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Research article

Quantile frequency connectedness between energy tokens, crypto market, and renewable energy stock markets

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ABSTRACT

Utilizing a quantile frequency connectedness approach, we explore the connectedness between energy tokens, crypto market, and renewable energy stock markets. The empirical results show that the connectedness measures of the series are characterized by asymmetry and heterogeneity across quantiles and different investment horizons. Specifically, the characteristic of clustering has been observed that energy tokens and crypto market are more interconnected, while the renewable energy stock markets are more interconnected with each other at median quantile. The linkages between energy tokens and renewable energy stock markets are quite weak under normal market conditions, suggesting the diversification opportunities in investing these financial assets. However, these series are more interconnected under extreme market conditions, with the renewable energy stock markets are on the dominating end of the propagation mechanism while the energy tokens and crypto market are net receivers of shocks. Further frequency decomposition shows that this strategy can hold in the short term, while in the long term investors could benefit from the diversification opportunities by investing both kinds of financial assets. Additionally, the dynamic analysis affirms that the connectedness measures are varied and event-dependent over time. Our results may help investors and policymakers have a better assessment and portfolio management.

1. Introduction

Governments around the world are accelerating the transition to a low-carbon economy and mitigating the risk of climate change, making the renewable energy investment an increasing emphasis of global financial investors or advisors. However, investing in renewable energy sources may encounter challenges such as high costs, limited availability, and the challenge of accounting for surpluses in electricity production. Furthermore, the timeline of getting returns in renewable energy sources is often very long, making investing in renewable energy more risky. In this context, developing distributed energy system by the application of blockchain technology is considered to be an important way towards energy sustainability [1]. According to a 2019 analysis from Global Market Insight, Inc., the market for blockchain technology in the energy sector is expected to grow from USD 200 million in 2018 to around USD 18 billion by 2025.[1] In particular, tokenization is an important way of integrating the blockchain technology into energy sector

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[1] https://www.gminsights.com/industry-analysis/blockchain-in-energy-market?utm_source=prnewswire.com&utm_medium=referral&utm_campaign=Paid_prnewswire.

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which has attracted a lot of attentions from academics and industries [2]. Organizations such as Power Ledger and WePower have been researching and developing platforms to tokenize renewable energy, with each token on the platform is essentially a digital self-setting power-purchase contract representing the energy they commit to produce and distribute. The energy tokens are tradeable with their price determined by the market demand and supply. By transferring the data onto blockchain, energy tokenization could help create clear ownership structure for renewable energy sources, facilitate energy trading, and thereby improve investment efficiency. Energy tokenization might standardize, simplify, and globalize the current energy investment ecosystem, and it could further benefit the renewable energy market by ensuring liquidity and extending access to capital. In this sense, energy tokens have the potential to spur the investors' interest in renewable energy sector.

Energy tokens are conceived to be cryptocurrencies. According to Charfeddine, Benlagha, and Khediri [3], cryptocurrencies can be categorized into two main classes – coins and tokens, which share some important common features while have their own characteristics. In details, coins are originally designed transaction mechanism to enable anonymous, secure, and decentralized peer-to-peer payments. The coins can be further divided into mining coins (such as Bitcoin and Litecoin) and non-mining coins (such as Ripple, Binance Coin). Mining is the process through which miners are rewarded for validating transactions using a specific algorithm on a blockchain. The huge amount of energy consumed by cryptocurrency mining has become a growing concern for investors and developers that there is an ongoing debate about whether the use of renewable energy can solve the problem. As for tokens, they are a type of assets issued via a smart contract built upon a distributed ledger that can represent a variety of different things. According to Härdle, Harvey, Reul [4], tokens can be grouped into four types – utility tokens (e.g., Golem, FileCoin, and Storj), security tokens, fungible tokens, and non-fungible tokens (NFTs). Utility tokens are programmable blockchain assets that serve a specific purpose within a decentralized application, such as providing discounts or rewards for retaining the token. Security tokens can represent stocks, bonds, derivatives, or other financial assets, which could allow the holders to share in the success of a project. Fungible tokens are a type of cryptocurrencies that are identical and similar in nature and functionality. Energy tokens of POWR and WPR that we focused on in this study fall into this category. In contrast to fungible tokens, NFTs are unique and non-interchangeable units of data that can be used to value and authenticate the ownership of digital assets such as artwork and virtual land parcels, etc.

In recent years, since the meteoric rise of cryptocurrencies has captivated investors' attention serving as financial diversification option or tools for hedging strategies, the linkages between cryptocurrencies and traditional financial assets has been widely studied, such as with crude oil [5], precious metals markets ([6–9]), and currency markets ([10,11]). Due to the universality of stock investment, the cryptocurrency-stock nexus has received considerable attention from the academia ([12–14]). Prior to the outbreak of COVID-19 pandemic, most of the related literature comes to the conclusion that, Bitcoin and other pioneer cryptocurrencies in the early years were conceived to be relatively isolated from stock markets, as the common price determinants for the two kinds of assets are rare ([15–17]). Since the outbreak of COVID-19 pandemic, the weak correlations between crypto market and stock markets has been challenged. For instance, Balcilar, Ozdemir, and Agan [18] estimates the volatility connectedness of 27 emerging stock markets and 7 highly capitalized cryptocurrencies and discover a growing risk spillover effect after the outbreak of COVID-19 pandemic.

As the blockchain technology is becoming more and more prevalent in the energy industry, more investment activities will be focused on cryptocurrencies and renewable energy stocks [19]. Therefore, investigating the connectedness between energy tokens and renewable energy stock markets is of key interest for portfolio diversification ([20]). Moreover, the empirical evidence points towards strong connection among cryptocurrencies. For instance, Yi, Xu, and Wang [21] states that the volatility connectedness in the cryptocurrency market has been cyclically fluctuating and has clearly been trending upward since the end of 2016. Hasan, Naeem, Arif, Shahzad, and Vo [22] observes the increased liquidity connectedness in the crypto market. We thus consume a linkage between energy tokens and the other cryptocurrencies exists. With all these in mind, we attempt to investigate the dependence of energy tokens, crypto market, and renewable energy stock markets.

The method we employ in our research is the quantile frequency connectedness approach proposed by Chatziantoniou, Abakah, Gabauer, and Tiwari [23] which permits us to explore the propagation mechanisms by virtue of quantile and frequency. The reason is that Jiang, Xu, and Zhang [24] shows strong evidence for the existence of tail-risk spillovers between cryptocurrencies and conventional assets. Attarzadeh and Balcilar [25] and Urom, Abid, Guesmi, and Chevallier [26] also find that Bitcoin and other financial markets are tenuously linked during non-crisis periods, while their connectedness strengthens substantially during times of crisis. Furthermore, Le [27] investigates the quantile time-frequency connectedness between the volatility of cryptocurrencies and that of renewable energy revealing that the dynamic connectedness is different across different frequencies. As a result, we decide to use the approach that allows for the analysis of connectedness over different quantiles and frequencies.

Compared to the previous literature, the contribution of our study lies into the following three aspects. First, with the rapid development of cryptocurrencies, more and more cryptocurrencies rather than Bitcoin have attracted investors' attention. Unlike most of the previous studies focusing on the on high-capitalized cryptocurrencies such as Bitcoin, Ethereum, Litecoin, and Ripple, we put our emphasis on the innovative energy tokens which share some commonalities but also have their own characteristics distinguished from the other types of cryptocurrencies. In this sense, our study may enrich the research on crypto-assets. Second, energy tokenization is one of the most promising solutions that being increasingly used in the renewable energy sector to support the process of energy transition. Energy tokens and their linkages with conventional financial assets have not yet been thoroughly explored. To the best of our knowledge, this study is the first attempt to examine the relationship between energy tokens and renewable energy stock markets, which may contribute to the research in the cryptocurrency-stock nexus. Third, compared with the analysis applying just the quantile or time-frequency connectedness methods, we employ a novel quantile frequency connectedness approach which enables us to provide a more comprehensive dependence structure of the investigated series under diverse market conditions and different investment horizons.

The rest of our research proceeds as follows: Section 2 demonstrates the methodology. Section 3 presents data sources. The empirical results are reported and discussed in section 4. Section 5 concludes.

2. Methodology

This study employs the quantile frequency connectedness approach proposed by Chatziantoniou, Abakah, Gabauer, and Tiwari [23], which enables to analyze the short-term and long-term connectedness dynamics over time and quantiles. This approach starts with estimating a quantile vector autoregresssion QVAR(p) outlined as follows,

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

where y_t and $y_{t-j}, j = 1, \ldots, p$ are $N \times 1$ dimensional endogenous variable vectors, τ is the quantile, p represents for the lag length, $\mu_t(\tau)$ is a $N \times 1$ dimensional conditional mean vector, $\Phi_j(\tau)$ stands for $N \times N$ dimensional QVAR coefficient matrix, and $u_t(\tau)$ is an $N \times 1$ dimensional error disturbance vector with an $N \times N$ dimensional variance-covariance matrix $\Sigma(\tau)$. Using Wold's theorem, the QVAR(p) can be transformed to QVAR(∞)

$$y_t = \mu_t(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau) u_{t-i} \tag{2}$$

with $\Psi_i(\tau)$ being the moving average lag coefficient matrix.

Subsequently, to measure the connectedness in the frequency domain, the frequency response function $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h$ was considered, with $i = \sqrt{-1}$ and ω denotes the frequency. Then the spectral density of y_t at frequency ω can be defined as a Fourier transform of QVAR(∞) as

$$S_y(\omega) = \sum_{h=-\infty}^{\infty} E\left(y_t y_{t-h}'\right) e^{-i\omega h} = \Psi\left(e^{-i\omega}\right) \Sigma_t \Psi'\left(e^{+i\omega}\right) \tag{3}$$

The frequency generalized forecast error variance decomposition (GFEVD) can thus be formulated as follows,

$$\psi_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1} \sum_{h=0}^{\infty} \left(\Psi(\tau)(e^{-i\omega h})\Sigma(\tau)\right)_{ij}^2}{\sum_{h=0}^{\infty} \left(\Psi(\tau)(e^{-i\omega h})\Sigma(\tau)\Psi(\tau)(e^{-i\omega h})\right)_{ii}} \tag{4}$$

As the rows of $\psi_{ij}(\omega)$ do not sum up to 1, it can be normalized in the following way:

$$\widetilde{\psi}_{ij}(\omega) = \frac{\psi_{ij}(\omega)}{\sum_{i=1}^{N} \psi_{ij}(\omega)} \tag{5}$$

with $\sum_{i=1}^{N} \widetilde{\psi}_{ij}(\omega) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\psi}_{ij}(\omega) = N$. $\widetilde{\psi}_{ij}(\omega)$ demonstrates the portion of the spectrum of variable i at frequency ω that can be attributed to a shock in variable j.

