



The spillover effects among fossil fuel, renewables and carbon markets: Evidence under the dual dilemma of climate change and energy crises

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ABSTRACT

The environmental emergency and energy crisis are serious challenges exposed to Europe, which results in a fundamental shift in the linkages regarding fossil fuel, renewable energy and carbon trade markets. This study investigates the spillover effects based on the quantile VAR network. We find that the impact of the extreme market on the connectedness network of underlying assets proves to be more pronounced compared to the standard conditions. The risk spillovers in extreme cases originate primarily from the renewable energy and carbon markets, while fossil fuels account for the most significant contributor under normal circumstances. Hence, investors are supposed to develop dynamic and flexible portfolios to hedge potential risks. Concerning the governments, corresponding initiatives should be implemented to facilitate the continuous evolution of the European Union carbon trading system and the energy transition. These provide a feasible solution to Europe's dual dilemma regarding energy security and the climate emergency.

1. Introduction

Climate change is now emerging as one of the most daunting challenges exposed to sustainable development [1,2]. Green House Gas (GHG) emissions are responsible for this environmental crisis, mainly resulting from burning fossil fuels [3,4]. According to the International Energy Agency (IEA), carbon dioxide (CO₂) emissions from the world's energy sector reached a record high in 2021.¹ As the process of industrialisation develops by leaps and bounds, the issue of CO₂ emissions has been placed on the urgent agenda [5]. In this regard, the carbon emission trading (CET) market designed by Kyoto Protocol² proves to be a significant institutional innovation, which treats CO₂ emission rights as a tradable commodity [6,7]. Likewise, it employs market mechanisms to curb emissions and stimulate low-carbon development cost-effectively [8]. Hence, although the CET market is policy-driven, it exhibits some financial features connected with traditional energy markets [9,10]. The price of conventional fossil fuels, determined by supply and demand, is inextricably linked with CO₂ emissions, affecting the carbon market [4].

Likewise, carbon pricing may be a potent instrument to swing the pendulum to renewable energy [11]. The purpose of such initiatives is to limit emissions by driving the production of coal and other fossil fuels costly. As a result, it witnesses the focus of many investors shifting from the traditional to the clean energy markets [12,13]. Therefore, the expansion of CET must not be separate from those of fossil fuel and renewable energy sectors owing to the intertwined price connectedness across these markets [14].

The European Union Emissions Trading Scheme (EU ETS), launched in 2005, is currently the largest carbon market in the world [15,16]. Since 2021, the EU ETS has entered the fourth phase of operation. It is a cap-and-trade mechanism where authorities regulate a total permissible quantity of CO₂ emissions within a certain period and grant permits for the tradable credits [7,17,18]. In this sense, this scheme is gradually replaced by auctions instead of free distribution [19]. The carbon market package aims to transform the economy to zero-emission by 2050, it has become the policy cornerstone for climate change and the flagship initiative of the EU to effectively reduce greenhouse gas emissions [16].

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¹ IEA analysis. Available online: <https://www.iea.org/news/global-co2-emissions-rebounded-to-their-highest-level-in-history-in-2021>.

² The Kyoto Protocol is an international agreement to reduce greenhouse gas emissions, especially carbon dioxide (CO₂).

However, although the financialisation of the carbon market boots the trading liquidity and convenience, it is also accompanied by price volatility and speculative behaviour. The EU ETS has suffered wild price swings amid financial tumult and energy policy uncertainty (e.g., the European Commission proposes to raise the 2030 emission reduction target from 40% to at least 55%). In addition, due to the economic recovery from the Corona Virus Disease 2019 (COVID-19) pandemic, an energy crunch has accelerated the shift from fossil fuels to renewables [20]. And the war between Russia and Ukraine has pushed energy prices and complicated the politics of carbon pricing [21].

