.729***	8.376***
Skewness	0.103	- 1.104***	- 0.391***	- 0.750***	- 0.218***	- 0.583***	- 0.538***	- 0.477***
	- 0.108	0	0	0	- 0.001	0	0	0
Ex.Kurtosis	27.384***	17.061***	5.118***	14.002***	5.296***	7.255***	5.532***	4.387***
	0	0	0	0	0	0	0	0
JB	45,212.701***	17,843.496***	1616.275***	11,955.497***	1702.417***	3255.653***	1914.795***	1215.347***
	0	0	0	0	0	0	0	0
ERS	- 14.934***	- 16.245***	- 16.020***	- 8.921***	- 4.847***	- 14.694***	- 10.227***	- 2.719***
	0	0	0	0	0	0	0	- 0.007
Q(20)	54.880***	58.348***	39.599***	66.316***	19.458**	16.925*	37.456***	21.056**
	0	0	0	0	- 0.022	- 0.06	0	- 0.011
Q2(20)	761.945***	1845.196***	531.958***	680.304***	240.929***	262.484***	1248.367***	139.795***
	0	0	0	0	0	0	0	0

Notes: ***, **, * indicate statistical significance at 1 %, 5 %, and 10 % levels; Skewness is tested using D'Agostino (1970) method; Kurtosis is assessed via the Anscombe and Glynn (1983) test; The JB notation refers to the Jarque and Bera (2024) test for normality; The ERS acronym stands for the unit-root test proposed by Elliott et al. (1992); $Q2(20)$ represents the weighted Portmanteau test statistics developed by Fisher and Gallagher (2012).

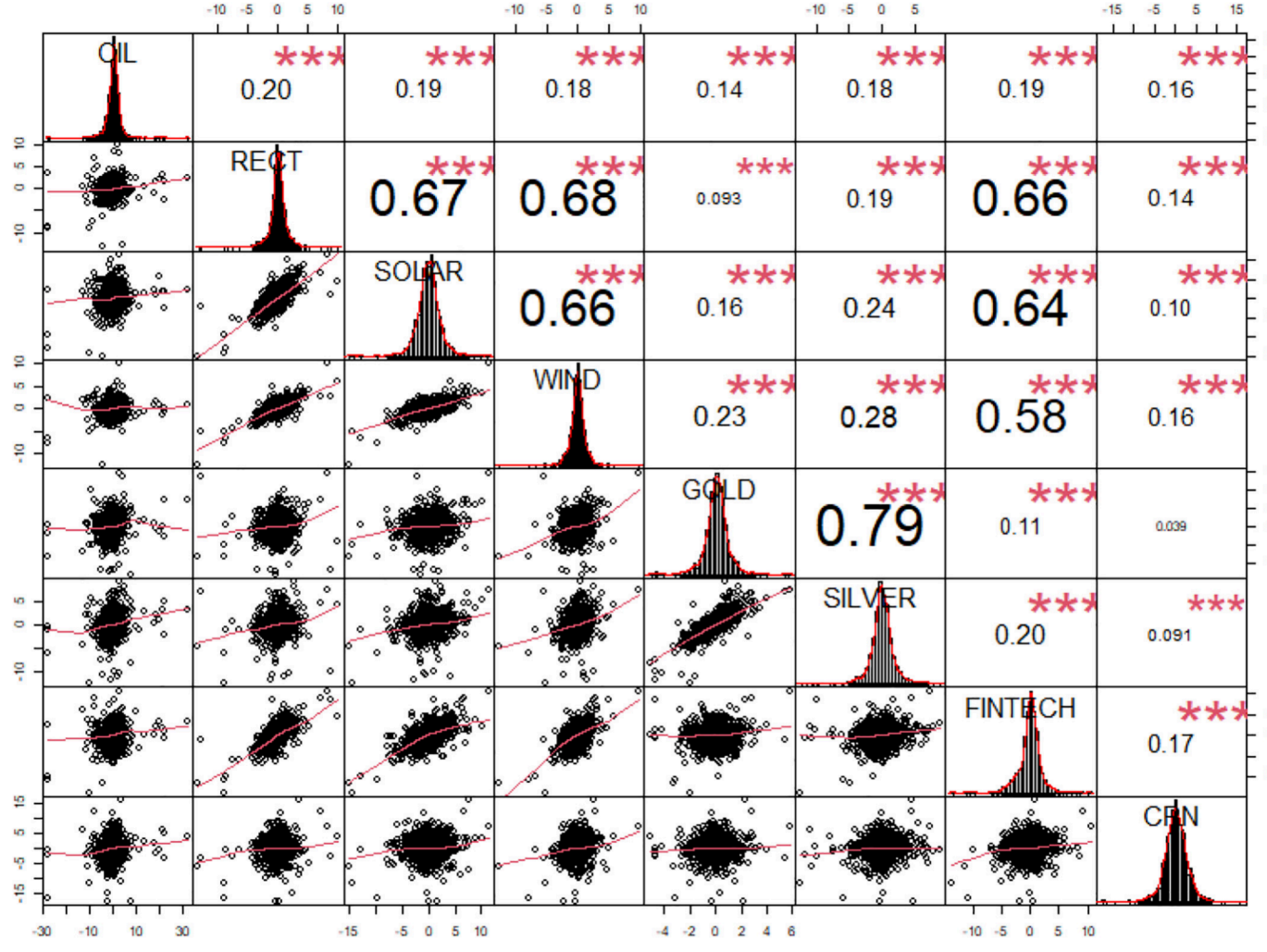


Fig. 2. Correlation matrix of fintech, carbon future and energy markets.

from the Fintech to other assets, we note that RECT, Wind, and Solar are the largest receivers. The spillover values passed by Fintech to RECT, Wind, and Solar are 17.7 %, 15 %, and 16.9 %. Our findings suggest that RECT, Wind, Solar, and Fintech are potentially interconnected since shocks from one market can potentially spread to others. In addition, we can find that the smallest spillover to other markets is the CRN, with a value of 6.1 %. The outcome shows that the other markets only experience a marginal impact from CNR shocks. It is noteworthy that the relationship between fintech and the Oil is weak compared to clean energy markets. Oil contributes 10.9 % to the overall system, which is stronger than the CRN and weaker than the other remaining markets. In addition, we also look at the "NET" value, and find that RECT, Solar,

Table 3
Static connectedness at the conditional median ($\tau = 0.5$).

	OIL	RECT	SOLAR	WIND	GOLD	SILVER	FINTECH	CRN	FROM
OIL	82.2	3.2	3.1	2.5	1.4	2.6	3	2	17.8
RECT	1.6	40.4	18.3	19.3	0.3	1.4	17.7	0.8	59.6
SOLAR	1.4	18.7	40.8	17.8	1.3	2.6	16.9	0.4	59.2
WIND	1.1	19.7	18.5	39.3	2	3.2	15	1.2	60.7
GOLD	1	0.5	1.7	2.9	57.4	35.5	0.8	0.1	42.6
SILVER	1.7	1.9	3.2	4.1	33	53.5	2.3	0.5	46.5
FINTECH	1.5	19.1	17.7	14.7	0.5	1.7	43.6	1.2	56.4
CRN	2.5	1.8	1	2.6	0.1	0.7	2.3	88.9	11.1
TO	10.9	65	63.4	64	38.6	47.7	58	6.1	353.8
NET	- 6.9	5.4	4.2	3.3	- 3.9	1.1	1.6	- 4.9	TCI
NPDC	1	7	6	4	2	3	5	0	44.2

Table 4
Static connectedness at the lower median ($\tau = 0.05$).

	OIL	RECT	SOLAR	WIND	GOLD	SILVER	FINTECH	CRN	FROM
OIL	20.6	11.5	11.4	11	11.4	11	11.9	11.2	79.4
RECT	9.8	17.8	14.5	14.6	9.5	9.9	14.5	9.5	82.2
SOLAR	9.7	14	17.7	14.1	10.3	10.4	14.3	9.4	82.3
WIND	9.6	14.1	14.4	17.1	10.5	10.7	13.8	9.8	82.9
GOLD	10.5	10.2	11.1	11.3	19.2	16.5	11.2	10	80.8
SILVER	10.3	10.8	11.6	11.4	16	17.9	11.7	10.3	82.1
FINTECH	10.1	14.1	14.1	13.5	10.2	10.4	17.4	10.2	82.6
CRN	11.2	11.3	11.2	11.7	10.9	10.8	12.2	20.8	79.2
TO	71.2	86	88.2	87.6	78.9	79.6	89.6	70.4	651.5
NET	- 8.2	3.8	5.9	4.6	- 1.9	- 2.5	7	- 8.8	TCI
NPDC	0	4	6	5	2	3	7	1	81.4

Table 5
Static connectedness at the upper median ($\tau = 0.95$).

	OIL	RECT	SOLAR	WIND	GOLD	SILVER	FINTECH	CRN	FROM
OIL	23.1	11.2	11.1	11	10.9	11	10.7	11.1	76.9
RECT	8.7	18.2	14.6	14.8	9.5	10	14.5	9.7	81.8
SOLAR	8.6	14.5	18	14.3	10.4	10.7	13.9	9.7	82
WIND	8.3	14.7	14.4	18.1	10.6	10.6	13.4	9.9	81.9
GOLD	9.1	10.4	11.3	11.6	19.9	17.2	10.2	10.3	80.1
SILVER	9.2	10.7	11.7	11.5	16.8	19.3	10.6	10.2	80.7
FINTECH	8.5	14.8	14.5	13.9	9.6	10.1	18.7	10	81.3
CRN	9.9	11.5	11.5	11.8	11	11.3	11.5	21.4	78.6
TO	62.4	87.6	89.2	88.9	78.7	80.8	84.8	71	643.3
NET	- 14.5	5.8	7.2	7	- 1.5	0.2	3.5	- 7.6	TCI
NPDC	0	5	7	6	2	3	4	1	80.4

Wind, Silver, and Fintech have positive net spillover values, indicating that these markets are net contributors, while Oil, Gold, and CRN are net receivers. The RECT (5.4 %) is the largest net contributor, followed by Solar (4.2 %), Wind (3.3 %), and Fintech (1.6 %); Oil (- 6.9 %) is the largest recipient, followed by CRN (- 4.9 %) and Gold (- 3.9 %).

To distinguish the connectedness in bear and bull markets, we estimate the connectedness at the different quantiles (0.05 and 0.95) in Table 4 and Table 5. It can be found that the TCI in the low quantile (81.4 %) and high quantile (80.4 %) is larger than that in the medium (44.2 %). That is, compared to normal market conditions, extreme conditions have a higher effect on spillover. This result is consistent with Dai et al. (2022), which claim that market spillover effects are larger during times of extreme market conditions than during times of normal market conditions. It may be because in extreme cases, especially under negative shocks, financial markets are exposed to systemic risk and connectedness increases significantly.

Secondly, compared to the median quantile, the spillover indices for the sending and receiving of each asset are much larger at the high and low quantiles. This indicates that each asset generates more spillovers during extreme market periods. As pointed out by Qin et al. (2024), traditional mean connectedness methods cannot capture risk spillovers in extreme market conditions. In other words, the quantile connectedness method offers the possibility for our subsequent portfolio construction in extreme market conditions.

To more clearly visualize the risk spillover relationships among various assets. Fig. 3 shows the return connectedness network between fintech, carbon future, and energy markets at the 0.05, 0.50, and 0.95 quantiles. The size of the nodes represents the magnitude of net spillovers: green nodes indicate network receivers, while red nodes indicate network contributors. The thickness of the edges indicates the magnitude of pairwise network spillovers, with arrows pointing in the direction of the spillovers.