To assess short-term or long-term connectedness rather than connectedness at a single frequency, all the $\widetilde{\psi}_{ij}(\omega)$ values at frequencies within a specific range $d = (a, b) : a, b \in (-\pi, \pi), a < b$ are aggregated and get $\widetilde{\psi}_{ij}(d) = \int_a^b \widetilde{\psi}_{ij}(\omega) d\omega$.

Utilizing the $\widetilde{\psi}_{ij}(d)$, the net pairwise directional connectedness (NPDC) index could be defined as

$$NPDC_{ij}(d) = \left[\widetilde{\psi}_{ij}(d) - \widetilde{\psi}_{ji}(d)\right] \tag{6}$$

If $NPDC_{ij} > 0$, it illustrates that variable j impact variable i more than vice versa, otherwise it indicates that variable i dominates variable j.

The total directional connectedness to others (TO) measuring how much of a shock in variable i is transmitted to other could be computed as

$$TO_i(d) = \sum_{j=1, i \neq j}^{N} \widetilde{\psi}_{ji}(d) \tag{7}$$

Similarly, the total directional connectedness from others (FROM) measuring how much variable i receives from shocks in other variables could be calculated by

$$FROM_i(d) = \sum_{j=1, i \neq j}^{N} \widetilde{\psi}_{ij}(d) \tag{8}$$

The net total directional connectedness (NET) can be depicted as

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{9}$$

The $NET_i(d)$ could be interpreted as the impact variable i has on the investigated system. If $NET_i(d) > 0$ ($NET_i(d) < 0$), it illustrates that variable i impacts the investigated system more/or less than itself being impacted. It then is conceived to be a net transmitter/or receiver of shocks.

The total connectedness index (TCI) measuring the degree of system interconnectedness could be constructed as

$$TCI(d) = N^{-1} \sum\nolimits_{i=1}^{N} TO_i(d) = N^{-1} \sum\nolimits_{i=1}^{N} FROM_i(d) \tag{10}$$

3. Data sources and preliminary analysis

In this study, we investigate the quantile time-frequency dependence of energy tokens, crypto currency, and renewable stock markets. Following Yousaf, Nekhili, and Umar [28], two energy tokens are selected, namely the Power Ledger (POWR) and WePower (WPR). Specifically, POWR is an Australian cryptocurrency and energy trading platform that allows for decentralized buying and selling of renewable energy. After several projects in their native Australia, Power Ledger is currently setting foothold in several countries like Japan, Malaysia, and Thailand as they believe the Asia Pacific region will become one of the most dynamic clean energy markets by 2030. Similarly, WPR is also a cryptocurrency facilitating energy trading on the Ethereum-based WePower platform. WePower raised USD $40 million making it one of the most sought-after blockchain projects of 2018, and it is the first blockchain enterprise to tokenize an entire grid. The daily prices of POWR and WPR are collected from CoinMarketCap. The energy tokens are cryptocurrencies in nature, we thus assume that crypto market may have significant effects on the returns of energy tokens, and adopt the Royalton CRIX Crypto Index (CRIX) to measure the performance in the crypto market. CRIX data is obtained from *S&P Dow Jones Indices* (www.spglobal.com). For the renewable energy stock market, two representative indices of Wilder Hill Clean Energy Index (ECO) and S&P Global Clean Energy Index (S&PGCE) are taken as proxies. ECO is calculated according to the weighted average of the corporate stocks of the top NASDAQ-listed clean energy firms that are dedicated to the technology and development of renewable energy sources. The S&PGCE tracks the performance of the top 100 global enterprises from both developed and emerging economies that are involved in clean energy-related businesses, and the data is obtained from *S&P Dow Jones Indices*.

As the data of CRIX starts from March 16, 2018, the entire dataset thus covers the period from March 16, 2018 to September 30, 2022 (1200 daily observations). The time series of the variables are shown in Fig. 1. We can see that the prices of POWR and WPR displayed similar trend before mid-2021, but diversified afterwards. POWR and CRIX have behaved similarly since 2019, especially during the period of 2021–2022. In regards of ECO and S&PGCE, they have displayed similar dynamics that steadily increasing after a decline induced by the outbreak of COVID-19 pandemic. This is attribute to the increased investment to renewable energy projects to mitigate the impact of pandemic. Since 2021, ECO and S&PGCE have been trending downward.

The raw data of the variables are non-stationary, therefore, we transform the data into log returns defined as $\ln(r_t / r_{t-1})$ with r_t

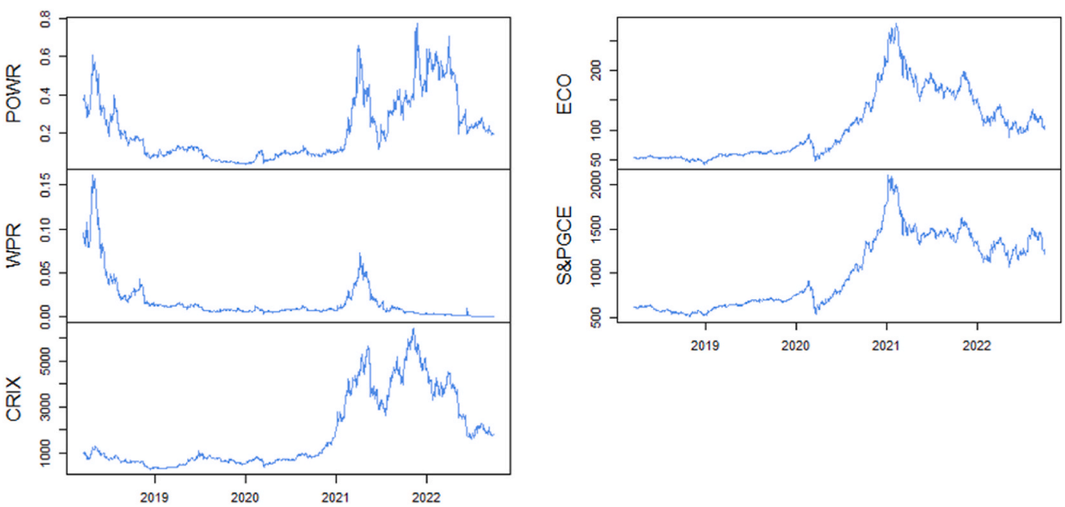

Fig. 1. Time series of the variables. Notes: The time series of POWR and WPR are the daily prices of the tokens, CRIX is the daily value of the index, ECO and S&PGCE are the daily prices of the renewable stocks.

representing the series. The summary statistics of the returns are presented in Table 1. As indicated by the skewness and kurtosis, all the series are asymmetric and leptokurtic, with most of the series are left skewed except for WPR. The Jarque-Bera test rejects the notion of normalcy at the 1 % threshold. The Augmented Dickey Fuller (ADF) unit root test and Philips-Perron test show that the returns of all the series are stationary.

Additionally, the correlation matrix of the series in Fig. 2 shows that, the coefficients among the series are all positive. The coefficient between ECO and S&PGCE is the highest with a value of 0.80, indicating that the returns of them are strongly correlated. POWR, WPR and CRIX are moderately correlated, while their correlations with ECO and S&PGCE are relatively weak. Moreover, the fitted lines of the bivariate scatter plots on the bottom of the diagonal illustrate that the correlation structures among the series are not constant across the joint distribution of returns, thus suggesting the necessary to utilize a QVAR method to characterize the full correlation structures.

4. Empirical results and discussions

4.1. Static quantile-frequency connectedness analysis

We start by interpreting the static quantile-frequency connectedness results of total, short-term (1–5 days) and long-term (longer than 5 days) connectedness at median ($\tau = 0.5$), extreme lower ($\tau = 0.05$), extreme upper ($\tau = 0.95$) quantiles. The median, extreme lower and upper quantiles correspond to normal, bearish and bullish market scenarios respectively. We also draw a comparison between these results with the mean-based connectedness measures retrieved from the approach proposed by Baruník and Křehlík [29]. The results are presented in Table 2. First of all, we can find that the mean-based TCI is 40.85, meaning that 40.85 % of the variation in the system is induced by the interactions among the series. The TCI at median quantile is similar with the mean-based TCI with a value of 39.99. By contrast, the TCIs at extreme lower (72.67) and upper quantiles (71.78) are larger, indicating that these series are more interconnected with each other under extreme market conditions. In addition, the TCI at extreme lower quantile is larger than that at extreme upper quantile, which is in line with various studies concluding that uncertainty or risk during periods of negative returns is usually higher than during periods when positive returns occur ([30,31]). It also implies that the studies focused on the relations between cryptocurrencies or crypto market with renewable stock markets at mean or median quantile (without considering extreme quantiles) might underestimate the connectedness, suggesting the necessary to explore the dependence under diverse economic scenarios rather than concentrating solely on the average market conditions. Furthermore, the frequency connectedness measures in parentheses show that the mean-based short-term TCI is around nine times larger than the mean-based long-term TCI, ten times larger at median quantile, and around six times larger at extreme quantiles. These results reveal that a shock to one series in the system mainly affects the short-term behavior, thus suggesting increased diversification opportunities for the investors in the long term.

Then we move on to the averaged connectedness measures of each investigated series. The indices of TO and FROM measure the average value of connections contributed to other series and those derived from constituent series respectively. The results clearly demonstrate that POWR, WPR and CRIX are more interconnected, while ECO and S&PGCE are more interconnected with each other at median quantile. The linkages between energy tokens and crypto market with the renewable energy stock markets are quite weak, indicating that using energy tokens in a portfolio together with renewable energy stocks has the advantage of increasing diversification under normal economic scenarios. However, the linkages between them significantly intensify under extreme upper and lower quantiles which is consistent with the findings in Ustaoglu [32], implying the reduced diversification opportunities under extreme market conditions. It is noteworthy mentioning that, the linkages among the series are not strong in the long term, affirming that long-term investment in energy tokens and renewable energy stocks can still be beneficial for portfolio diversification, no matter what the market condition is.