In light of the rising concerns of Europe regarding the energy crisis dilemma and climate change issues, member states must define the balance between energy security and price stability, as well as their commitments to achieve net-zero targets. There is a profound transformation regarding the linkages among the carbon, conventional and renewable energy markets [12]. Moreover, financial liberalisation and technological developments convey the wisdom of dependencies and increasing integration between different sectors. Based on the above, this paper intends to explore the dynamic connectedness between the EU carbon trading system and the conventional and renewable energy markets. The purpose is to support policymakers in formulating a rational carbon trading strategy to facilitate the restructuring of energy consumption and improve the feasibility of achieving emission reduction targets [22]. In addition, considering incorporating carbon markets in suitable portfolios as possible hedging and diversification options [15, 23], we hope to provide valuable suggestions for investors and other market participants who consider risk diversification and portfolio management.

There are several contributions to the existing research. First, although some studies have examined the return or volatility spillover among fossil fuel, renewable energy and carbon trading markets, they focus exclusively on normal market conditions and time-frequency investigations [12,14]. As a result, possible changes in impacts under extreme market conditions need to be addressed, which does not capture the holistic view of market development. Therefore, this paper employs the quantile vector autoregression (QVAR) framework to explore the correlation among these markets, which can identify the dynamic changes in the network across multiple market states. In addition, many studies have devolved into the impact of economic turmoil, particularly during the COVID-19 epidemic [13,24]. However, the related fields of research on the energy crisis have been conducted near vacuum. It is recorded that dramatic fluctuations in the European carbon market and energy prices occurred during the energy crisis. There have been more significant shocks in European markets compared to the pandemic, which is more likely to affect the connectedness network. In this regard, we further evaluate the effects of the energy crisis on the transmission of returns among markets, with a particular emphasis on risk spillovers during this context. The information holds significant implications for investors and governments, providing insights for those seeking to design investment and development strategies in the face of the twin crises of energy security and climate emergency.

The remainder of this study is structured as follows: Section 2 covers a review of the relevant literature. Section 3 details the quantile vector autoregression (QVAR) framework. Section 4 explains the data. Section 5 illustrates the results of the empirical analysis and robustness tests. Section 6 mentions the conclusions and pertinent implications.

2. Literature review

This research evaluates the spillover effects and connectedness across the fossil, renewable, and carbon markets. The literature on this theme is divided into the following four sections.

2.1. Traditional and renewable energy markets nexus

On the way toward carbon neutrality, renewables as substitutes for

fossil fuels (i.e., crude oil, natural gas, and coal) have been widely commended for their effectiveness in mitigating CO₂ emissions [5]. Regarding the clean stock market, Xia et al. [25] evaluate its response to energy prices' asymmetric and extreme effects. They reveal that the outcomes vary by the types of fossil fuel, with oil and coal playing a more prominent role. While Song et al. [26] claim that only oil significantly impacts the returns and volatility of clean energy stocks compared with other fossil fuels. As oil is one of the major fossil energy sources [27,28], some studies have focused on its relationship to the renewable energy market. Specifically, Kocaarslan and Soytas [29] illustrate the time-varying and asymmetric relationship, and Bondia et al. [30] disclose a long-term correlation between them. Furthermore, Reboredo [31] contends that extreme uncertainty in oil markets has witnessed investors' enthusiasm to embrace renewables. Therefore, clean energy retains the aura of hedging against crude oil price (OP) volatility, especially in the short term [32]. Also, numerous scholars have attempted to explore the spillover effect in this field [33,34]. Umar et al. [35] highlight the limited connectedness between clean-energy stocks and traditional energy markets. Elsayed et al. [36] reach similar results concerning OP and seven other financial markets, including the clean-energy sector. In addition, Du and He [37] assert that the volatility connections between OP and green energy stocks have intensified since the global financial crisis (GFC). Saeed et al. [38] analyse the extreme spillovers across associated stock markets, indicating the higher connectedness in the extreme left and right tails.

Nevertheless, Henriques and Sadorsky [39] highlight that technology stocks strongly influence green energy, but the effects of OP shocks prove to be limited. Likewise, Ferrer et al. [40] explore the interaction between the U.S. clean stock and the oil market, and the results confirm the short-term but not strong long-run connectedness. Zeppini and Van Den Bergh [41] construct a global model for competitive dynamics of fossil fuels and renewable energy, which concludes that peak oil induces a transition to coal rather than renewable energy and worsens climate change.