From the figure, we can draw the following conclusions at extreme quantiles ($\tau = 0.05$ or 0.95): First, the edges are thicker and the connections are more complex, which further confirms that the connectedness between markets are tighter at high/low quantiles compared to the median. Second, almost all nodes have increased in size, indicating that the net spillover effect of each asset has been enhanced. In other words, in extreme market conditions, each individual markets exhibit greater sensitivity to shocks. Finally, compared to the median, the roles of net senders and net receivers change in extreme markets. For example, in extreme negative market conditions ($\tau = 0.05$), the largest receiver shifts from Oil to CRN, and the largest contributor changes from RECT to Fintech. This seems to suggest that Fintech is more sensitive to

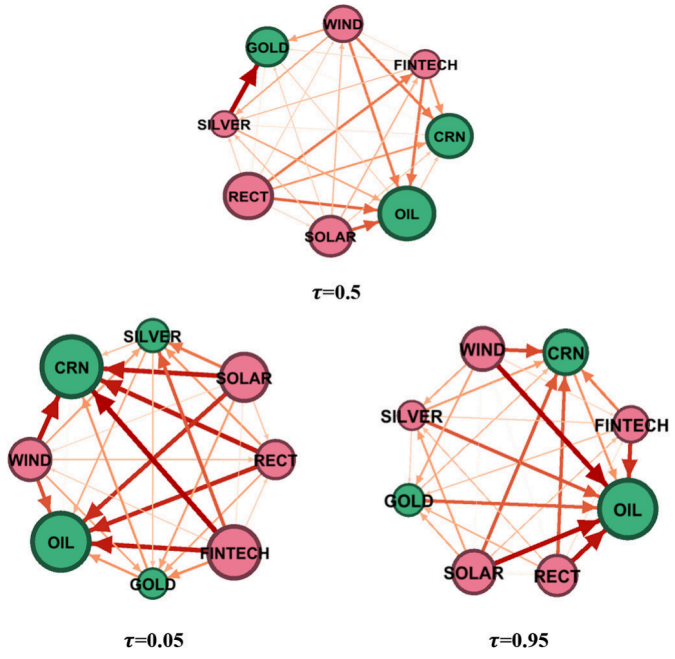


Fig. 3. The return connectedness network between fintech, carbon future and energy markets at the 0.05, 0.50, and 0.95 quantiles.
Note: Red and green nodes represent the contributors and receivers, respectively, with the arrow thickness indicating the strength of the connectedness. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

negative news. In addition, we find that Silver has changed from a contributor in normal market conditions to a receiver, which indicates that it is at a disadvantage in short-term extreme negative markets. In the extremely positive market ($\tau = 0.95$), the largest contributor changes from RECT to Solar, and the net receiver role of Oil is further strengthened. Such changes are important for investors and policymakers, and indicate the need to adapt portfolios and policies to different market conditions.

5.1.2. Dynamic quantile connectedness

Using static quantile connectedness analysis, we find differences in the spillover effects between the energy, carbon futures, and fintech markets under different market conditions. To further analyze the dynamic features of inter-market connectedness, we used the QVAR model with a 200 rolling window and a 20-step forecasting horizon. Figs. 4 to 6 depicts the dynamic total, net, and pairwise directional connectedness between markets under different conditions. The black shadow represents the spillover levels under normal market conditions ($\tau = 0.5$), corresponding to the values on the left y-axis, while the red line and grey line represent extreme negative ($\tau = 0.05$) and extreme positive ($\tau = 0.95$) market conditions respectively, corresponding to the values on the right y-axis.

Fig.4 illustrates the dynamic changes of the total connectedness index (TCI) across different market conditions. Under normal market conditions ($\tau = 0.5$), we observe that the TCI fluctuates between 25 % and 65 % over time. On one hand, this indicates significant spillover effects among the fintech, carbon futures, and energy markets under normal market conditions. On the other hand, the variance in TCI demonstrates the time-varying nature of these spillover effects. In addition, we find that inter-market connectedness can be affected by event shocks. At the beginning of 2020, we find an unprecedented increase of over 30 % in the level of TCI, and this high level of connectedness persisted until early 2021. During this period, the main influence was from the COVID-19 pandemic. The losses affected by the pandemic have caused tremors across financial markets, including fintech and energy markets, and increased connectedness from 30 % to 65 % in a two-month period. In other words, the outbreak of the COVID-19 pandemic has increased trepidation and uncertainty in the financial markets, enhancing the links between the fintech, energy, and carbon futures sectors. In addition, around February 2022, an increase in total connectedness can also be observed, and this is due to the systemic risk contagion triggered by the Russia-Ukraine conflict. Those results are consistent with Thanh Ha et al. (2024). Our findings emphasize the time-varying nature of the TCI, confirming that market linkages strengthen due to transient events.

We further observed the dynamic TCI under extreme market conditions (($\tau = 0.05$ or 0.95). We find that the connectedness between fintech, carbon future, and energy markets are greater under extreme conditions than under normal conditions, and their dynamic

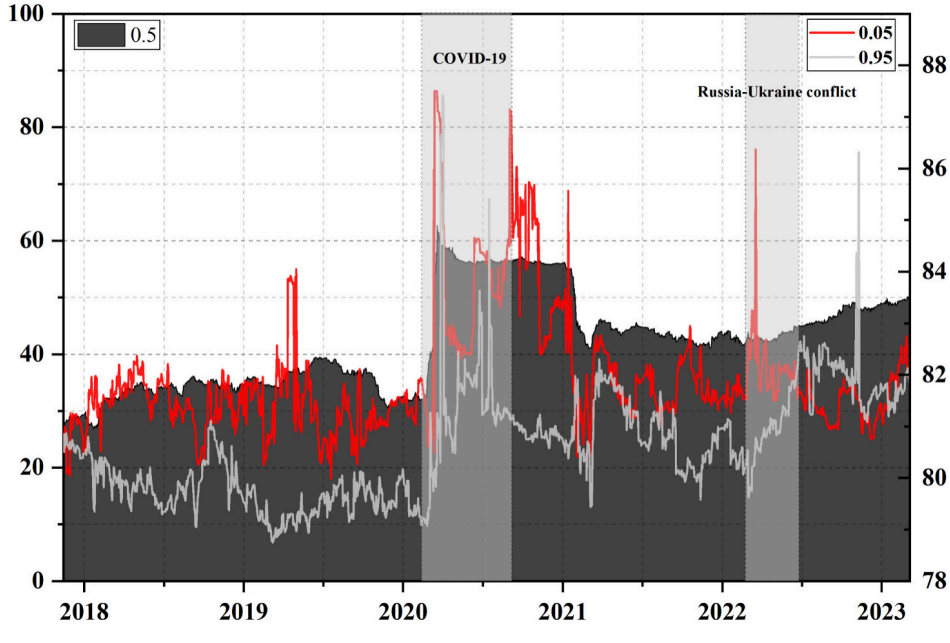


Fig. 4. Dynamic total connectedness at the 0.05, 0.50, and 0.95 quantiles.
Note: Results are based on the QVAR with a 200-period rolling window and a 20-period forecast horizon.

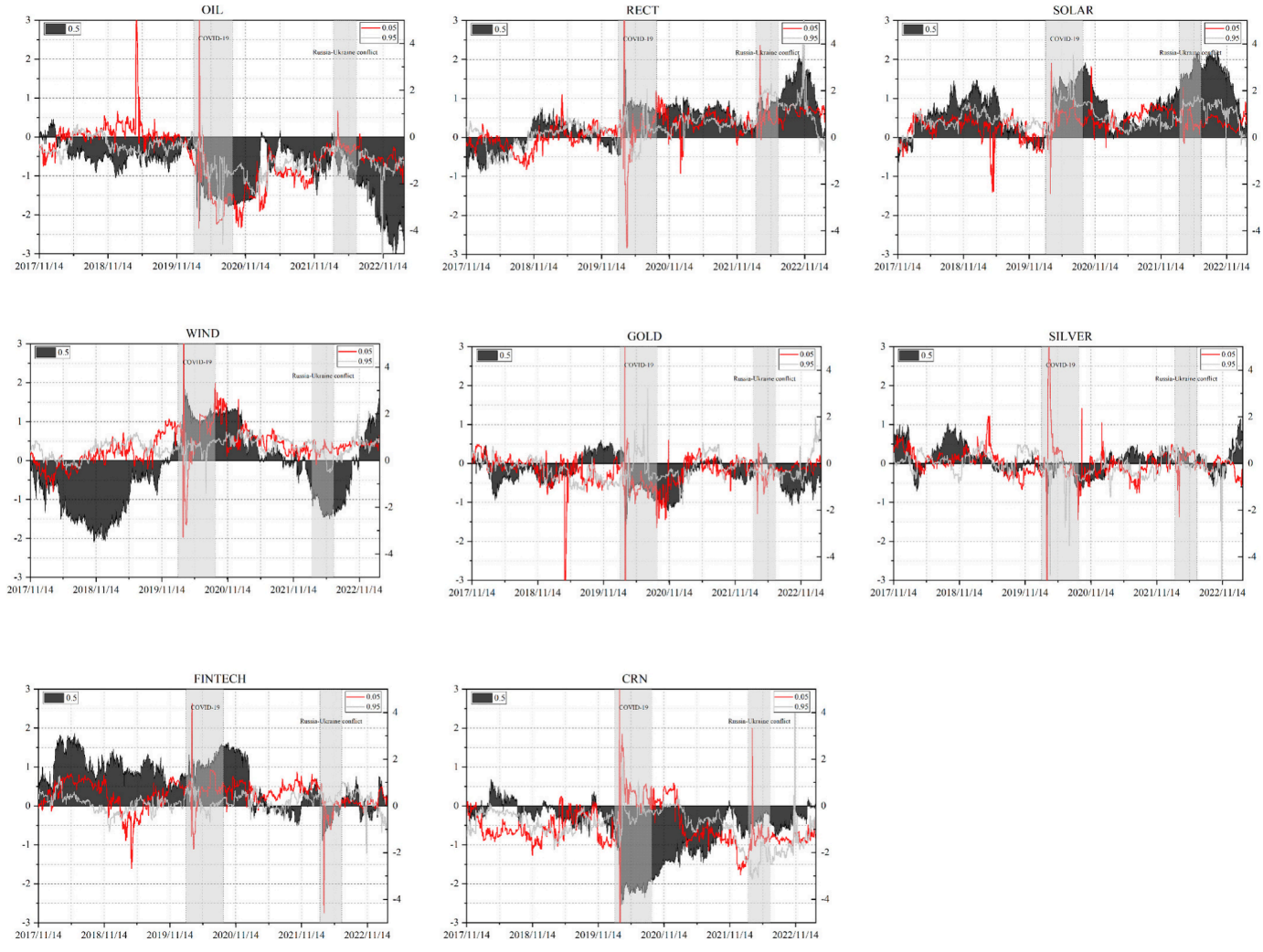


Fig. 5. Dynamic net connectedness at the 0.05, 0.50, and 0.95 quantiles.
Note: Results are based on the QVAR with a 200-period rolling window and a.

connectedness fluctuates between 78 % and 88 %. This is consistent with the results from static analysis. Additionally, we also find that the connectedness intensity is stronger at lower quantile (0.05) compared to upper quantile (0.95). In other words, Extreme negative shocks dominate the connectedness within the system for the most of the analysis period. This illustrates that the dependence in the tails is asymmetric. This could be due to investors care more about losses than gains (Dahlquist et al., 2017). Furthermore, we find that during the COVID-19 pandemic and the Russia-Ukraine conflict, the TCI at the 0.05 and 0.95 quantiles showed significant short-term increases. This demonstrates that TCI is also affected by event shocks in extreme market conditions. Despite facing different market situations, this impact may vary. In conclusion, our findings suggest that dynamic spillover effects among markets are more significant in extreme market conditions, particularly in extreme negative markets, compared to normal market conditions. The variations in spillover effects across different market conditions underscore the importance for investors to adjust their strategies flexibly and promptly to mitigate investment risks.