Furthermore, the difference between TO and FROM is NET which determines a series' role as net transmitter or receiver. The results show that a series' role might be different across different quantiles. Specifically, POWR and ECO are net transmitters, while WPR, CRIX, and S&PGCE are all net receivers of shocks at median quantile. However, the mean-based NET indices and the indices under extreme quantiles indicate that POWR, WPR and CRIX are all net receivers, while ECO and S&PGCE are on the dominating end of the spillovers transmission, suggesting that the renewable energy stock markets can be used by investors to predict the movements of energy tokens under extreme market conditions. Additionally, further frequency decomposition of the NET indices of the series shows that this strategy could hold in the short term, while each series' role in the long term have proved to be asymmetry and heterogeneous at extreme lower and upper quantiles. Under extreme lower quantile, CRIX and ECO assume long-term net transmitting roles while the

Table 1
Descriptive statistics.

	POWR	WPR	CRIX	ECO	S&PGCE
Mean	−0.001	−0.004	0.000	0.001	0.001
Std. Dev	0.079	0.098	0.046	0.026	0.018
Skewness	−0.469	0.870	−0.503	−0.422	−0.452
Kurtosis	10.211	16.580	3.590	4.009	7.341
Jarque-Bera test	5191.7***	13722.2***	686.4***	828.7***	2701.2***
ADF-test	−10.675***	−10.616***	−9.7304***	−9.3144***	−8.9506***
Philips-Perron test	−35.701***	−41.063***	−34.159***	−33.952***	−31.36***

Notes: "***" is associated to 1 % significance level.

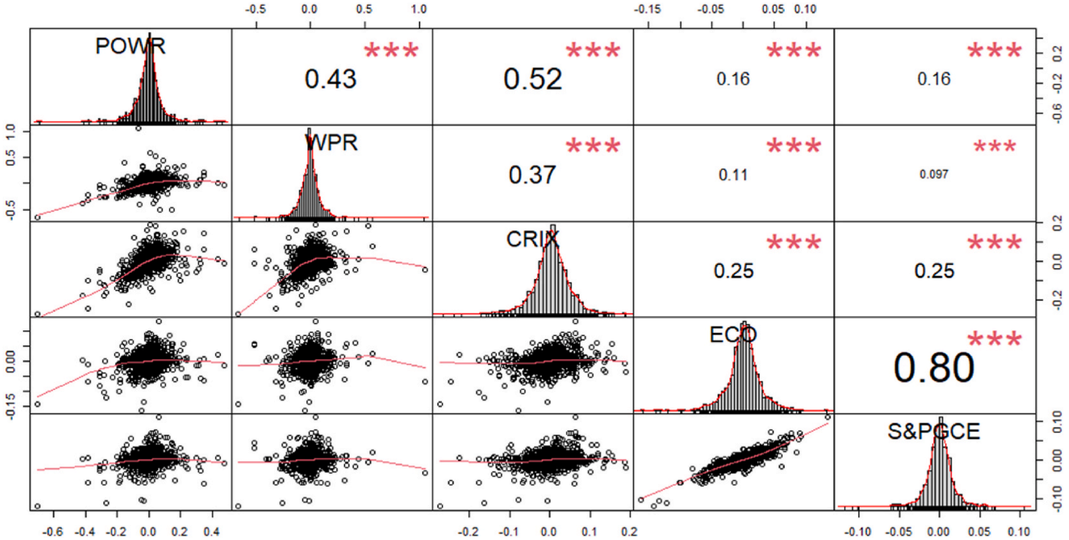

Fig. 2. The correlation matrix chart of the variables. Notes: The diagonal presents the distribution of each variable. On the bottom of the diagonal are the bivariate scatter plots with a fitted line. On the top of the diagonal are Spearman coefficients and the corresponding significance level ("***" is associated to 1 % significance level).

other series are net receivers. In contrast, under extreme upper quantile, POWR, WPR and CRIX are long-term net transmitters while ECO and S&PGCE are net receivers of shocks.

Finally, the net pairwise connectedness networks in Fig. 3 enable us to interpret the possible directions and intensity of the averaged net pairwise spillovers among the series. The blue nodes represent the net transmitters, while yellow nodes represent the net receivers. Node size indicates the degree of net connectedness, with arrows between them marking the direction of spillovers. The mean-based network (the first column) shows that, all the series are interconnected with each other except that the linkage between POWR and CRIX can only be observed in the long term. In the long term, ECO, S&PGCE and CRIX are interconnected, while their linkage with POWR and WPR is weak. At median quantile (the second column), the networks have shown similar characteristics with the mean-based networks except that the linkage between WPR and S&PGCE is even weaker. When coming to the networks at extreme quantiles, the characteristics of the interconnectedness are relatively different. Specifically, at 0.05 quantile (the third column), POWR, WPR and CRIX are more interconnected with S&PGCE in the short term, while more interconnected with ECO in the long term. This indicates that during periods of extreme negative returns, energy tokens and crypt market are more influenced by S&PGCE in the short term, and more influenced by ECO in the long term. This might attribute to the different sectors allocation of the companies within the indices ECO and S&PGCE. According to WilderShares, companies selected within the ECO Index generally include those focusing on technologies for greener, renewable energy, while companies included in the S&PGCE Index are mainly allocated in sectors of utilities (49.6 %), IT (26.8 %), industrials (20.2 %), energy (2.3 %), and materials (1.2 %). As a result, the shocks in ECO are more about technological changes and will cause long-term spillovers, while the shocks in S&PGCE are more about the renewable energy products and will transmit spillovers in the short term. In contrast, at 0.95 quantile (the fourth column) that is during periods of extreme positive returns, POWR, WPR and CRIX are more interconnected with S&PGCE than with ECO in both short and long term, as S&PGCE is more related with the renewable energy products.

4.2. Dynamic connectedness

The static analysis above presents the averaged connectedness of the series, while the dynamic analysis can provide us richer information by depicting the dynamics of the connectedness measures across quantiles, time and frequencies.

4.2.1. Total connectedness index

We start with checking the median-quantile and mean-based total connectedness indices presented in Fig. 4. The results of TCI at median quantile are based on QVAR model, while the mean-based TCI is obtained by applying the Baruník and Křehlík [29] approach, with 100-days rolling window size, a lag length of order 1 (based on HQ criterion and Schwarz Criterion) and 10-step-ahead generalized forecast error variance decomposition. It seems that the median quantile and mean-based TCIs have behaved similarly during the whole sample period. In details, from 2019 to the beginning of 2020, both of the TCIs decreased from around 40 %–30 %. Since the outbreak of the COVID-19 pandemic, the world was characterized by the shutdown of normal day-to-day functions, severe market swings, and huge global uncertainty. The pandemic has triggered an unprecedented decline in economic activity and an episode of global risk aversion, the TCIs then abruptly intensified from 30 % to more than 50 %. It indicates that the return spillovers propagate more intensely during extreme events such as the COVID-19 pandemic relative to calm periods, which is in consistent with series of

Table 2
Static quantile-frequency returns connectedness.