2.2. Tradition energy and carbon emission trade markets nexus

Since the establishment of the EU ETS, there has been a flurry of research regarding the linkage between the carbon market and traditional energy. By investigating the time-varying correlation between fossil fuels and carbon futures, Gong et al. [4] argue that coal prices significantly affect the evolution of carbon assets. This conclusion can be partly supported by Liu and Chen [42], who also highlight that these markets are interacted and may be affected by historical events. Based on the emission trading scheme, energy and capital markets, Ma et al. [43] scrutinise the dynamic linkage among them and indicate that the price fluctuation exhibits clustering characteristics. In this regard, the changes in carbon asset prices may be influenced by energy, the extent of which depends on the type of energy source [44]. Furthermore, Wu et al. [10] capture the dynamic frequency connectedness across China's carbon, fossil energy and sectoral stock markets. Their study reveals that v. Ji et al. [15] assess the carbon features and the Brent oil market, indicating that carbon assets are vulnerable to the fluctuation of oil prices. Considering the EU ETS, Wang and Guo [45] find strong spillovers from the oil and natural gas markets. This finding aligns with Balçilar et al. [46], who take the extreme volatility and time-varying risk transmission into account. Dai et al. [47] demonstrate that carbon assets perform as effective short-run hedges against the spillover risks in energy markets, although the hedging efficacy falls over the long term.

However, subsequent studies establish the contrary evidence. In this regard, Zhang and Sun [48] illustrate that the EU ETS exhibits significant volatility spillover effects on coal and natural gas. Still, it cannot be acknowledged regarding the crude oil market. Ji et al. [49] explore the price determinants in the carbon markets in China. They find that oil is observed to be positively linked, while coal shows negative impacts. According to Chen et al. [50], the evidence of volatility spillovers

between the EU ETS and fossil fuel markets is limited. Likewise, Koch [51] believes that the carbon features are only weakly connected to other traditional fossil fuels, particularly in adverse market circumstances. As a result, carbon assets gain prominence in portfolio diversification [52], which aims to hedge investment risk and mitigate CO₂ emissions driven by traditional energy.

2.3. Renewable energy and carbon emission trade markets nexus

With the rapid expansion of the green energy industry, more emerging evidence indicates that carbon and renewable are inextricably intertwined. Hanif et al. [53] analyse the connectedness between carbon assets and clean energy stock. They suggest that significant spillover effects between them are monitored in the short and long term. Dai et al. [54] stress that the scale of the carbon market and the price are tightly linked to the level of green energy development. Lin and Jia [55] evaluate the impacts of different distribution strategies of carbon market revenue on the spread of renewables. The results indicate that such costs tend to increase when taxes do not adequately subsidise non-fossil energy. According to Yan et al. [56], the simultaneous implementation of carbon cap-and-trade mechanisms and clean portfolio standards on renewable sector investment provide a feasible way to stimulate the energy transition effectively. In addition, Liu and Zhang [7] believe that carbon assets play a more significant role in driving the expansion of the green industry. A similar conclusion can be drawn from Fang et al. [57], who highlight that a mature market serves as a panacea to foster the growth of non-fossil energy. Nevertheless, based on the carbon market in China, Zhang et al. [11] point out that the emission trade scheme does not contribute to the development of renewable energy in the policy implementation regions, but it is confirmed to have a positive influence on surrounding areas. Abrell and Weig [58] believe that the target of achieving carbon neutrality raises the share of renewable generation, which ultimately leads to zero carbon prices. Likewise, according to Kumar et al. [59], there is no significant association between the clean energy stock market and EU ETS.