To further distinguish net contributors and net receivers in the markets, the results of net dynamic connectedness are shown in Fig. 5. It should be noted that negative values in the figure correspond to net receivers in the system, while positive values represent net contributors in the system.

In normal market conditions, we can divide all variables into three groups of assets: the first group is Oil, CRN, and Gold, which show net receivers for almost the entire sample period. The second group is RECT and Solar, which again act almost as net contributors. The third group is Wind, Silver and Fintech, whose roles switch between the net receiver and net contributor. Interestingly, Wind played the role of a contributor during the COVID-19 pandemic but became a net receiver during the Russia-Ukraine conflict. This indicates that the direction of risk spillovers for the same market can change when facing different unexpected events. Additionally, Silver, as a traditional safe-haven asset, has its net spillover mainly influenced by market supply and demand, without showing significant event dependency. In addition, we also find a significant increase in the net spillover effects of Fintech during the COVID-19 pandemic, possibly due to the rapid development of contactless Fintech services due to concerns about disease transmission (Ha, 2023). As the epidemic gradually eased, coupled with the impact of the energy market, the role of Fintech during the Russia-Ukraine conflict shifted between the net receiver and net contributor. In addition, against the backdrop of the climate crisis, countries are gradually beginning to emphasize energy transition and elevate the status of clean energy in the energy markets. This has made the net contribution effect of RECT and Solar more significant, while Oil has become the main receiver of risk.

However, under extreme markets, the role shifts of receivers or contributors are more pronounced in the fintech, carbon futures, and energy markets. This result demonstrates that there are significant differences between the net market spillovers caused by extreme shocks. Moreover, event dependence can still be captured under extreme market

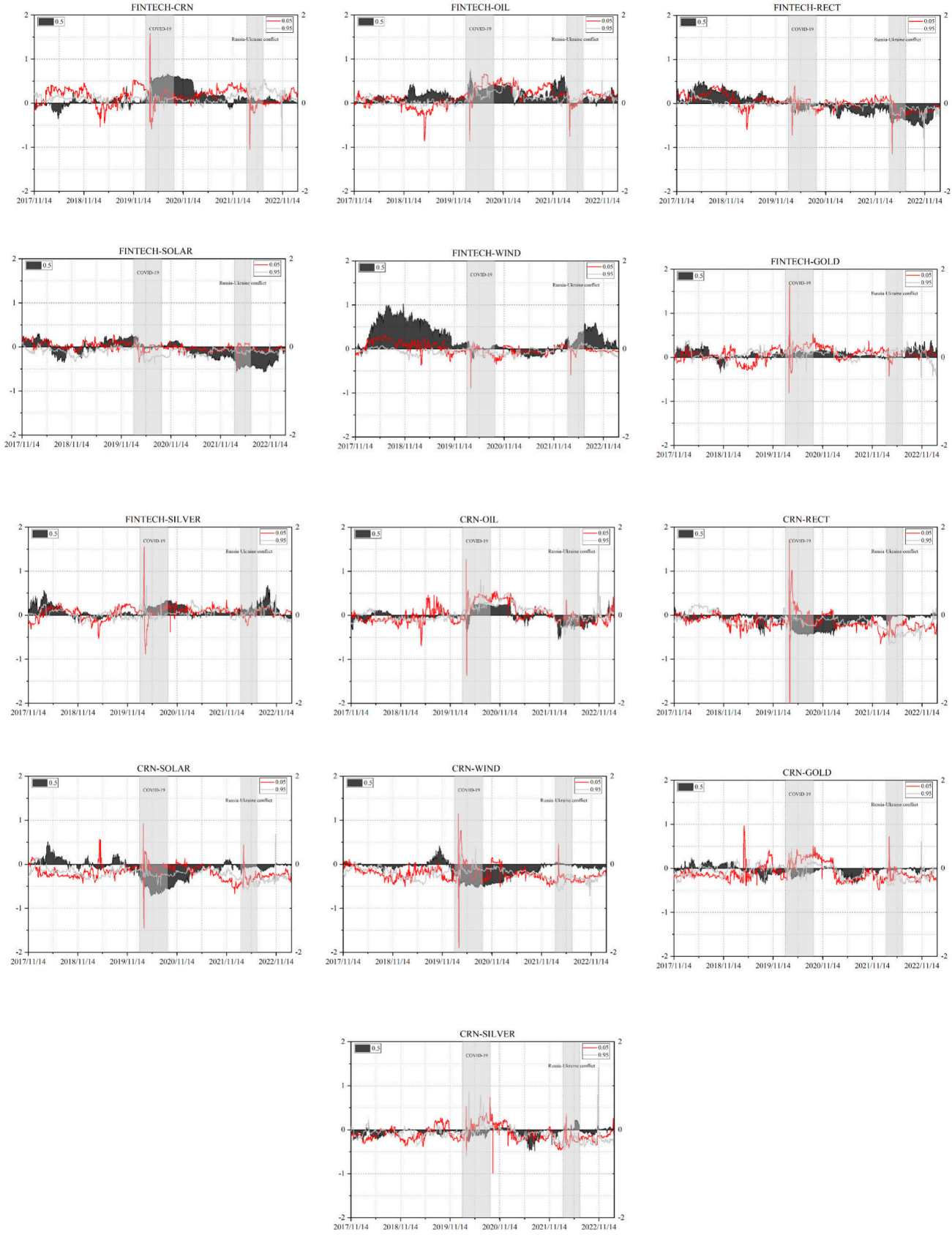


Fig. 6. Dynamic pairwise directional connectedness at the 0.05, 0.50, and 0.95 quantiles.
Note: Results are based on the QVAR with a 200-period rolling window and a.

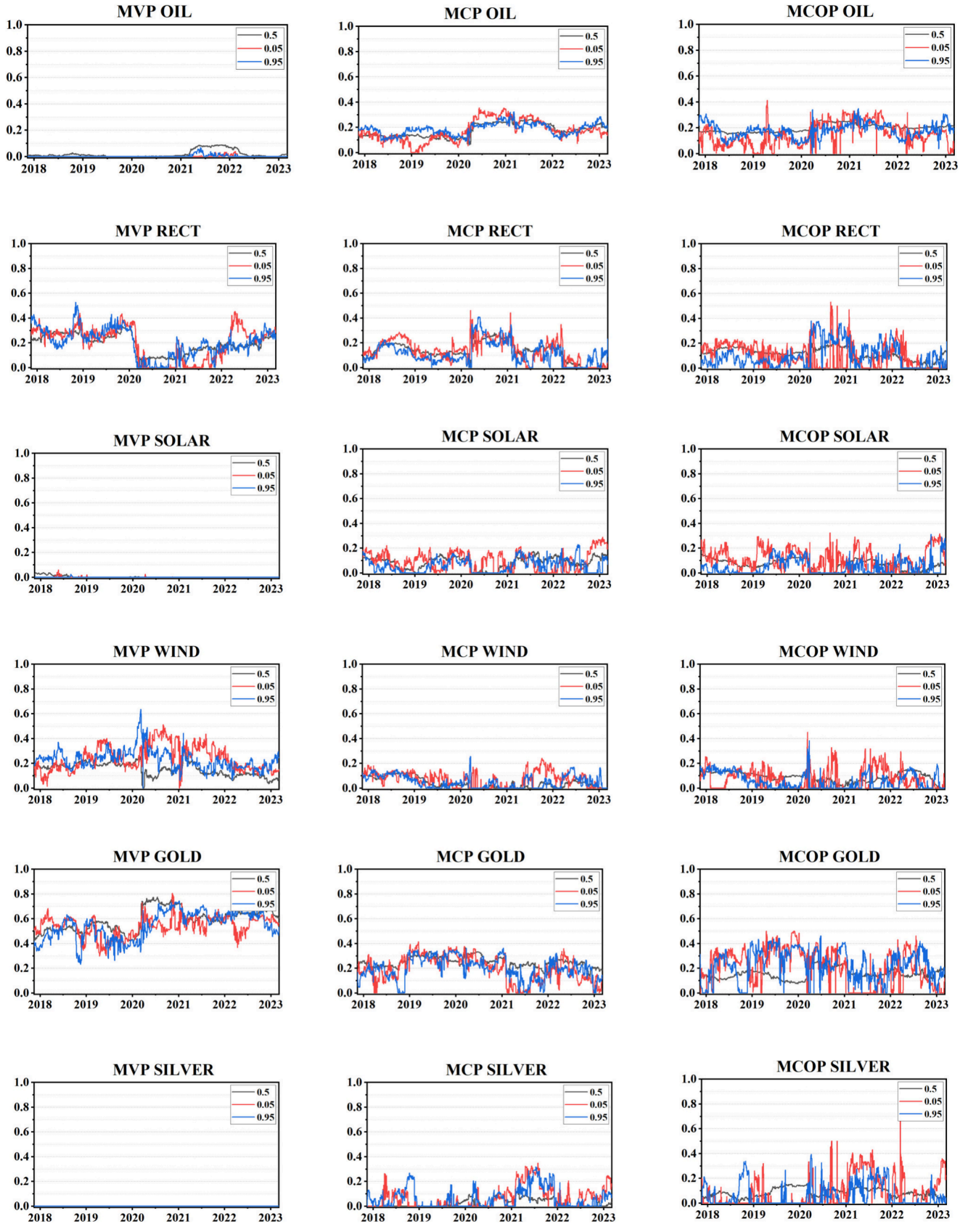


Fig. 7. Dynamic multivariate portfolio weights at the 0.05, 0.50, and 0.95 quantiles.
Note: The results for MVP, MCP and MCOP are based on QVAR with a 200-period rolling window and a 20-period forecast horizon.