Panel A. Mean-based connectedness						
	POWR	WPR	CRIX	ECO	S&PGCE	FROM
POWR	59.60 (54.63, 4.97)	15.42 (14.11, 1.31)	17.39 (15.79, 1.60)	3.96 (3.51, 0.45)	3.63 (3.21, 0.42)	40.40 (36.63, 3.77)
WPR	16.16 (14.58, 1.58)	67.29 (62.14, 5.15)	11.46 (10.29, 1.17)	2.64 (2.43, 0.20)	2.45 (2.23, 0.22)	32.71 (29.53, 3.18)
CRIX	17.57 (15.69, 1.88)	10.67 (9.53, 1.14)	59.96 (54.45, 5.50)	6.16 (5.43, 0.73)	5.64 (4.91, 0.73)	40.04 (35.56, 4.49)
ECO	3.24 (3.01, 0.23)	1.98 (1.81, 0.17)	5.31 (4.88, 0.43)	54.65 (49.06, 5.59)	34.82 (31.28, 3.54)	45.35 (40.99, 4.37)
S&PGCE	3.27 (2.96, 0.31)	2.10 (1.84, 0.27)	4.92 (4.43, 0.49)	35.43 (30.93, 4.50)	54.28 (47.81, 6.46)	45.72 (40.16, 5.56)
TO	40.24 (36.24, 4.01)	30.17 (27.29, 2.89)	39.09 (35.40, 3.69)	48.18 (42.31, 5.87)	46.55 (41.64, 4.91)	TCI 40.85 (36.57, 4.27)
NET	−0.16 (−0.40, 0.24)	−2.54 (−2.25, −0.29)	−0.96 (−0.16, −0.80)	2.83 (1.32, 1.51)	0.82 (1.48, −0.65)	
Panel B. Connectedness at median quantile (τ = 0.5)						
	POWR	WPR	CRIX	ECO	S&PGCE	FROM
POWR	61.18 (56.58, 4.60)	15.00 (13.88, 1.12)	17.14 (15.72, 1.42)	3.47 (3.16, 0.31)	3.21 (2.91, 0.30)	38.82 (35.68, 3.14)
WPR	15.73 (14.48, 1.25)	68.64 (63.98, 4.66)	10.83 (9.93, 0.90)	2.55 (2.41, 0.14)	2.25 (2.11, 0.14)	31.36 (28.93, 2.43)
CRIX	17.28 (15.65, 1.63)	10.54 (9.61, 0.94)	61.03 (55.91, 5.12)	5.65 (5.04, 0.61)	5.50 (4.84, 0.67)	38.97 (35.12, 3.85)
ECO	3.30 (3.01, 0.29)	2.12 (1.97, 0.16)	5.25 (4.83, 0.42)	55.01 (49.25, 5.77)	34.32 (30.90, 3.42)	44.99 (40.70, 4.29)
S&PGCE	3.65 (3.31, 0.34)	2.29 (2.04, 0.25)	5.00 (4.60, 0.40)	34.88 (30.54, 4.34)	54.18 (48.11, 6.07)	45.82 (40.49, 5.33)
TO	39.95 (36.44, 3.51)	29.96 (27.50, 2.46)	38.21 (35.07, 3.14)	46.55 (41.15,5.40)	45.28 (40.76, 4.53)	TCI 39.99 (36.18, 3.81)
NET	1.13 (0.77, 0.37)	−1.41 (−1.43, 0.03)	−0.76 (−0.05, −0.71)	1.56 (0.45, 1.11)	−0.53 (0.27, −0.80)	
Panel C. Connectedness at extreme lower quantile (τ = 0.05)						
	POWR	WPR	CRIX	ECO	S&PGCE	FROM
POWR	26.05 (22.07, 3.98)	18.81 (15.56, 3.24)	20.12 (16.71, 3.41)	17.60 (14.51, 3.08)	17.43 (14.28, 3.15)	73.95 (61.06, 12.89)
WPR	19.18 (16.22, 2.96)	28.03 (24.26, 3.77)	18.94 (16.00, 2.94)	17.10 (14.53, 2.57)	16.75 (14.05, 2.70)	71.97 (60.79, 11.18)
CRIX	18.83 (16.15, 2.68)	17.77 (15.17, 2.60)	26.21 (22.69, 3.52)	18.27 (15.53, 2.74)	18.91 (16.11, 2.80)	73.79 (62.97, 10.82)
ECO	15.79 (13.69, 2.10)	15.86 (13.54, 2.32)	16.76 (14.37, 2.39)	27.72 (23.60, 4.13)	23.86 (20.26, 3.60)	72.28 (61.86, 10.42)
S&PGCE	15.31 (12.63, 2.69)	15.58 (12.75, 2.83)	16.98 (14.01, 2.97)	23.52 (19.26, 4.25)	28.61 (23.40, 5.21)	71.39 (58.64, 12.74)
TO	69.11 (58.68, 10.43)	68.02 (57.02, 11.00)	72.81 (61.09, 11.72)	76.48 (63.84, 12.65)	76.95 (64.69, 12.26)	TCI 72.67 (61.06, 11.61)
NET	−4.84 (−2.38, −2.46)	−3.95 (−3.77, −0.18)	−0.98 (−1.88, 0.90)	4.21 (1.98, 2.23)	5.56 (6.05, −0.48)	
Panel D. Connectedness at extreme upper quantile (τ = 0.95)						
	POWR	WPR	CRIX	ECO	S&PGCE	FROM
POWR	28.16 (25.28, 2.88)	19.16 (17.24, 1.92)	19.68 (17.85, 1.83)	16.45 (14.77, 1.68)	16.55 (14.54, 2.01)	71.84 (64.40, 7.43)
WPR	19.48 (17.72, 1.75)	29.10 (26.18, 2.92)	18.63 (16.79, 1.84)	16.43 (14.90, 1.52)	16.37 (14.83, 1.54)	70.90 (64.25, 6.65)
CRIX	19.93 (17.42, 2.50)	18.19 (16.08, 2.11)	27.81 (24.72, 3.09)	17.00 (15.05, 1.95)	17.08 (14.88, 2.19)	72.19 (63.44, 8.75)
ECO	15.74 (13.87, 1.87)	15.16 (12.99, 2.17)	16.51 (14.26, 2.25)	28.13 (24.79, 3.35)	24.45 (21.27, 3.18)	71.87 (62.39, 9.48)
S&PGCE	15.92 (13.00, 2.92)	15.76 (12.44, 3.31)	16.65 (13.41, 3.24)	23.77 (19.45, 4.31)	27.91 (22.36, 5.55)	72.09 (58.31, 13.78)
TO	71.07 (62.02, 9.05)	68.27 (58.76, 9.50)	71.47 (62.31, 9.16)	73.64 (64.18, 9.46)	74.45 (65.52, 8.93)	TCI 71.78 (62.56, 9.22)
NET	−0.77 (−2.38, 1.61)	−2.64 (−5.49, 2.85)	−0.73 (−1.13, 0.40)	1.77 (1.78, −0.01)	2.36 (7.22, −4.86)	

Notes: The values above the parentheses are total connectedness measures, while the values in parentheses are the corresponding short-term and long-term connectedness respectively (the sum of them equals total connectedness).

studies (e.g. Refs. [18,30]). From mid-2020 to the end of 2021, the TCI fluctuates between 30 % and 40 %. However, the TCIs increased significantly at the first quarter of 2021, which may attribute to the outbreak of Russia-Ukraine conflict that unbalanced the global energy market.

In addition, it is important for investors or policy makers to understand the dynamics across different investment horizons. The frequency analysis indicates that the short-term and long-term TCIs behave similarly in most of the sample period, however, the changes of TCI are mainly originated from the short-term dynamics. We can also observe that the mean-based long-term TCI is larger than the median quantile long-term TCI at some points. This is especially significant when looking at March 2020 when the COVID-19 pandemic outbroke, implying that the mean-based connectedness approach may overestimate the initial effect of COVID-19 pandemic. The reason is that the VAR model used in computing the mean-based connectedness is based on OLS regressions which are usually sensitive to outliers [23].

The divergence between the median quantile and mean-based long-term TCIs also indicates the need to move beyond mean-based connectedness measures to understand the dynamics across diverse quantiles. We thus move on to the analysis of the dynamic TCI over time and quantiles as shown in Fig. 5. We can find that the TCIs increase from median quantile to extreme quantiles along the vertical axis, echoing the results presented in the static analysis. In addition, the connectedness appears to be slightly asymmetric that the spillovers are higher at the extreme lower quantile than at the extreme upper quantile. This could demonstrate that market uncertainty or risk during periods of negative returns – such as periods of crisis, is higher than that during periods when positive returns occur which might be marked with many technological improvements. Moreover, we can also clearly identify a structural change of the TCI along the horizontal axis which is induced by the outbreak of COVID-19 pandemic.

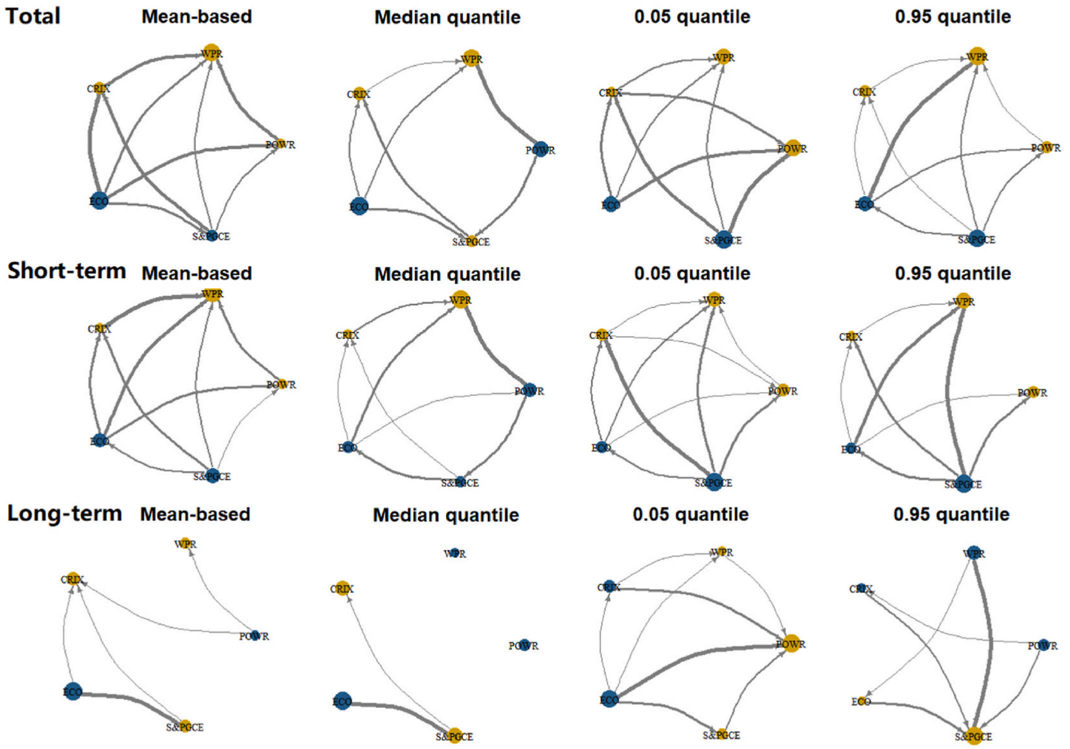

Fig. 3. Networks of net pairwise directional connectedness at different frequencies and quantiles
Notes: Figures in the first row represent the network of net pairwise directional connectedness at mean, median and extreme quantiles. Figures in the second and the third rows are the short-term and long-term net pairwise directional connectedness at mean, median and extreme quantiles respectively.

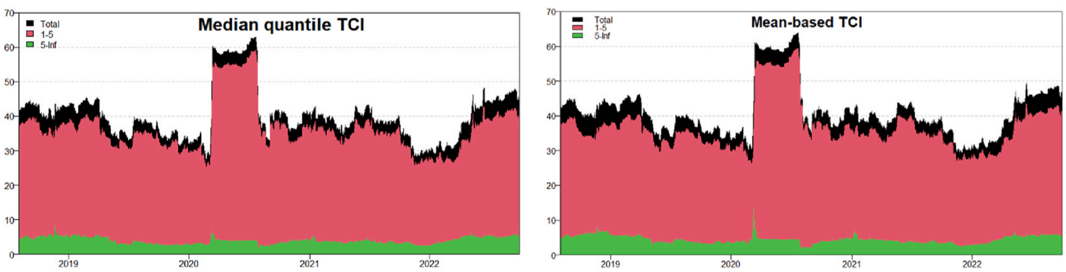

Fig. 4. Total and frequency decomposition of the dynamic TCIs at median-quantile and mean-based quantile. Notes: The black area demonstrates the total TCI while the red and green areas represent the short-term and long-term TCI respectively.