2.4. The traditional, renewable, and carbon emission trade markets nexus

As the nexus between carbon and energy markets has been extensively explored, several studies set out to include renewable energy sectors in their analyses. Ding et al. [12] clarify the Time-frequency spillovers across carbon, traditional and clean energy markets. The study demonstrates that the clean energy and oil markets are the net transmitter of risk spillovers from the carbon asset in the short term, but no significant outcomes are found in the long run. Ji et al. [15] focus on the risk and return connectedness among carbon and energy markets, including the renewable energy sector. The finding indicates that the fluctuations in carbon price are influenced significantly by Brent oil. Likewise, the influence of the carbon market may extend beyond those nations that have implemented such mechanisms [60]. Naeem et al. [61] further reveal an increase in connectedness among the underlying markets during the Global Financial Crisis (GFC) and shale oil revolution period by considering the oil, carbon, electricity, and clean energy market. Regarding the Chinese emission trading scheme, Zhang and Zhang [62] consider that such a system can effectively decrease energy consumption and stimulate renewable usage, pushing the energy structure to shift from fossil to non-fossil. In addition, Nie et al. [63] reveal that the carbon features are a receiver, whereas clean energy always serves as a transmitter in their analysis of the co-movement about these markets. However, Lin and Chen [64] consider the scenario of carbon, coal, and renewable energy; their study suggests that the spillover effects between the coal and Beijing trading market cannot be confirmed.

The initial research sheds light on the transmission mechanisms of volatility between fossil fuels and renewables. Nevertheless, the analysis of integrating carbon markets into the systemic framework remains

embryonic. As the drive to combat climate emergency gathers pace, it has begun to gain prominence and become increasingly fundamental to achieving net-zero emissions. Consequently, investors should map out the dynamic strategies to incorporate carbon markets into their energy market portfolios as an asset class. Furthermore, Ji et al. [15] explore the dynamic connectedness between energy and carbon markets, while Ding et al. [12] focus on risk diversification across different investment horizon perspectives. However, they do not consider the possible changes in impact under various market conditions, as illustrated by shifts in the quantile. The spillover effects among these markets may vary, and in particular, there are significant enhancements regarding the risk spread in the left and right tails of the system. Hence, this paper extends the work of Ji et al. [15] based on the QVAR framework. It allows us to capture the evolution of spillover effects under different market conditions, which provides a comprehensive analysis of the connectedness network among these markets.

3. Spillover effects based on the quantile VAR model

Within the framework of the vector autoregression (VAR) model and generalised variance decomposition, Diebold and Yilmaz [65,66] introduce an information spillover index. In contrast to the traditional model, it is more stable and provides a viable path to identify the degree of spillover between the variables [67]. Furthermore, Ando et al. [68] establish a novel evaluation approach that distinguishes the heterogeneous effects of the dimensional distribution of shocks by accounting for quantile regression and a factor structure. Based on the R software, we consider the quantile factor VAR(p) to construct the information spillover network in this paper, as follows:

$$y_t = \mu_{(\tau)} + \sum_{j=1}^p \Phi_{j(\tau)} y_{t-j} + r_{t(\tau)} \quad (1)$$

where y_t and $\mu_{(\tau)}$ denote the endogenous variable vectors and a vector of intercepts, respectively. In addition, τ represents a given quantile index, ranging from 0 to 1. Φ is the coefficient matrix of $n \times n$ at the j th lag. Also, the residual process can be expressed as r_t . The QVAR framework is converted as follows to accommodate the need for a variance:

$$y_t = \sum_{j=1}^p A_j r_{t-j(\tau)} \quad (2)$$

The coefficient matrix A_i is derived from the formula: $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$. Specifically, A_0 represents an n -dimensional

We evaluate the h -step forward error variance decomposition (FEVD) constructed by Koop et al. [69] and Pesaran and Shin [70] in light of the Cholesky-factor ordering issue. Such a strategy allows the VAR framework to eliminate the reliance on the orthogonal decomposition result on the order of the variable [67]. Hence, we formulate the QFVAR below:

$$Q_{\tau}(y_t | F_{t-1}) = \sum_{j=1}^p D_{j(\tau)} r_{t-j(\tau)} \quad (3)$$

where $f^* = (1, f_t)'$ and $D_{j(\tau)} = \Phi_{1(\tau)} D_{j-1(\tau)} + \Phi_{2(\tau)} D_{j-2(\tau)} + \dots$, with $j = 1, 2, \dots$