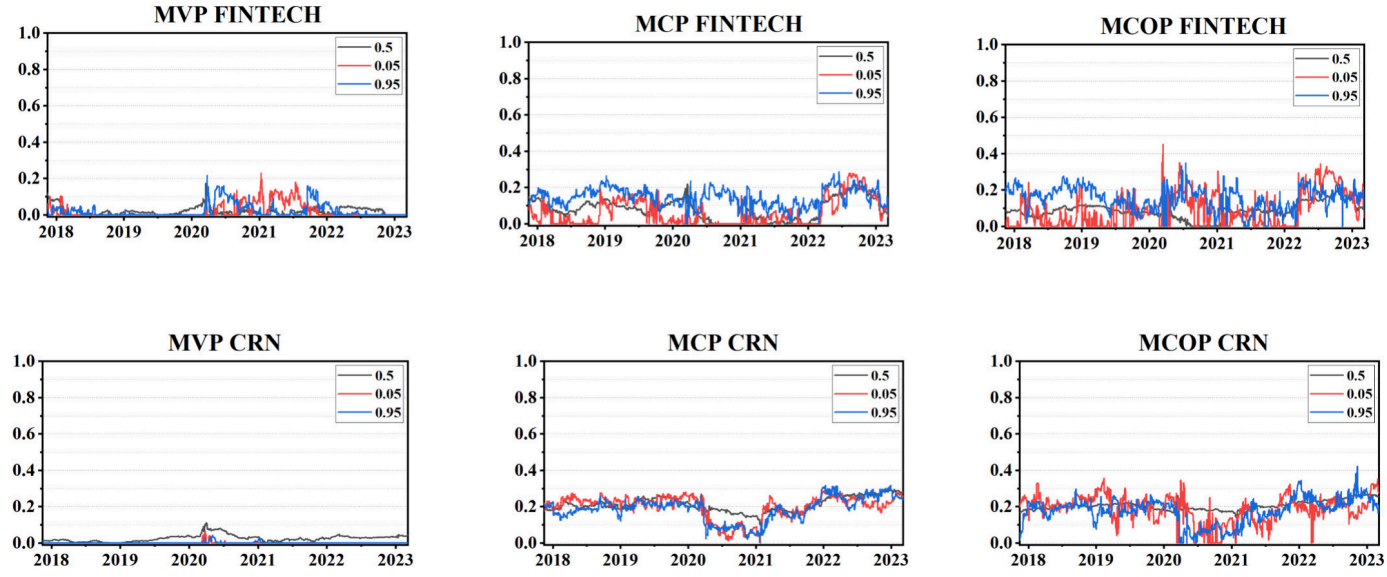


Fig. 7. (*continued*).

conditions, proving once again that net spillovers can increase in response to unexpected events such as COVID-19 or the Russia-Ukraine conflict. In summary, the above results show that the system is unstable under extreme conditions. Therefore, policymakers or investors need to keep an eye on the dynamics of net spillovers in fintech, carbon future and energy markets under extreme conditions, and this is useful for them to make the right policies and adjust their portfolios.

To further illustrate the direction and magnitude of connectedness between the fintech, carbon futures, and energy markets, Fig.6 presents the pairwise directional connectedness results under different market conditions. We have the following main findings: First, Fintech dominates the Oil and CRN markets, with its spillover effects further strengthening during the COVID-19 pandemic. When facing the clean energy markets, the role of Fintech changes over time, highlighting its diversified effects on the clean energy market. Secondly, CRN is dominated by most markets, especially the clean energy markets. Third, under extreme market conditions, the spillover effects between pairs of assets fluctuate significantly over time, posing higher demands on investors for portfolio adjustments and risk management.

In summary, whether in total, net, or pairwise connectedness analysis, we find that spillover effects in extreme market conditions are greater than in normal market conditions. Moreover, these spillover effects are asymmetric and complex in extreme market conditions. For relevant investors, adjusting portfolios in different market conditions is crucial as it helps stabilize the market and prevent significant losses. Therefore, based on the previous analysis of connectedness, this paper focuses on the construction of diversified portfolios under different market conditions in the following discussion.

5.2. Portfolio analysis

In this part, we use three approaches to present multivariate portfolios in different market conditions: minimum connectedness portfolios (MCOP), minimum correlation portfolios (MCP), and minimum variance portfolios (MVP). It should be noted that the MVP method aims to minimize portfolio volatility to the greatest extent, while the MCP method focuses on reducing the correlation between assets, and the primary goal of the MCOP method is to reduce the connectedness between assets. Our results are based on the connectedness analysis discussed previously. We focused on analyzing the dynamic weights of the portfolio, hedge effectiveness ratio, and cumulative returns. Additionally, we used the Sharpe ratio to evaluate the relative performance of different portfolios.

Table 6
Averaged portfolio weights and hedge effectiveness at the 0.5 quantile.

Minimum Variance Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.02	0.03	0.00	0.08	0.94	0.00
RECT	0.19	0.08	0.07	0.30	0.70	0.00
SOLAR	0.00	0.01	0.00	0.03	0.87	0.00
WIND	0.15	0.05	0.07	0.23	0.58	0.00
GOLD	0.59	0.09	0.45	0.74	0.24	0.00
SILVER	0.00	0.00	0.00	0.00	0.81	0.00
FINTECH	0.02	0.02	0.00	0.08	0.84	0.00
CRN	0.03	0.02	0.00	0.07	0.92	0.00
Minimum Correlation Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.17	0.05	0.11	0.25	0.85	0.00
RECT	0.13	0.07	0.00	0.25	0.30	0.00
SOLAR	0.09	0.05	0.00	0.15	0.70	0.00
WIND	0.04	0.04	0.00	0.12	0.02	0.76
GOLD	0.25	0.04	0.19	0.32	- 0.77	0.00
SILVER	0.02	0.03	0.00	0.08	0.57	0.00
FINTECH	0.08	0.06	0.00	0.19	0.62	0.00
CRN	0.21	0.04	0.15	0.28	0.81	0.00
Minimum Connectedness Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.20	0.03	0.16	0.25	0.84	0.00
RECT	0.12	0.05	0.04	0.18	0.22	0.00
SOLAR	0.07	0.04	0.00	0.13	0.67	0.00
WIND	0.09	0.04	0.01	0.14	- 0.09	0.11
GOLD	0.16	0.04	0.09	0.24	- 0.97	0.00
SILVER	0.08	0.04	0.03	0.14	0.52	0.00
FINTECH	0.09	0.04	0.00	0.16	0.58	0.00
CRN	0.21	0.03	0.17	0.26	0.79	0.00

Note: The results for MVP, MCP and MCOP are based on QVAR with a 200-period rolling window and a 20-period forecast horizon.

5.2.1. Allocation weights and hedge effectiveness

Fig.7 shows time-varying dynamic portfolio weights for fintech, carbon future and energy markets in different market conditions. Firstly, we find that the weight allocation of MVP differs significantly from that of MCP and MCOP. Since Gold has a much smaller variance compared to other assets, the MVP optimization allocated almost all the weight to

Table 7
Averaged portfolio weights and hedge effectiveness at the 0.05 quantile.

Minimum Variance Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.00	0.00	0.00	0.01	0.94	0.00
RECT	0.20	0.13	0.00	0.37	0.70	0.00
SOLAR	0.00	0.00	0.00	0.00	0.87	0.00
WIND	0.24	0.10	0.11	0.42	0.58	0.00
GOLD	0.54	0.08	0.38	0.64	0.24	0.00
SILVER	0.00	0.00	0.00	0.00	0.81	0.00
FINTECH	0.02	0.04	0.00	0.11	0.84	0.00
CRN	0.00	0.00	0.00	0.00	0.92	0.00
Minimum Correlation Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.17	0.08	0.04	0.31	0.84	0.00
RECT	0.14	0.09	0.00	0.27	0.25	0.00
SOLAR	0.10	0.07	0.00	0.23	0.68	0.00
WIND	0.07	0.06	0.00	0.17	- 0.05	0.37
GOLD	0.19	0.10	0.01	0.35	- 0.89	0.00
SILVER	0.07	0.08	0.00	0.26	0.53	0.00
FINTECH	0.06	0.07	0.00	0.21	0.59	0.00
CRN	0.20	0.06	0.05	0.27	0.80	0.00
Minimum Connectedness Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.14	0.09	0.00	0.30	0.85	0.00
RECT	0.10	0.09	0.00	0.24	0.29	0.00
SOLAR	0.11	0.08	0.00	0.26	0.70	0.00
WIND	0.07	0.07	0.00	0.21	0.00	0.99
GOLD	0.21	0.14	0.00	0.41	- 0.79	0.00
SILVER	0.09	0.12	0.00	0.33	0.56	0.00
FINTECH	0.09	0.09	0.00	0.28	0.61	0.00
CRN	0.19	0.07	0.05	0.30	0.81	0.00

Note: The results for MVP, MCP and MCOP are based on QVAR with a 200-period rolling window and a 20-period forecast horizon.

Table 8
Averaged portfolio weights and hedge effectiveness at the 0.95 quantile.

Minimum Variance Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.00	0.01	0.00	0.02	0.93	0.00
RECT	0.20	0.11	0.00	0.38	0.68	0.00
SOLAR	0.00	0.00	0.00	0.00	0.86	0.00
WIND	0.23	0.08	0.12	0.36	0.55	0.00
GOLD	0.54	0.11	0.35	0.69	0.19	0.00
SILVER	0.00	0.00	0.00	0.00	0.80	0.00
FINTECH	0.02	0.04	0.00	0.11	0.83	0.00
CRN	0.00	0.00	0.00	0.00	0.91	0.00
Minimum Correlation Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.19	0.05	0.11	0.26	0.84	0.00
RECT	0.11	0.09	0.00	0.29	0.23	0.00
SOLAR	0.06	0.05	0.00	0.15	0.67	0.00
WIND	0.05	0.05	0.00	0.13	- 0.08	0.19
GOLD	0.20	0.09	0.02	0.33	- 0.94	0.00
SILVER	0.06	0.08	0.00	0.24	0.52	0.00
FINTECH	0.15	0.05	0.07	0.22	0.58	0.00
CRN	0.19	0.06	0.07	0.29	0.79	0.00
Minimum Connectedness Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	*p*-value
OIL	0.18	0.06	0.09	0.27	0.85	0.00
RECT	0.10	0.09	0.00	0.29	0.26	0.00
SOLAR	0.05	0.06	0.00	0.17	0.68	0.00
WIND	0.06	0.06	0.00	0.16	- 0.04	0.48
GOLD	0.23	0.12	0.00	0.39	- 0.87	0.00
SILVER	0.06	0.09	0.00	0.25	0.54	0.00
FINTECH	0.15	0.06	0.04	0.25	0.60	0.00
CRN	0.18	0.07	0.05	0.28	0.80	0.00

Note: The results for MVP, MCP and MCOP are based on QVAR with a 200-period rolling window and a 20-period forecast horizon.

Gold. However, it should be noted that this optimization approach has significant drawbacks. The portfolio becomes overly concentrated in a single asset, lacking diversification and increasing the risk when the performance of the single asset is poor. Additionally, although volatility is reduced, the overall return potential of the portfolio may decrease due to the absence of other high-yielding assets. This fact is also confirmed in the following analysis. Conversely, compared to MVP, the dynamic weights of MCP and MCOP are more evenly distributed across each asset. This allocation method better leverages the advantages of diversification, thereby reducing investment risk.

Secondly, although the dynamic weight allocations of MCP and MCOP are quite similar, there are also some differences. Under normal market conditions, compared to MCP, the dynamic portfolio weights of MCOP exhibit lower volatility. For example, in Table 6, the standard deviation of the dynamic investment weights for almost all assets under MCOP is smaller than that under MCP. This conclusion is consistent with Broadstock et al. (2022). They pointed out that compared to MCP, MCOP has the potential to achieve lower volatility at equivalent return performance. However, in extreme market conditions, such conclusions are shaken. According to our research, we find that in extremely negative or extremely positive market conditions, compared to MCP, MCOP's dynamic portfolio weight volatility is greater. For example, in extremely negative market conditions, the standard deviations of the dynamic weights for Gold under MCP and MCOP are 0.1 and 0.14, respectively. These differences illustrate the variations in portfolio weight between normal market conditions and extreme market conditions, further emphasizing the importance of our research.

Another interesting finding is that, compared to traditional safe-haven assets (Oil and Silver), CRN exhibits lower volatility in dynamic investment weights. Even in extreme market conditions, the weight changes for CRN remain relatively stable, particularly in MCP portfolios. We believe that this finding confirms CRN as an effective choice for hedging market stability from the perspective of dynamic weight adjustments. Furthermore, compared to normal market conditions, changes in investment weights during extreme market conditions are more sensitive to significant events.