4.2.2. Net directional connectedness index

4.2.2.1. Net total directional connectedness over time and quantiles. As stated by Chatziantoniou, Abakah, Gabauer, and Tiwari [23] that, the results concerning the net propagation power of each variable are of major interest in the connectedness literature. By analyzing the net directional connectedness over time and quantiles shown in Fig. 6 we find that, the roles of the series as net transmitters or receivers of shocks are varied and event-dependent over time, and characterized by asymmetry and heterogeneity over different quantiles. Specifically, we can divide the sample period into four phrases and explore the transmission power of the series within each phrase. The four phrases are pre-pandemic period (March 2018–March 2020), March to the end of 2020 (typically marked by the outbreak of COVID-19 pandemic), 2021 (marked by the crypto market boom), and 2022 with the outbreak of Russia-Ukraine conflict as a typical event.

In the pre-pandemic period when the energy tokenization experienced rapid development, the energy tokens are generally net transmitters. In the case of POWR, we observe that it is the main net transmitter before 2020, then switches to a net receiver with the outbreak of COVID-19 pandemic. Similar characteristic has been observed when looking at WPR except for an earlier switch from transmitter to receiver of the shocks. With regards to the other series, the results are mixed but they can be conceived as net receivers of

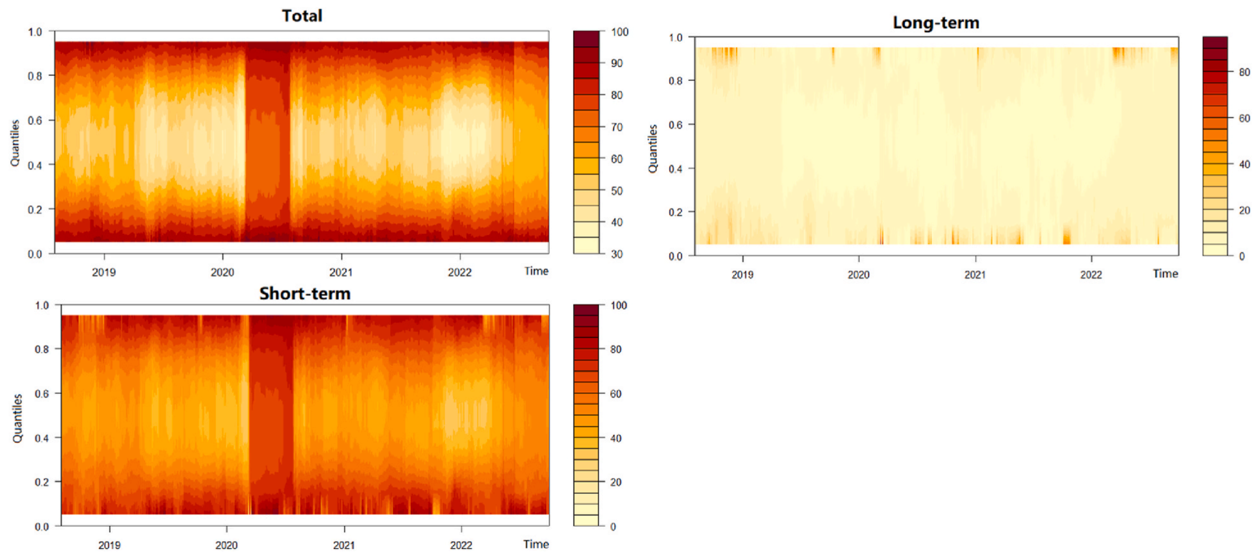

Fig. 5. Total, short-term, and long-term TCIs over time and quantiles. Notes: The figures represent the total, short-term, and long-term dynamic TCIs respectively over time and quantiles. Warmer shades indicate higher levels of connectedness.

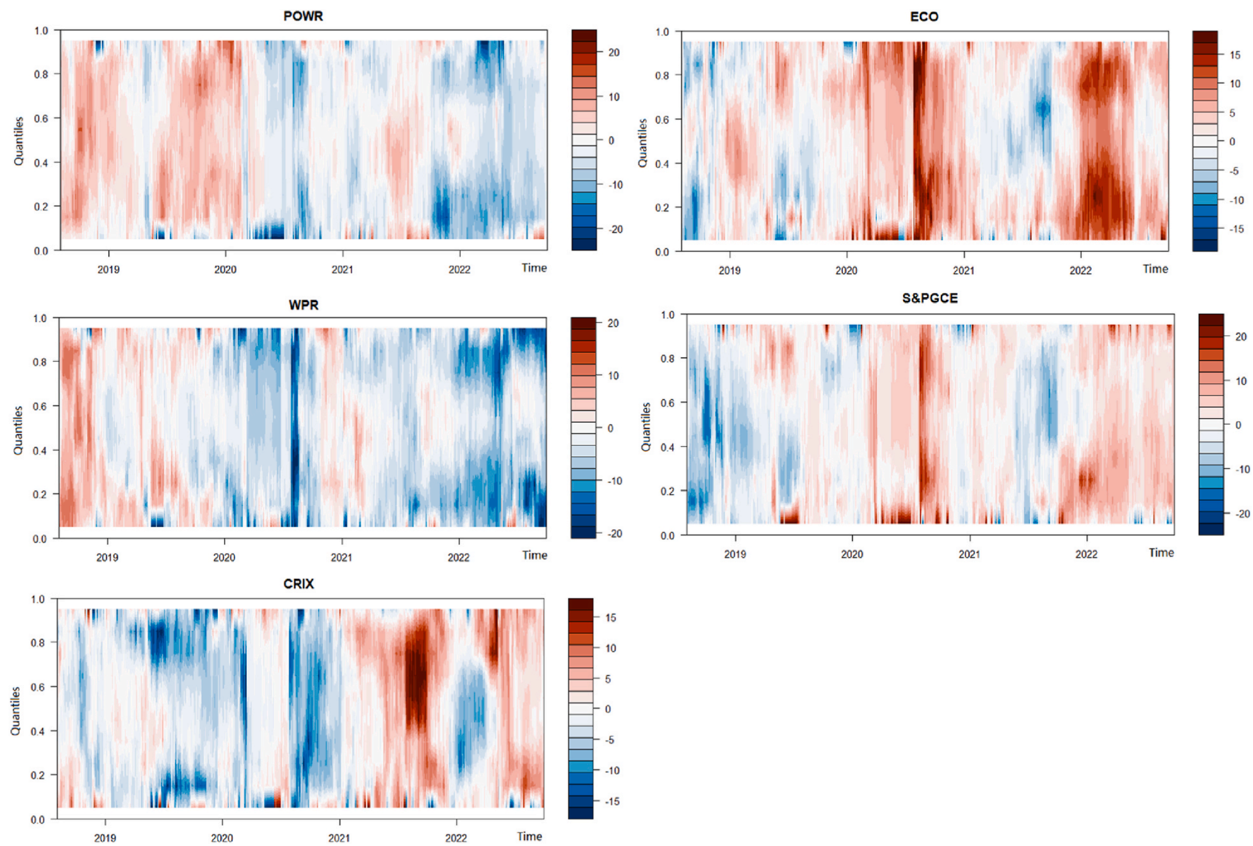

Fig. 6. Net directional connectedness of each variable over time and quantiles. Notes: Red shades indicate net transmitting roles of the series, while blue shades indicate net receiving roles. The deeper color corresponds with the higher level of connectedness.

shocks in most of the cases during this period. Furthermore, a slight asymmetry occurs at the energy tokens' net directional connectedness along the vertical axis that the spillovers are higher on the upper end than on the lower end. It seems as if the results were contradictory to the static analysis, however, it makes sense as common positive returns of energy tokens are more likely to occur during prosperous periods.

The second phrase is marked by the outbreak of COVID-19 pandemic. During this period, POWR, WPR and CRIX are all net receivers of spillovers, while ECO and S&PGCE assume net transmitting roles which can be attributed to the development of renewable industry. The COVID-19 pandemic has played a game-changing role in accelerating the clean energy transition in the power industry as renewable energy demand jumped after the COVID-19 lockdown across the world and many countries spent a lot of money on sustainable and green energy projects. According to a report[2] issued by the International Energy Agency, renewable markets have shown their resilience to the crisis half a year after the outbreak of the pandemic. Therefore, we can find that the net directional connectedness of ECO and S&PGCE intensified at around mid-2020. In addition, the net directional connectedness of them are also asymmetric along the quantiles that higher at lower end than on the upper end. It is consistent with the static analysis that risk is usually higher during periods of negative returns than it is during periods of positive returns.

During the third period which coincides with the boom of the crypto market, CRIX has assumed a net transmitting role, while the other series are roughly net receivers of shocks. Notably, the net connectedness of CRIX increases along the extreme quantiles, however, decreases at the very end with the highest values at around 75 % quantile. At the end of 2021, the crypto market experienced a major sell-off and the values fell sharply due to the tightening of global monetary policies. Thus, CRIX becomes a net recipient of shocks at the beginning of 2022 – the fourth phrase. However, the outbreak of Russia-Ukraine conflict has caused the increase of the global risk aversion. The CRIX switch to a net transmitter again due to the hedge and safe-haven properties of cryptocurrencies against the intensified geopolitical pressures. Moreover, renewable energy stock markets also assume the transmitting roles in the system, which is attribute to the fact that the Russia-Ukraine conflict promotes governments around the world attempts to seek out cleaner energy sources and accelerate the development of environmentally-sound alternatives to fossil fuels.

4.2.2.2. Frequency decomposition of net directional connectedness. In order to investigate the net directional connectedness in the frequency domain, we decompose the connectedness into short-term and long-term measures with the results presented in Fig. 7. We can find that, the net directional connectedness in the short term have presented similar characteristics with the net total directional connectedness measures in Fig. 6, indicating that the role of each variable as a net transmitter or receiver is mainly determined by the short-term dynamics, while the long-term dynamics either weaken or strengthen the net transmission power.

Specifically, although the total and short-term net directional connectedness of POWR are varied over time, the long-term connectedness draws a relative clearer picture that assumes the transmitting role before 2021, being a net receiver until mid-2022, and then switches to net transmitter afterwards. Compared with POWR, the long-term connectedness of WPR and CRIX are less regularly. In the case of the two renewable energy stock markets proxies, the long-term dynamics of ECO point to the fact that it is a net transmitter throughout the most sample period of time, just temporarily has a net receiving role. The long-term dynamics of S&PGCE have switched from a net receiving role to a transmitting role at around mid-2021. This is important to investors as the long-term characteristics of the renewable energy stock markets' influence on the system are quite clear, helping them to better assess the investment risks in the long-term horizon.