The preceding demonstrates the extent to which variable j effects variable i . As the system is exposed to different shocks, the quantile variation in the parameters reveals the dynamic linkages among y_t . In this way, the percentage of FEVD provides the foundation for forming a spillover index, which assesses the direction and intensity of information spillover within the sector inside the spillover network.

$$FEVD = \frac{\omega_{ii}^{-1} \sum_{l=0}^h (e_j D_{l(\tau)} \Omega e_i)^2}{\sum_{l=0}^h e_j' D_{l(\tau)} \Omega D_{l(\tau)}' e_j} \quad (4)$$

where e_j means the predicted variable and h is the forecast horizon, e_i stands for a vector whose value of i th element is 1 and others denote 0, for $i, j = 1, 2, 3, \dots, m$. D represents an impact vector that can be measured by the multiplication value of the coefficient matrix and a nonorthogonal QVAR model. ω_{ii} denotes the standard deviation of r_i , whereas $\sum$ indicates the error vector covariance matrix.

In order to identify the risk of the spillover effect across all of these markets [65,66], we construct a $m \times m$ variance decomposition matrix based on the FEVD in Equation (4), as shown:

$$\mathbb{A}_{(\tau)}^{(h)} = \begin{bmatrix} \theta_{1 \leftarrow 1, (\tau)}^{(h)} & \theta_{1 \leftarrow 2, (\tau)}^{(h)} & \cdots & \theta_{1 \leftarrow m, (\tau)}^{(h)} \\ \theta_{2 \leftarrow 1, (\tau)}^{(h)} & \theta_{2 \leftarrow 2, (\tau)}^{(h)} & \cdots & \theta_{2 \leftarrow m, (\tau)}^{(h)} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{m \leftarrow 1, (\tau)}^{(h)} & \theta_{m \leftarrow 2, (\tau)}^{(h)} & \cdots & \theta_{m \leftarrow m, (\tau)}^{(h)} \end{bmatrix} \quad (5)$$

where we obtain the level of risk spillover between market i and j with the specified definition of $\theta_{j \leftarrow i, (\tau)}^{(h)} \equiv FEVD(y_{jt}; \mu_{it(\tau)}, h)$. The spillover risk of other markets can be measured by the sum of the first line in $\mathbb{A}$, which manifests the capability of the risk taken with respect to market i . Likewise, the spillover from the market j to i can be interpreted as:

$$O_{i \leftarrow j, (\tau)}^{(h)} = \theta_{i \leftarrow j, (\tau)}^{(h)} \quad (6)$$

On the condition that there are more correlations among the markets, the i is most susceptible to experiencing spillover effects from others. Hence, we evaluate its level in the spillover network to determine the total influence of several markets on a single market below:

$$F_{i \leftarrow \cdot, (\tau)}^{(h)} = \sum_{j=1, j \neq i}^m \theta_{i \leftarrow j, (\tau)}^{(h)} \quad (7)$$

Additionally, the information from sector i is also simply distributed to other marketplaces. In this regard, the effects of single market i on other markets can be quantified as follows:

$$T_{\cdot \leftarrow i, (\tau)}^{(h)} = \sum_{j=1, j \neq i}^m \theta_{j \leftarrow i, (\tau)}^{(h)} \quad (8)$$

As a result, we can calculate the net connectedness of market i :

$$N_{i \leftarrow i, (\tau)}^{(h)} = T_{\cdot \leftarrow i, (\tau)}^{(h)} - F_{i \leftarrow \cdot, (\tau)}^{(h)} \quad (9)$$