The average combined weights and hedging effectiveness (HE) of the MVP, MCP, and MCOP allocation strategies in various market conditions are shown in Tables 6 to 8. Table 6 presents the results under normal market conditions. If we invested an average of 2 % in Oil, 19 % in RECT, 0 % in Solar, 15 % in Wind, 59 % in Gold, 0 % in Silver, 2 % in Fintech, and 3 % in CRN under MVP, the volatility of each asset in the portfolio would be statistically significantly reduced by 94 %, 70 %, 87 %, 58 %, 24 %, 81 %, 84 %, and 92 %, respectively. At a significance level of 0.1 %, these volatility reductions are statistically and monetarily significant. When it comes to MCP, we find that volatility of each asset in the portfolio would be statistically significant decreased by 85 %, 30 %, 70 %, 2 %, - 77 %, 57 %, 62 %, and 81 %, respectively, if we invested an average of 17 % in Oil, 13 % in RECT, 9 % in Solar, 4 % in Wind, 25 % in Gold, 2 % in Silver, 8 % in Fintech, and 21 % in CRN. Notable among these is Gold, which sees a 77 % increase in portfolio volatility. In addition, compared to MVP, the weight of Gold decreased from 59 % to 25 %, while the weight of CRN increased from 3 % to 21 %, and other assets have similar changes. On average, we can still confirm that MCP portfolios include more assets and have a more even asset distribution, which is positive for investors pursuing diversified investment strategies. What's more, the volatility of each asset in the MCOP would be statistically significantly reduced by 84 %, 22 %, 67 %, - 9 %, - 97 %, 52 %, 58 %, and 79 %, respectively, if we invested an average of 20 % in Oil, 12 % in RECT, 7 % in Solar, 9 % in Wind, 16 % in Gold, 8 % in Silver, 9 % in Fintech, and 21 % in CRN. It is worth noting that in terms of hedging effectiveness (HE) for individual assets, MCP generally outperforms MCOP under normal market conditions.

Tables 7 to 8 show the average asset weights and hedging efficiency

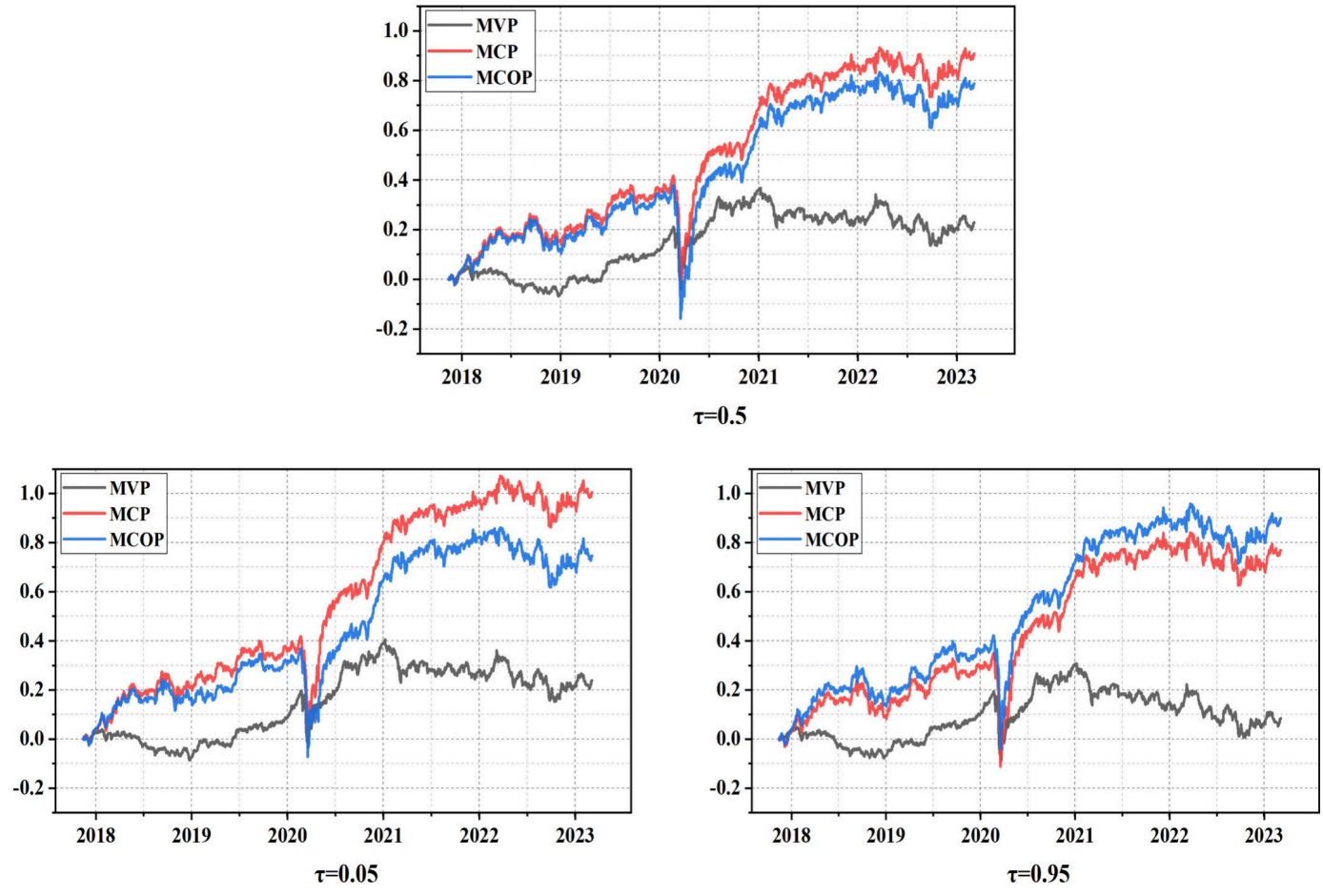


Fig. 8. Cumulative returns of MVP, MCP and MCOP at the 0.05, 0.50, and 0.95 quantiles.
Note: The results for MVP, MCP and MCOP are based on QVAR with a 200-period rolling window and a 20-period forecast horizon.

in extreme market conditions. These three portfolios in extreme markets show some interesting differences compared to normal market conditions. Specifically, under the method of MVP portfolio, assets with an average weight of 0 in a normal market are Solar and Silver, while in an extremely negative market, CRN and Oil are added to assets with an average weight of 0. Such results seem to indicate an increase in the variance of carbon and oil under extremely negative market conditions. In addition, we can also find that under extreme positive market conditions, the least weighted asset of the MCP portfolio is Wind, while under normal market conditions, the least weighted asset of the MCP is Sliver. These conclusions once again demonstrate the differences in portfolios under different market conditions. Another interesting finding is that in extreme market conditions, the hedging effectiveness (HE) of assets in the MCOP portfolio surpasses that of MCP, which contrasts with the conclusions drawn under normal market conditions. This indicates that portfolio selection should be adjusted according to different market conditions.

5.2.2. *Cumulative returns of different portfolios*

To better evaluate the performance of the three portfolios under different market conditions, Fig.8 calculates the cumulative returns of the portfolios across various market scenarios. We find that: first, in the two major crisis periods (COVID-19 and the Russia-Ukraine conflict), the cumulative returns of the three portfolios all decline significantly, indicating that the diversification effect of the turbulent period is destroyed. Second, regardless of market conditions, the MVP portfolio exhibits lower volatility compared to the other portfolios, but its cumulative returns are also lower than the others. This suggests that while the MVP portfolio offers stable returns, its profitability is limited. This is because the MVP portfolio allocates most of its weight to Gold, thereby lacking other high-yielding assets and reducing the overall return potential of the portfolio. This conclusion is consistent with Abdullah et al. (2023). Finally, we can obviously see that in the case of normal and extreme negative market, the cumulative return of MCP is significantly better than that of MVP and MCOP, while in the case of extreme positive market, the cumulative return of MCOP is significantly better than that of MVP and MCOP. Therefore, it can be seen that the optimal investment strategy varies under different market conditions. Investors need to continuously adjust their portfolios in response to changing market conditions to maximize cumulative returns.

5.2.3. *Sharpe ratios of different portfolios*

In the study that follows, we further assess the portfolio's performance by presenting the Sharpe ratios of several portfolios made up of carbon futures, energy markets, metals markets, and fintech indexes. It is worth noting that in order to show diversified portfolios, we have included metal assets in most of our portfolios because precious metals are considered traditional safe-haven assets (Bouoiyour et al., 2019). In other words, we focus on whether there is a difference in the hedging effect of Fintech and CRN on different energy markets (OIL and Clean Energy), while metal assets are included in most portfolios and we hope to build a more diversified portfolio. These results are presented in Table 9.

We first observed that among the portfolios constructed by MVP, the "OIL+ Metal+ Fintech "portfolio has a higher Sharpe ratio than the "OIL+ Metal+ CRN" portfolio in both extremely negative and extremely positive markets. While in normal market conditions, the Sharpe ratio of "OIL+ Metal+ CRN "is significantly higher. Such results seem to

Table 9
Sharpe ratios for different portfolios.

Sharpe ratios			
	MVP	MCP	MCOP
Panel A quantile = 0.05, extreme negative market			
OIL+ Metal+ Fintech	0.031	0.029	0.030
OIL+ Metal+ CRN	0.030	0.059	0.056
OIL+ Fintech + CRN	0.017	0.050	0.050
Clean Energy+ Metal	0.022	0.020	0.021
Clean Energy+ Metal+ CRN	0.020	0.056	0.059
Clean Energy+ Metal+ Fintech	0.027	0.011	0.009
Clean Energy+ Fintech	0.002	0.007	0.009
Clean Energy+ Fintech+ CRN	0.000	0.047	0.048
Panel B quantile = 0.5, normal market			
OIL+ Metal+ Fintech	0.030	0.029	0.023
OIL+ Metal+ CRN	0.038	0.061	0.056
OIL+ Fintech + CRN	0.026	0.049	0.049
Clean Energy+ Metal	0.016	0.018	0.017
Clean Energy+ Metal+ CRN	0.020	0.051	0.047
Clean Energy+ Metal+ Fintech	0.014	0.009	0.010
Clean Energy+ Fintech	0.001	0.011	0.012
Clean Energy+ Fintech+ CRN	0.009	0.052	0.044
Panel C quantile = 0.95, extreme positive market			
OIL+ Metal+ Fintech	0.031	0.030	0.027
OIL+ Metal+ CRN	0.029	0.056	0.057
OIL+ Fintech + CRN	0.014	0.049	0.049
Clean Energy+ Metal	0.012	0.017	0.021
Clean Energy+ Metal+ CRN	0.011	0.050	0.056
Clean Energy+ Metal+ Fintech	0.014	0.009	0.013
Clean Energy+ Fintech	0.001	0.012	0.010
Clean Energy+ Fintech+ CRN	0.001	0.048	0.047

Note: The results for MVP, MCP and MCOP are based on QVAR with a 200-period rolling window and a 20-period forecast horizon.

illustrate that in extreme market situations, Fintech seems to be a better hedge tool for OIL and Metal. A similar conclusion can be drawn for clean energy-related portfolios. In extreme market conditions, the "Clean Energy+ Metal+ Fintech" portfolio has a greater Sharpe ratio than the "Clean Energy+ Metal+ CRN" portfolio, while in normal market conditions, the opposite is true. It should be stressed again that our analysis above is based on an MVP-constructed portfolio, and although it provides a lower cumulative return over the sample period, it is more stable than those constructed with MCP and MCOP, which is valuable for risk-averse investors. When considering the portfolio constructed by MCP and MCOP, we can find that CRN has a better hedging effect for both OIL and Clean Energy. Especially in extreme positive markets and extreme negative markets, both the "OIL+ Metal+ CRN" portfolio and the "Clean Energy+ Metal+ CRN" portfolio had the highest Sharpe ratios. This seems to imply that CRN is a better hedge against extreme risks in energy markets under a portfolio constructed by MCP and MCOP.