Furthermore, as mentioned above that, ECO and S&PGCE are the main transmitters of shocks during the pandemic in 2020 and the period after 2022 which coincides with the Russia-Ukraine conflict. Some interesting points could be found by comparing the dynamics of ECO and S&PGCE in these two periods. We can find that the extent of total net directional connectedness of ECO and S&PGCE during the pandemic in 2020 is stronger than that during the period after 2022. However, the long-term dynamics are notably stronger during the latter period. This might indicate that, Russia-Ukraine conflict has played a more direct and profound role on energy markets than the COVID-19 pandemic in the long term. The reason might be that, as a public health crisis, the impact of COVID-19 pandemic is comprehensive. In comparison, price volatility, supply constraints, security concerns and economic uncertainty induced by the Russia-Ukraine conflict have a more profound effect on global energy markets.

4.2.3. Net pairwise directional connectedness analysis

4.2.3.1. Net pairwise directional connectedness at median quantile. In this section, we would like to present a detailed explanation of the bilateral dynamics among the series at median quantile (as shown in Fig. 8), and also compare with the corresponding mean-based counterparts (as shown in Fig. 9). First of all, in regards of the relations between energy tokens, we can see that POWR has been a net transmitter of shocks during most of the sample periods, indicating that a shock in POWR will induce a net change in the WPR while it is not the case vice versa. However, the spillover between POWR and WPR has been negligible since mid-2021, implying that investors can benefit from the diversification effect by investing into these two energy tokens.

When it comes to the linkage between energy tokens and crypto market index, we find that POWR and WPR have dominated CRIX until the outbreak of COVID-19 and afterwards they have gradually become net pairwise receivers of shocks from CRIX. However, it is noteworthy that POWR and WPR are rather long-term net pairwise transmitters while are short-term net pairwise transmitters. This could indicate that, the fast development of energy tokens due to the increased investment in renewable energy has caused net

[2] Renewables 2020 – Analysis and forecast to 2025, https://www.iea.org/reports/renewables-2020.

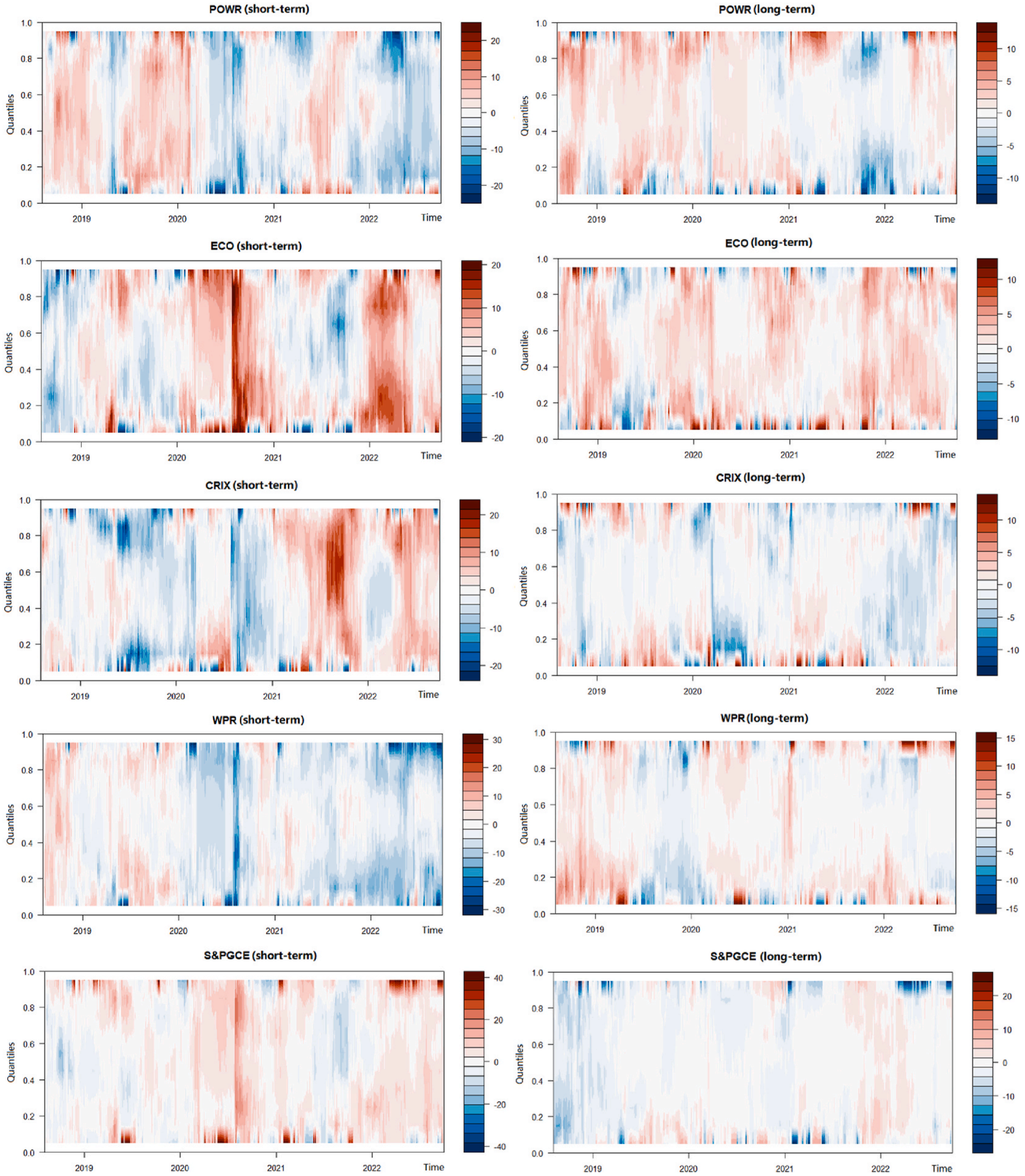

Fig. 7. Short-term and long-term net directional connectedness of each variables over time and quantiles. Notes: The heat maps in left column represent the short-term net directional connectedness of each variables over time and quantiles, while the heat maps in right column represent the long-term counterparts. Red shades indicate net transmitting roles of the series, while blue shades indicate net receiving roles. The deeper color corresponds with the higher level of connectedness.

spillover to the crypto market in the long term, while the short-term market fluctuations cause spillovers from crypto market to the energy tokens.

Then we move on to the relations between energy tokens, CRIX and renewable stocks. Notably, we have found similar event-dependent (COVID-19 pandemic, crypto market boom and Russia-Ukraine conflict) dynamics at specific intervals. In more details, in 2021 which was marked by the burgeoning expansion of crypto market, the energy tokens and CRIX dominated the renewable stock markets. However, during the pandemic in 2020 and after the year of 2022, the renewable stocks are net pairwise connectedness transmitters. Additionally, the net pairwise connectedness from renewable stocks to energy tokens and cryptocurrency mainly originated from the short-term dynamics during the pandemic, while after 2022 the connectedness was mainly driven by the long-term dynamics. This shows again that, compared with COVID-19 pandemic, the Russia-Ukraine conflict may have more profound and long-lasting influence on energy market, therefore renewable energy stocks have long-term spillover effect on energy tokens and crypto market rather than temporary impact.

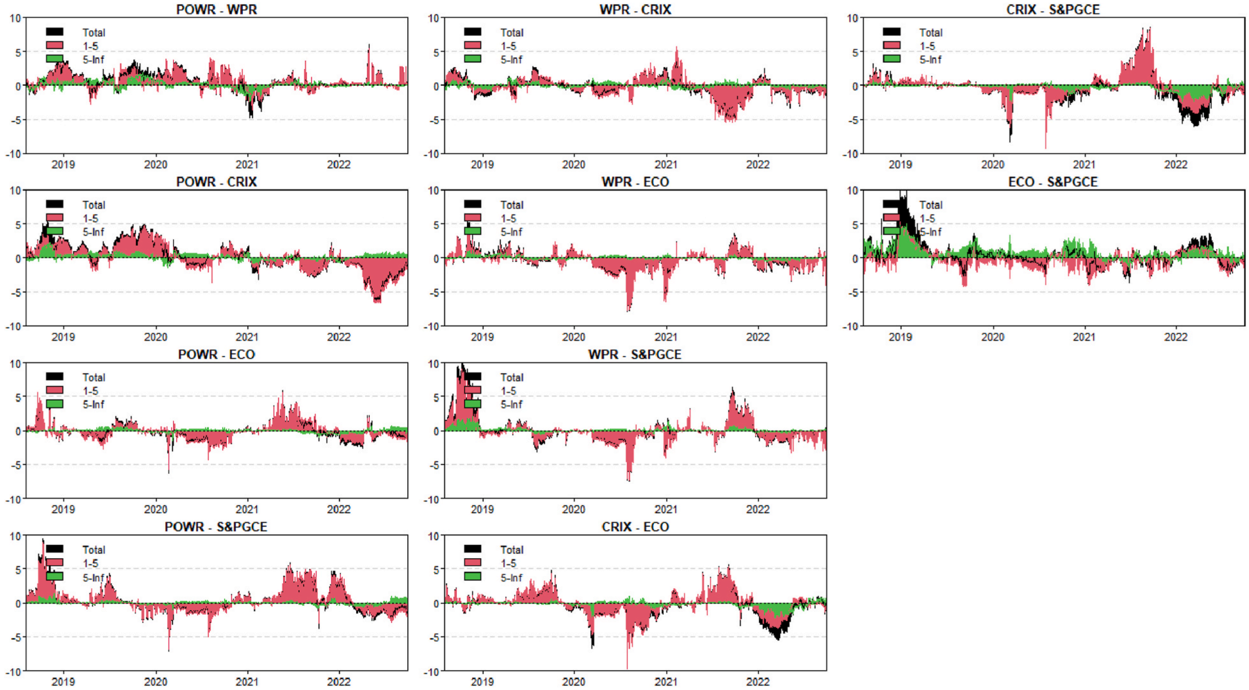

Fig. 8. Total, short-term, and long-term net pairwise directional connectedness at median quantile. Notes: The black area demonstrates the total dynamic connectedness while the red and green areas represent the short-term and long-term connectedness respectively.

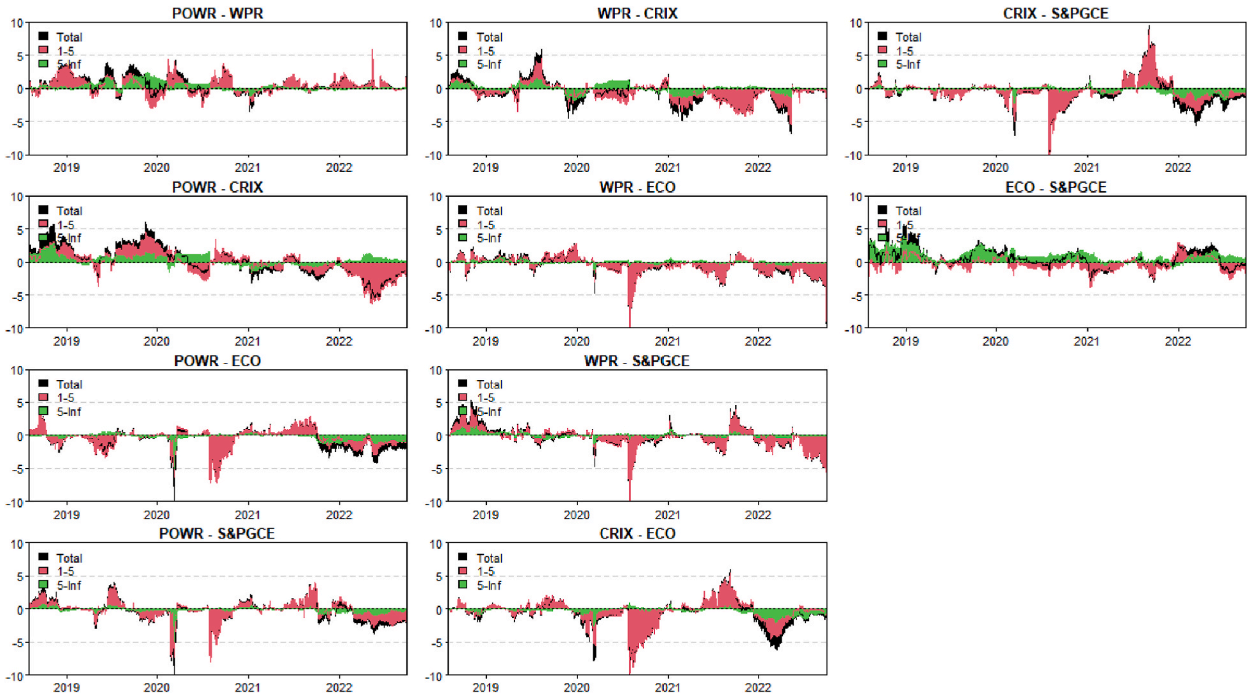

Fig. 9. Total, short-term, and long-term net pairwise directional connectedness at mean-based quantile.
Notes: The black area demonstrates the total dynamic connectedness while the red and green areas represent the short-term and long-term connectedness respectively.

Finally, regarding the linkage between ECO and S&PGCE, it is quite interesting to find that during the most sample period, ECO is mainly dominating in the long term as only during the period from mid to the end of 2021 that it has been dominated, whereas on the other side S&PGCE is rather a short-term net pairwise transmitter of spillovers. This could be explained by the different sector allocation of the companies within these indices we have mentioned in section 4.1 that, the shocks in ECO are more about technological changes and will cause long-term net pairwise spillovers to S&PGCE. In turn, the shocks in S&PGCE are more about the renewable energy products and will transmit net pairwise spillovers to the ECO index in the short term.

4.2.3.2. Net pairwise directional connectedness at extreme quantiles. Figs. 10 and 11 depict the net pairwise directional connectedness at extreme lower and upper quantiles respectively. We can clearly observe that the connectedness measures are highly volatile in both figures, and the value in two figures is different, affirming the asymmetry of the connectedness we have mentioned above. In details, under extreme lower quantile in Fig. 10 we can find that POWR, WPR and CRIX are dominated by ECO and S&PGCE during most of the time period, except that during 2021 when the energy tokens experienced significant rise and fall in sync with the crypto market, the energy tokens have dominated ECO and S&PGCE. We can thus argue that during the bearish period of negative returns, the energy tokens and crypto market are vulnerable to the conventional renewable energy stock markets.

Moving on to the extreme upper quantile as shown in Fig. 11, similar results can be found regarding to the total and short-term net pairwise directional connectedness that, POWR, WPR and CRIX are dominated by ECO and S&PGCE. However, ECO and S&PGCE are dominated by POWR, WPR and CRIX in the long term. This might be attribute to the fact that technological changes are more likely to occur during periods of positive returns. As an application of blockchain technology in the energy sector, energy tokenization has been widely recognized as an important approach to promote energy transition with great potential to attract attentions from investors and financial advisors. Therefore, long-term spillovers can be observed from energy tokens to renewable energy stock markets during economic scenarios with positive returns.

4.3. Robustness test

In the basic analysis above, the window size was set to 100-days. Here we set the rolling window sizes to be 50 and 150 days respectively to verify the robustness of the empirical results. The results presented in Figs. 12 and 13 demonstrate that the TCIs have a similar trend with those for a window size of 100-days shown in Fig. 4. The results concerning the net directional connectedness and net pairwise directional connectedness also present similar characteristics.[3] It reveals that the connectedness between energy tokens, crypto market, and renewable energy stock markets is unaffected by the rolling window size and frequency settings, thus ensuring the robustness of our findings.

5. Concluding remarks

The renewable energy sector is one of the strategically important sectors that needs continuous influx of funding. However, the entry threshold for investing in the industry is relatively high. Energy tokenization is one of the most promising solutions that being increasingly used in the renewable energy industry, and energy tokens are becoming a class of cryptocurrencies that attracting more and more attentions from investors and entrepreneurs concerned about the environment. Therefore, we constructed a system comprising of energy tokens, crypto market, and renewable energy stock markets and conducted the static and dynamic analysis by employing a quantile frequency connectedness approach. The main conclusions of our study are as follows.

The static analysis shows the characteristic of clustering that energy tokens and crypto market are more interconnected, while the renewable energy stock markets are more interconnected with each other under normal market conditions. The linkages between energy tokens and renewable energy stock markets are quite weak, suggesting the diversification opportunities in investing these financial assets under normal market conditions. However, these series are more interconnected under extreme market conditions, with the renewable energy stock market are on the dominating end of the propagation mechanism while energy tokens and crypto market are net receivers of shocks, suggesting that the renewable energy stock markets can be used by investors to predict the movements of energy tokens. Further frequency decomposition shows that this strategy can hold in the short term, while in the long term investors could benefit from the diversification opportunities by investing both kinds of financial assets.

Compared to the static results, the dynamic analysis shows richer information about the dependence relationship among the series. The dynamic analysis demonstrates that the connectedness measures are time-varying and event-related. In consistent with many previous literatures that we also observe a structural change in the connectedness of the series in response to the unprecedented monetary injections used to combat the COVID-19 pandemic-induced economic stagnation. Moreover, we find that the uncertainty of the system increases since the first quarter of 2022, which may attribute to the outbreak of Russia-Ukraine conflict. Upon further checking of the detailed connectedness measures, we find that the Russia-Ukraine conflict may have played a more profound and long-lasting role than the COVID-19 pandemic on the dynamics among energy tokens, crypto market and renewable energy stock markets. In addition, it seems that the connectedness measures of the series are asymmetric and heterogeneous at diverse quantiles and different investment horizons. The extreme positive and negative shocks induce the connectedness to intensify in an asymmetry pattern. Thus, just analyzing the connectedness at single frequency or quantile might mask these dynamics.

[3] Detailed results can be obtained from corresponding author upon request.

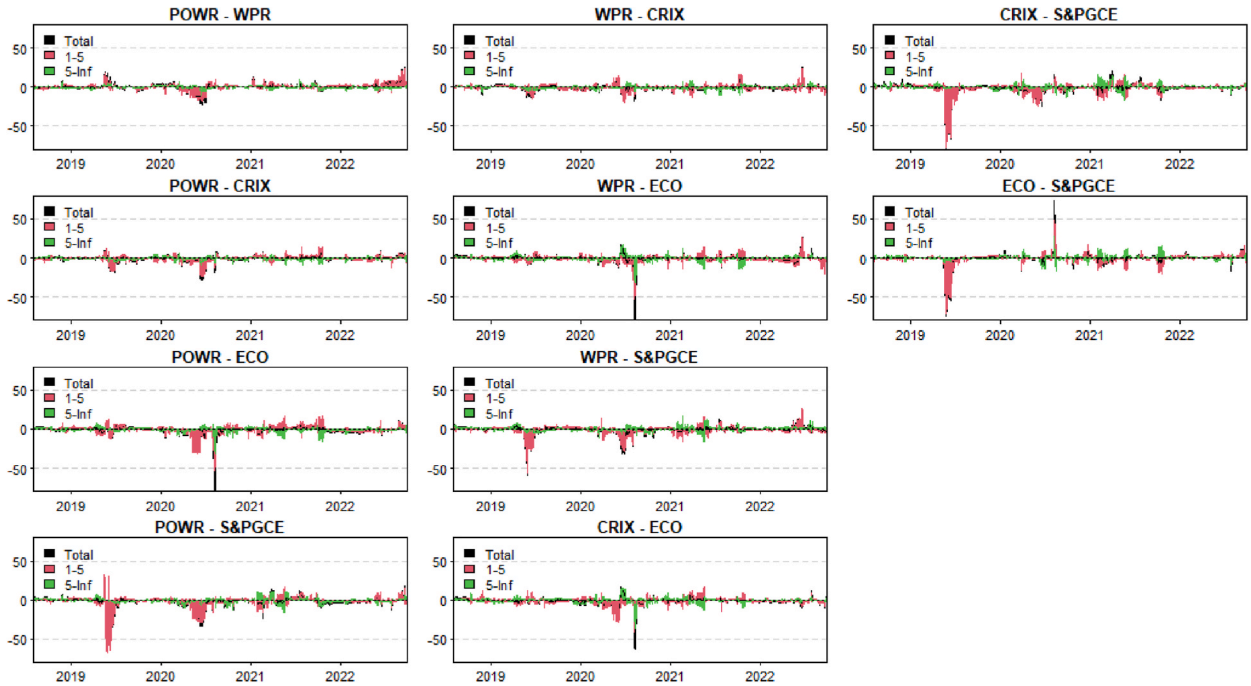

Fig. 10. Total, short-term, and long-term net pairwise directional connectedness at extreme lower (τ = 0.05) quantile
Notes: The black area demonstrates the total dynamic connectedness while the red and green areas represent the short-term and long-term connectedness respectively.