In addition, in order to further illustrate the hedging effect of the combination of Fintech and CRN on the energy markets, we also constructed an investment portfolio of "Energy Market (OIL and Clean Energy) + Fintech + CRN". We find that in most market situations, the combination of Fintech and CRN is better at hedging OIL, which is reflected in the three different construction methods. It should be further noted that for most portfolios, the addition of carbon futures assets is beneficial. For example, "Clean Energy+ Fintech+ CRN" has a significantly higher Sharpe ratio than the "Clean Energy+ Fintech" portfolio in the MCP and MCOP approaches, further confirming the hedge effect of CRN in the energy market.

In summary, our above results well demonstrate the hedging effect of CRN and Fintech on energy markets. Specifically, in extreme market situations, we find it beneficial to add CRN to the energy markets, which is a stable and operational asset when investors consider hedging against price fluctuations in Clean Energy and OIL. In addition, if investors consider both CRN and Fintech, such a combination is better suited to hedge the risk of the OIL. It should be noted that our portfolio is constructed based on historical data, which to some extent reflects the characteristics of certain assets in a specific time period, and investors should be flexible to adjust portfolios according to different market conditions and methods.

5.3. Robustness checks

5.3.1. Connectedness analysis in frequency domain

In Section 5.1.2, we discussed the time-domain connectedness between fintech, carbon futures, and energy markets. However, some literature suggests that the connectedness between markets changes with variations in the frequency domain (Le, 2023; Sheikh et al., 2024). Therefore, we adopted the method of Chatziantoniou et al. (2022) to further investigate the impact of frequency domain changes on market connectedness under different market conditions. Fig.9 shows the frequency domain connectedness network results, where we define the short term as 1–5 days (one week), the medium term as 1–22 days (one month), and the long term as more than 22 days.

Firstly, it was observed that in the short term, under different market conditions, the net receivers and net contributor roles of various assets in the network did not undergo significant changes. That is, Oil and CRN remain the main net receivers, while the clean energy markets remain the main contributors, which strongly supports our previous conclusions. It is noteworthy that our connectedness results also show that the overall level of spillover is mainly driven by the short term. This means that investors engaging in fintech, carbon futures, and energy markets' information exchange focus primarily on the short term. Additionally, we find that CRN plays the role of a net receiver in most cases in medium and long term, which once again demonstrates its characteristics as a hedging asset.

In our results, we also find some anomalies. For example, Wind changed from a short-term net sender to a medium- to long-term net receiver. This indicates that the spillover effect of wind energy has changed across different frequency domains, requiring regulators to strengthen risk management to adapt to these changes in real time. Additionally, in extreme market conditions, Oil shifts from a risk receiver to a net contributor in the medium to long term. This indicates that its risk spillover effect is intensified over the medium to long term. In conclusion, although there are subtle differences in the results across different frequency domains, this underscores the need for investors to focus on portfolio construction under various market conditions and frequency domains. This paper provides an excellent attempt in this regard.

5.3.2. Connectedness and multivariate portfolio analysis based on asymmetric TVP-VAR approach

This section primarily analyzes the connectedness between fintech, carbon futures, and energy markets using a symmetric TVP-VAR approach and constructs a diversified investment portfolio based on three methods: MVP, MCP, and MCOP. As previously mentioned, the asymmetric TVP-VAR primarily focuses on the connectedness of upward and downward markets. Its positive scenario indicates positive market returns, while the negative scenario indicates negative market returns. This distinction merely describes the overall market trend and cannot capture extreme market conditions. Adekoya et al. (2022) were the first to apply the results of the asymmetric TVP-VAR to the dynamic diversification exercise of three investment portfolio methods. We adopt this method mainly to compare it with the QVAR method discussed earlier, aiming to better illustrate the similarities and differences in the relevant conclusions and the marginal contribution of this study.

Fig.10 shows the result of asymmetric total connectedness, indicating that the connectedness between fintech, carbon futures, and energy markets exhibits time-varying characteristics, with a significant increase in total connectedness during the COVID-19 pandemic. This

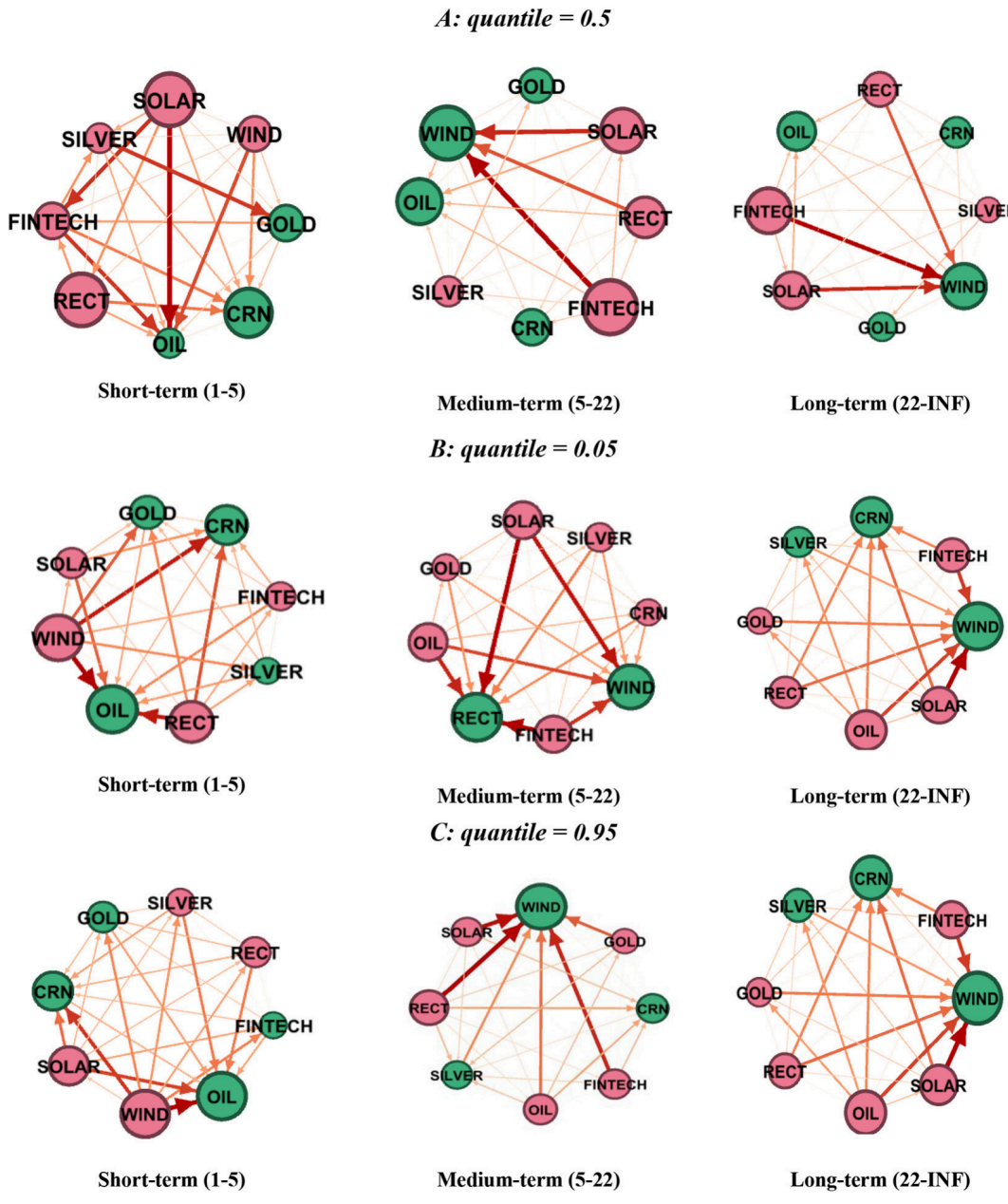


Fig. 9. The return connectedness network between fintech, carbon future and energy markets at the 0.50,0.05, and 0.95 quantiles in different frequency domain. Note: Red and green nodes represent the contributors and receivers, respectively, with the arrow thickness indicating the strength of the connectedness. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

demonstrates that spillover effects also exhibit event-dependence. Furthermore, similar to the conclusions drawn earlier, we find that the spillover effects between downward markets (negative) are greater than those between upward markets (positive), demonstrating the asymmetry of spillover effects. These results strongly support our previous research findings. However, significant disparities also appear in these results. In contrast to the QVAR connectedness results, this method shows relatively balanced volatility across all spillover levels, even in upward or downward markets, where spillover levels did not show significant fluctuations. Additionally, we found that the spillover index was not sensitive to major international events like the Russia-Ukraine conflict, indicating potential limitations of this method in capturing extreme market risks.

Based on the results of asymmetric TVP-VAR model, we constructed three diversified investment portfolios: MVP, MCP, and MCOP, as outlined in Section 5.2.1. Fig.11 depicts the dynamic changes in asset weights across different investment portfolios. We find that in the MVP, most of the weight is allocated to Gold, while the weight distribution in MCP and MCOP portfolios is more balanced. This is consistent with our earlier findings. However, the dynamic changes in weight distribution across all portfolios are relatively small. It is worth discussing that the lower volatility of weights seems to facilitate portfolio adjustments for investors. However, the current results focus on the long-term states of upward and downward markets, which means that these dynamic weight results may not be applicable to extreme market conditions.

The average portfolio weights and hedging effectiveness (HE) of the MVP, MCP, and MCOP allocation strategies based on the asymmetric TVP-VAR model are shown in Tables 10 to 12. We found that under the MVP portfolio, the weights allocated to Solar and Silver in both upward and downward markets are zero, and the weights for Oil and CRN are also close to zero. This reflects that the weight distribution of this portfolio is overly concentrated. Additionally, in both upward and

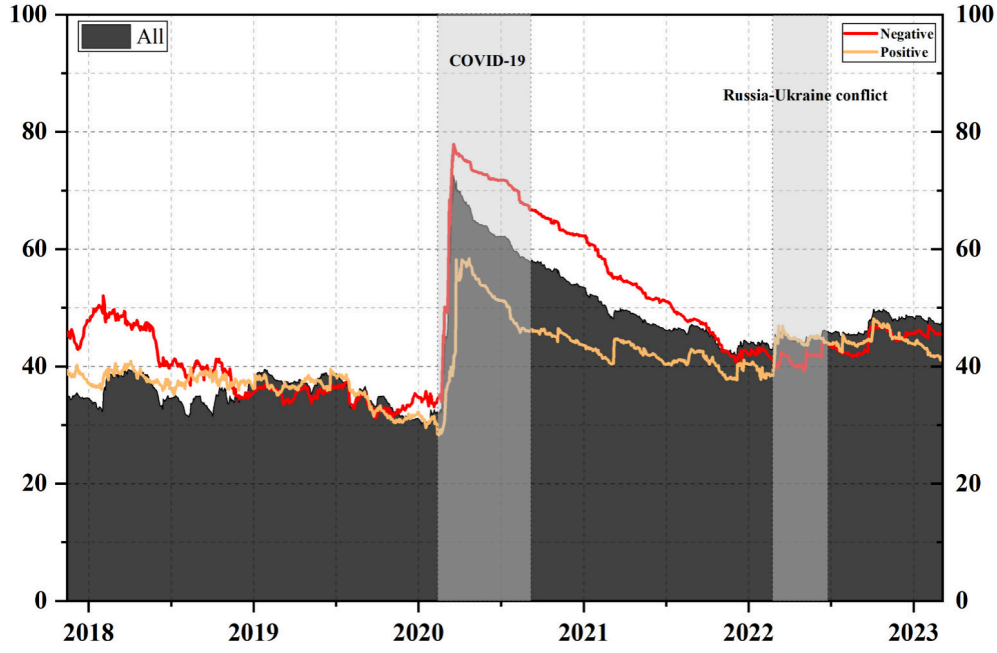


Fig. 10. Dynamic asymmetric total connectedness.
Note: Results are based on the asymmetric TVP-VAR model with lag length of order one (BIC) and a 20-period forecast horizon. Black area represents the symmetric total connectedness while the orange and red line illustrate the positive and negative total connectedness, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

downward markets, the hedging efficiency of assets in the MCOP portfolio is greater than that in the MCP portfolio. This conclusion has positive implications for investors in their selection of different investment portfolios. In a word, the above results demonstrate the differences in portfolio structures across different market conditions, highlighting the importance of adopting effective asset diversification strategies in portfolio management.

5.3.3. Adjustments to the rolling window and forecast horizon

We conducted further robustness tests by varying the rolling window and forecast horizon. Considering the sensitivity of empirical results to model parameters, we adjusted the forecast horizon to 10 and the rolling window to 250. To control the length of this section, Fig. 12 only displays the cumulative returns of the three portfolios under different market conditions. All other results remain consistent with those presented earlier, and additional robustness test results are available upon request. These results indicate that our conclusions remain robust and valid across different forecast periods and rolling windows.

6. Discussion

The findings from our quantile connectedness indicate that there are significant differences in spillover effects between the fintech, carbon futures, and energy markets under different market conditions. Our empirical findings show that these inter-market spillover effects exhibit strong time-varying characteristics and event dependencies, especially under extreme market conditions. During the COVID-19 pandemic and the Russia-Ukraine conflict, spillover effects are significantly amplified. Research by Le (2023) also pointed out this finding. Unlike previous studies, our result identifies the net contributors and net receivers of spillover shocks within the network under different market conditions, revealing that the net spillover roles of fintech, carbon futures, and energy markets change frequently under extreme market conditions. This provides valuable insights for investors' investment management strategies, suggesting that under extreme market conditions, it is crucial to be more flexible in formulating investment management strategies and to adopt diversified investment portfolios to reduce risks.

In the section on constructing diversified portfolios, we compare three investment strategies: MVP, MCP, and MCOP. Our analysis reveals that compared to MVP, the investment weight distributions of MCP and MCOP are more balanced, demonstrating the advantages of diversified portfolios. Additionally, we find that the dynamic investment weights of MCOP exhibit lower volatility compared to MCP, consistent with the findings of Broadstock et al. (2022). However, our research further indicates that under extreme market conditions, the dynamic investment weight volatility of MCOP is greater than that of other portfolios. This difference underscores the importance of focusing on portfolio construction under varying market conditions. Moreover, using the Sharpe ratio, we point out that carbon futures and fintech can serve as effective hedging tools for the energy market, providing valuable insights for risk management practices in the energy markets.

It is important to highlight that this paper employs a novel framework to explore quantile connectedness. Specifically, we combine quantile connectedness with diversified portfolio analysis to investigate risk spillover effects and investment strategies under extreme market conditions. Mainik et al. (2015) proposed a portfolio optimization strategy based on the Extreme Risk Index (ERI) and emphasized the importance of considering tail dependence in portfolio construction. Sui et al. (2021) pointed out that the quantile method fully captures the joint behavior of all extreme and normal market fluctuations, describing the dependence structure across all quantiles, enabling participants to better respond to market changes. Based on this, the quantile connectedness framework proposed in this paper provides a new and comprehensive evaluation system for hedging strategies in extreme markets. It considers almost all market conditions and offers investors richer and more practical information to cope with complex price movements.

7. Conclusion

In the face of escalating climate crises, energy transition has become increasingly urgent. In recent years, influenced by major international events (the COVID-19 pandemic or Russia-Ukraine conflict), extreme price fluctuations in energy markets have become more frequent. During extreme market conditions, when energy market prices experience sharp

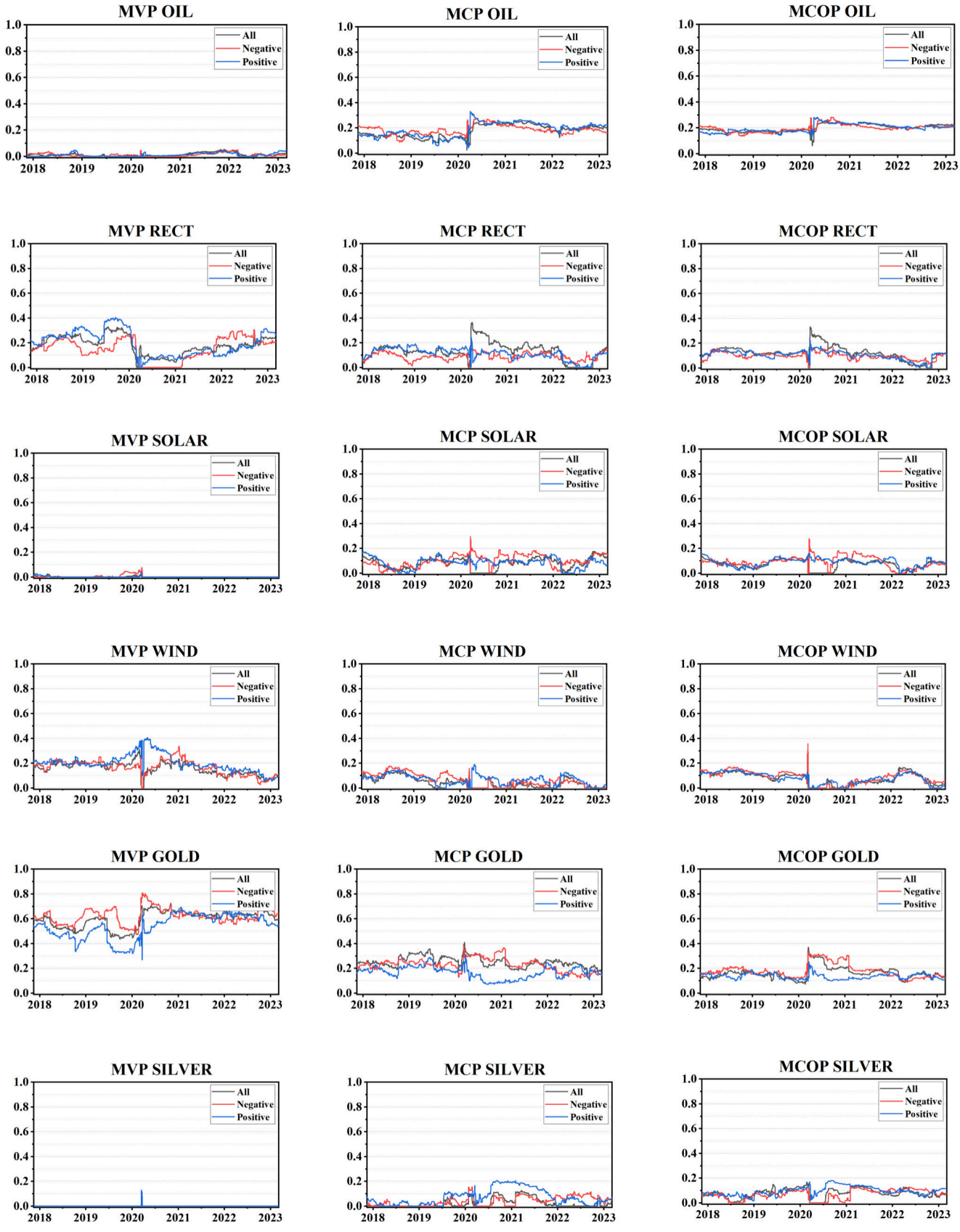


Fig. 11. Dynamic multivariate portfolio weights.
Note: The results for MVP, MCP and MCOP are based on the asymmetric TVP-VAR model with lag length of order one (BIC) and a 20-period forecast horizon.

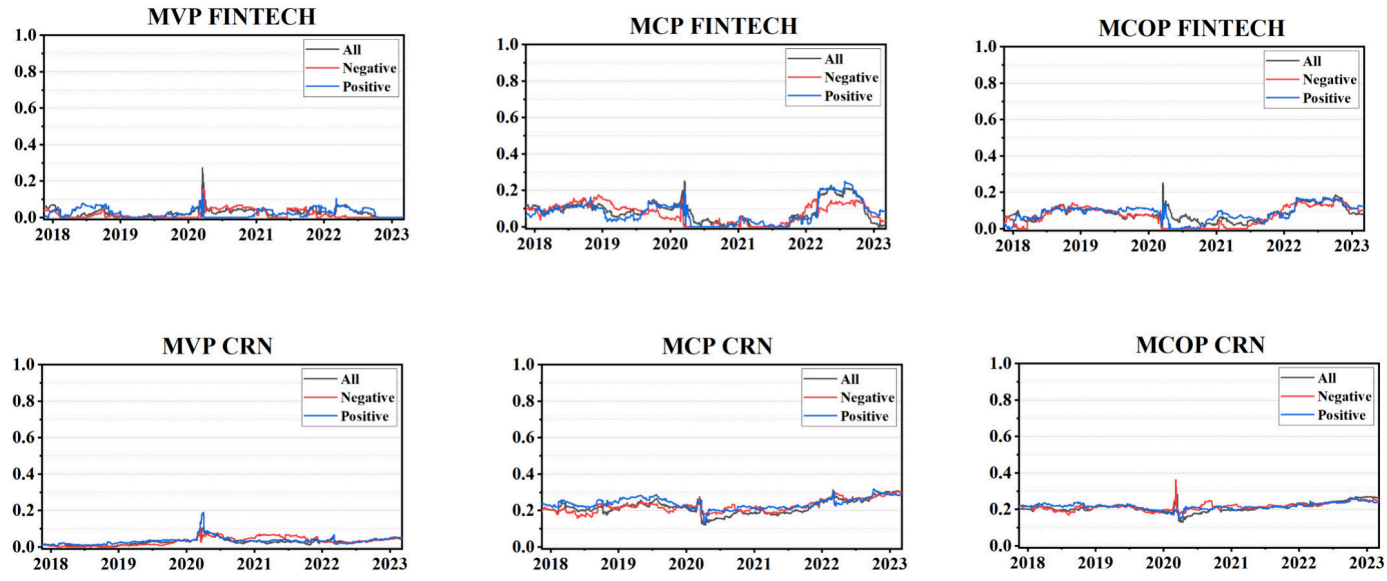


Fig. 11. (*continued*).

Table 10
Averaged portfolio weights and hedge effectiveness based on positive and negative returns.