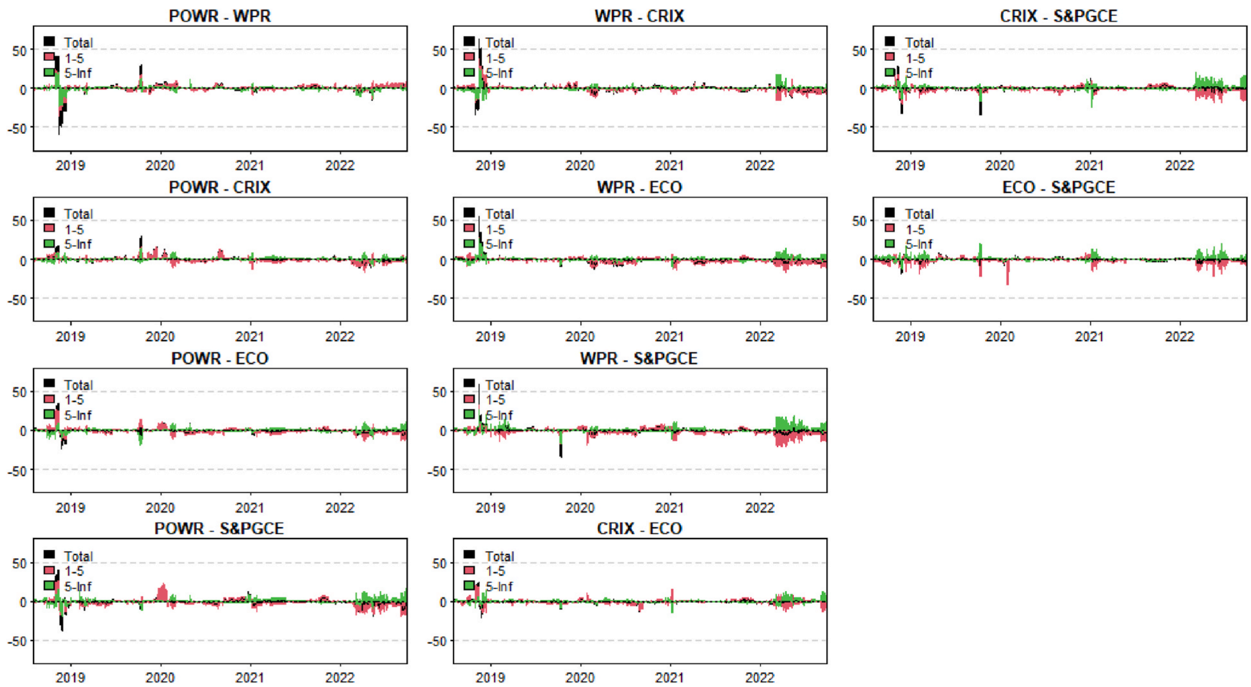

Fig. 11. Total, short-term, and long-term net pairwise directional connectedness at extreme upper (τ = 0.95) quantile
Notes: The black area demonstrates the total dynamic connectedness while the red and green areas represent the short-term and long-term connectedness respectively.

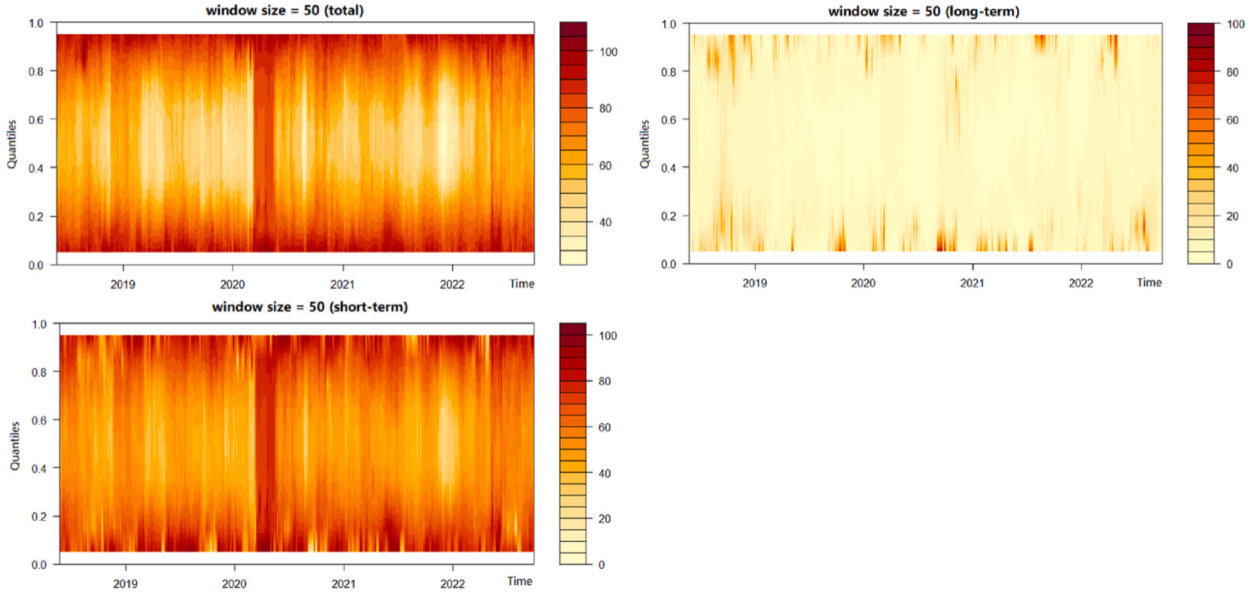

Fig. 12. Total, short-term, and long-term dynamic TCIs over time and quantiles with rolling window sizes of 50. Notes: Warmer shades indicate higher levels of connectedness.

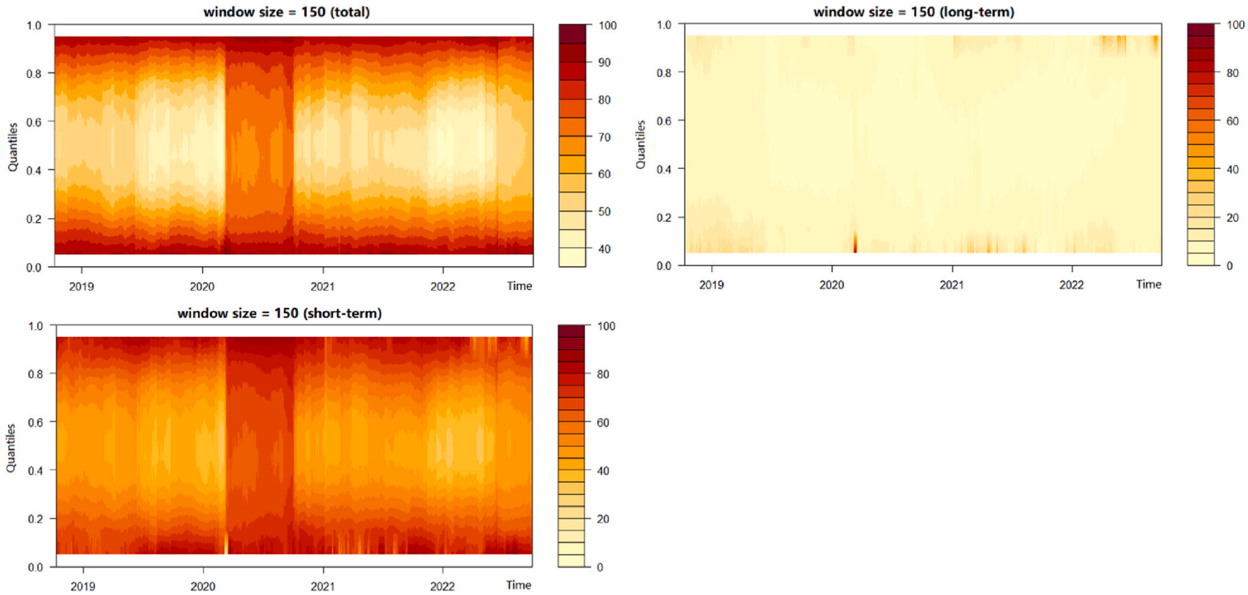

Fig. 13. Total, short-term, and long-term dynamic TCIs over time and quantiles with rolling window sizes of 150
Notes: Warmer shades indicate higher levels of connectedness.

The results imply that the studies focused on the relations between cryptocurrencies or crypto market with renewable stock markets at mean or median quantile (without considering extreme quantiles) might underestimate the connectedness, suggesting the necessary to explore the dependence under diverse economic scenarios rather than concentrating solely on the average market conditions. Furthermore, the investigation of connectedness measures at different frequencies reveal that a shock to one series in the system mainly affects the short-term behavior, thus suggesting increased diversification opportunities for the investors in the long term. It is noteworthy mentioning that, the linkages among the series are not strong in the long term, affirming that long-term investment in energy tokens and renewable energy stocks can still be beneficial for portfolio diversification, no matter what the market condition is.

Generally speaking, even though it is still in its infancy, energy tokenization is conceived to be one of the most promising applications of blockchain technology, and it is expected to revolutionize the production, distribution, and use of electricity. Our study provides a clear interpretation of the potential patterns and magnitude of the return spillovers between energy tokens, crypto market and renewable energy stock markets, which may assist the investors to build sustainable portfolios, or help the policy makers to formulate efficient regulatory policy. However, in consideration of a long enough sample period, our study only investigated two energy tokens while some recently emerged energy tokens such as Energy Web Token, Efforce and SunContract are not included. Those energy tokens could be explored in subsequent research.

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Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Xu Wang: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Jinling Liu:** Writing – original draft, Data curation. **Qichang Xie:** Writing – review & editing, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships.

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