ALL	MVP			MCP			MCOP		
	Mean	HE	*p*-value	Mean	HE	*p*-value	Mean	HE	*p*-value
OIL	0.01	0.94	0.00	0.18	0.86	0.00	0.20	0.85	0.00
RECT	0.18	0.71	0.00	0.12	0.31	0.00	0.11	0.28	0.00
SOLAR	0.00	0.88	0.00	0.08	0.71	0.00	0.07	0.70	0.00
WIND	0.16	0.60	0.00	0.04	0.05	0.35	0.08	0.00	0.96
GOLD	0.60	0.31	0.00	0.25	- 0.65	0.00	0.16	- 0.73	0.00
SILVER	0.00	0.83	0.00	0.02	0.58	0.00	0.08	0.57	0.00
FINTECH	0.03	0.84	0.00	0.09	0.63	0.00	0.09	0.61	0.00
CRN	0.03	0.93	0.00	0.22	0.83	0.00	0.21	0.83	0.00

Note: The results for MVP, MCP and MCOP are based on the asymmetric TVP-VAR model with lag length of order one (BIC) and a 20-period forecast horizon.

Table 11
Averaged portfolio weights and hedge effectiveness based on positive returns.

Positive	MVP			MCP			MCOP		
	Mean	HE	*p*-value	Mean	HE	*p*-value	Mean	HE	*p*-value
OIL	0.01	0.95	0.00	0.19	0.85	0.00	0.19	0.85	0.00
RECT	0.19	0.72	0.00	0.10	0.10	0.05	0.10	0.12	0.01
SOLAR	0.00	0.89	0.00	0.09	0.64	0.00	0.09	0.65	0.00
WIND	0.20	0.61	0.00	0.06	- 0.26	0.00	0.08	- 0.22	0.00
GOLD	0.53	0.37	0.00	0.17	- 1.03	0.00	0.14	- 0.97	0.00
SILVER	0.00	0.84	0.00	0.07	0.48	0.00	0.09	0.49	0.00
FINTECH	0.03	0.84	0.00	0.08	0.48	0.00	0.09	0.50	0.00
CRN	0.03	0.93	0.00	0.24	0.79	0.00	0.22	0.80	0.00

Note: The results for MVP, MCP and MCOP are based on the asymmetric TVP-VAR model with lag length of order one (BIC) and a 20-period forecast horizon.

Table 12
Averaged portfolio weights and hedge effectiveness based on negative returns.

Negative	MVP			MCP			MCOP		
	Mean	HE	*p*-value	Mean	HE	*p*-value	Mean	HE	*p*-value
OIL	0.01	0.94	0.00	0.18	0.84	0.00	0.20	0.84	0.00
RECT	0.14	0.75	0.00	0.08	0.30	0.00	0.09	0.31	0.00
SOLAR	0.00	0.87	0.00	0.10	0.64	0.00	0.09	0.65	0.00
WIND	0.17	0.63	0.00	0.07	- 0.04	0.46	0.09	- 0.02	0.64
GOLD	0.63	0.30	0.00	0.23	- 0.97	0.00	0.18	- 0.94	0.00
SILVER	0.00	0.83	0.00	0.04	0.54	0.00	0.07	0.54	0.00
FINTECH	0.02	0.86	0.00	0.08	0.60	0.00	0.07	0.61	0.00
CRN	0.03	0.93	0.00	0.23	0.80	0.00	0.22	0.80	0.00

Note: The results for MVP, MCP and MCOP are based on the asymmetric TVP-VAR model with lag length of order one (BIC) and a 20-period forecast horizon.

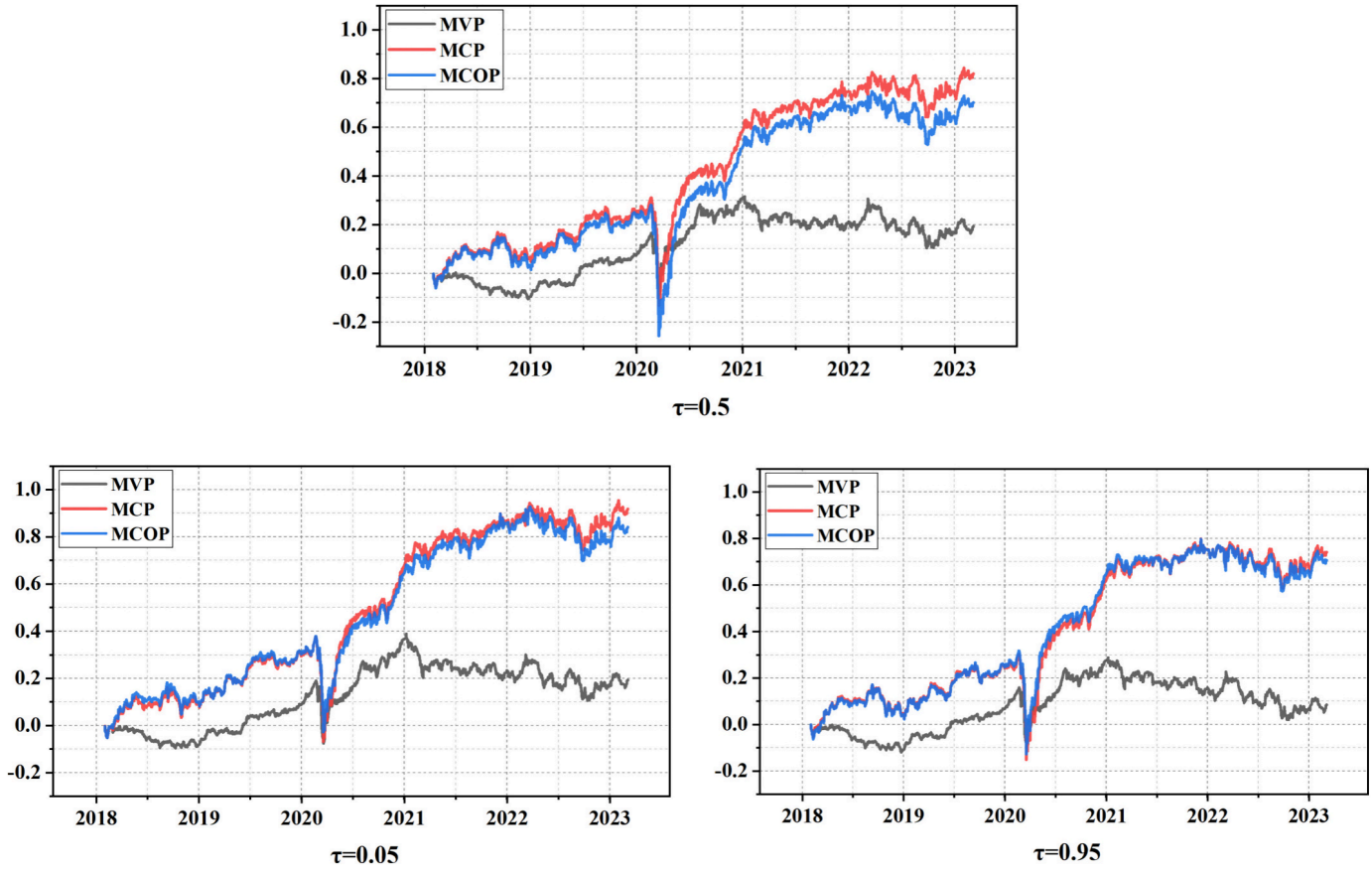


Fig. 12. Cumulative returns of MVP, MCP and MCOP at the 0.05, 0.50, and 0.95 quantiles.
Note: The results for MVP, MCP and MCOP are based on QVAR with a 250-period rolling window and a 10-period forecast horizon.

increases or declines, investors may suffer greater losses as a result. On the other hand, the rise of fintech and carbon futures markets has brought diversification opportunities to investors. Therefore, the issue of how to construct diversified investment portfolios to withstand extreme market risks has become an important topic.

This paper analyzes the connectedness between fintech, carbon futures, and energy markets, offering insights into hedging and investment strategies. Using a daily dataset span from January 4, 2017, to March 6, 2023, we integrate the quantile connectedness method with the construction of diversified investment strategies, forming a novel analytical framework. This framework enables the analysis of correlation effects among various assets under different market conditions, while also capturing the differences across different investment portfolios. Our research holds significant implications for market regulators and investors alike.

The following are this paper's primary conclusions: First, we find that the spillover effect between the carbon future and the clean energy markets is weak, while there is a strong two-way spillover effect between the fintech and the clean energy markets. Additionally, the spillover effect of fintech on the crude oil market is small. Carbon futures and oil are the receivers in the entire market, while clean energy and fintech are the contributors in the market. Second, under changing market conditions, the interconnectedness of the fintech, carbon futures, and energy markets changes over time and is susceptible to major international events like the COVID-19 outbreak and the Russia-Ukraine conflict. In addition, in extreme market conditions, connectedness between markets increases significantly. Third, net spillovers vary as market conditions change and unexpected events, and policymakers and investors need to focus on net spillovers in extreme market conditions. Fourthly, from the comparison of the three portfolios of MVP, MCP, and MCOP, we find that the portfolio of MCP or MCOP is superior to that of MVP, which has a positive significance for investors' diversified portfolio selection. In addition, the portfolio practice of different assets also shows again that under different market conditions, carbon futures are an effective hedging asset for the clean energy market. When we consider both carbon markets and fintech, the combination is better suited to hedge the risk of the crude oil market. Finally, in the robustness tests, we find that different frequency domains have a subtle impact on connectedness but do not change the net spillover roles of the main markets. We also compared the similarities and differences in spillovers and portfolios under the asymmetric TVP-VAR model, highlighting the advantage of QVAR in capturing extreme market risks. We further reinforced the robustness of our conclusions by altering the rolling window and forecast horizon.

Our results have implications for investors and policymakers. For investors, our findings can aid them in making predictable investing choices despite extreme market conditions. For instance, as can be observed from the time-varying variations in asset weights, carbon futures can be thought of as a comparatively stable asset under extreme markets in comparison to other assets. Therefore, the carbon market is not only a good choice when hedging the risk of the clean energy market, but also it is more operable in extreme market weight adjustment. Instead, investors should be cautious when considering the fintech and clean energy markets at the same time, as there are strong two-way spillovers between the two assets. For policymakers, spillovers based on various market conditions highlight the significance of tail risk transmission in the fintech, carbon futures, and energy markets, which is important for monitoring policy. To assist investors and asset managers in reducing risks, policymakers should reinforce the emergency response mechanism for big catastrophes through suitable measures, such as the COVID-19 pandemic or the Russia-Ukraine conflict. In addition, considering that the development of the carbon market is conducive to

further promoting the energy transition, especially hedging the risks brought by the clean energy market, countries should vigorously promote the development of the carbon market, strengthen, and improve the system-related to carbon trading, and give play to the key role of the carbon market in the energy transition process. The development of financial technology can also maintain the stable transformation of the fossil energy market to a certain extent, which is very important for the future development of the energy market.

Our research also has limitations. We analyzed the connectedness and portfolios of fintech, carbon futures, and energy markets from a global perspective. Future research could focus on specific regional and national markets to enhance the applicability of the conclusions. Moreover, at present, we cannot find any general principles or patterns applicable to all situations to understand the risk spillover effects between markets, and this is a direction for further development in future research.

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Author contributions

Xianfang Su designed the main stages in the research and revised the manuscript critically for important content. Jian He acquired and analyzed the data, and drafted the initial manuscript. All authors read and approved the final manuscript.

CRediT authorship contribution statement

Xianfang Su: Writing – review & editing, Validation, Supervision, Software, Methodology, Funding acquisition, Conceptualization. **Jian He:** Writing – original draft, Supervision, Resources, Formal analysis, Data curation.

Declaration of competing interest

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

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107904.

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