Suppose that $N_{i \leftarrow i, (\tau)}^{(h)} > 0$, it indicates the net information spillover from market i to the whole network. In this sense, the larger $N_{i \leftarrow i, (\tau)}^{(h)}$ means that the market i contributes more positively (transmitter) to this system. On the contrary, $N_{i \leftarrow i, (\tau)}^{(h)} < 0$ reveals that it serves the role of a receiver to absorb the net information spillover from the network. Then, the overall network spillover index is calculated as follows:

$$S_{(\tau)}^{(h)} = m^{-1} \sum_{i=1}^m F_{i \leftarrow \cdot, (\tau)}^{(h)} \quad (10)$$

where S shows the market connectedness, which is usually regarded as a proxy for market risk [71]. An increase in the value will lead to detrimental effects on overall system stability. In addition, it also tends to be influenced by the path and degree of spillovers from the single market and the role reversal (transmitter or receiver). To this end, the quantile connectedness technique allows us to capture the movement of the spillover index across time, providing a detailed and reliable analysis of the market links [72].

4. Data and descriptive analysis

4.1. Data

This study concerns the daily statistics that span from January 1, 2018, to June 15, 2022. In 2018, the EU proposed a European vision for carbon neutrality by 2050. As a result, it implements reform policy packages such as the market stability reserve (MSR) mechanism, which marks a watershed moment in the evolution of the trading scheme. Since the European Climate Exchange (ECX) occupies the largest trading volume in Europe, we select the futures price of its European Union Allowance (EUA) as the proxy of the carbon market [73]. Regarding traditional energy, we concentrate on three fossil fuel categories: Rotterdam Coal Futures (RC), Brent crude oil futures (OIL) and ICE Dutch TTF Natural Gas Futures (NG). Additionally, the clean market (RE) is reflected by the European Renewable Energy Total Return (ERIX) index in our analysis. It comprises the major producer of wind, solar, biomass and water energy generation in Europe [31,74], which can portray well the correlation with European energy futures prices [25]. EUA is available through the Intercontinental Exchange (ICE) and OIL sources from the U.S. Energy Information Administration (EIA). The remaining can be captured on the Investment Websites.

4.2. Descriptive analysis

Fig. 1 captures the trend of these markets across the whole sample interval. Generally, the carbon trade system has rising tendencies over the long term. We can notice that the COVID-19 pandemic has had little impact on the European conventional, renewable, and carbon markets, with only oil and new energy assets suffering a short-term decline in the early stages of the outbreak. The subsequent energy crisis and the Russia-Ukraine conflict push oil prices to skyrocket [27], and the gas and coal sectors follow a similar pattern that experiences a roller coaster of market conditions. The new energy market, however, turns to a downward trend at that time. Therefore, this period is imperative to investigate as it has witnessed dramatic fluctuations in asset prices [75]. With the energy crisis still lingering, this study focuses on this period as a sub-sample to explore the connectedness between these markets.

The summary statistics are shown in Table 1. All the indexes are denominated in Euros for consistency, with series being the first difference of the natural logarithms. Among all the markets, the highest mean is recorded for carbon assets. It also resembles the NG in that both experience excessively volatile with standard deviation values of 3.062 and 5.295, respectively. The evidence of high and low volatilities implies the probability of interdependence among the assets [76]. In addition, the negative skewness reveals that EUA, COA, and RE perform left-skewed distribution, while the OIL and NG are right-skewed. We find that all series follow the leptokurtic distribution significantly, and the Jarque-Bera tests further indicate that the underlying statistics depart from the normal distribution. Likewise, they are confirmed to be stationary in terms of the augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Based on the above characteristics, all the results support our option to employ the QVAR approach to explore the interdependence of those series [24].

5. Empirical results

This section investigates the connectedness among fossil fuels, renewable energy, and carbon trade markets through the static and dynamic framework. In addition to the analysis of the mean-based VAR spillover effects in each part, we apply the QVAR model to extend the examination to the scenarios of lower ($\tau = 0.05$) and upper quantile ($\tau = 0.95$), which allows us to quantify the influence of different shocks on the dynamics of the entire network under the extreme conditions [77]. In this paper, we choose a 10-step ahead forecast error variance

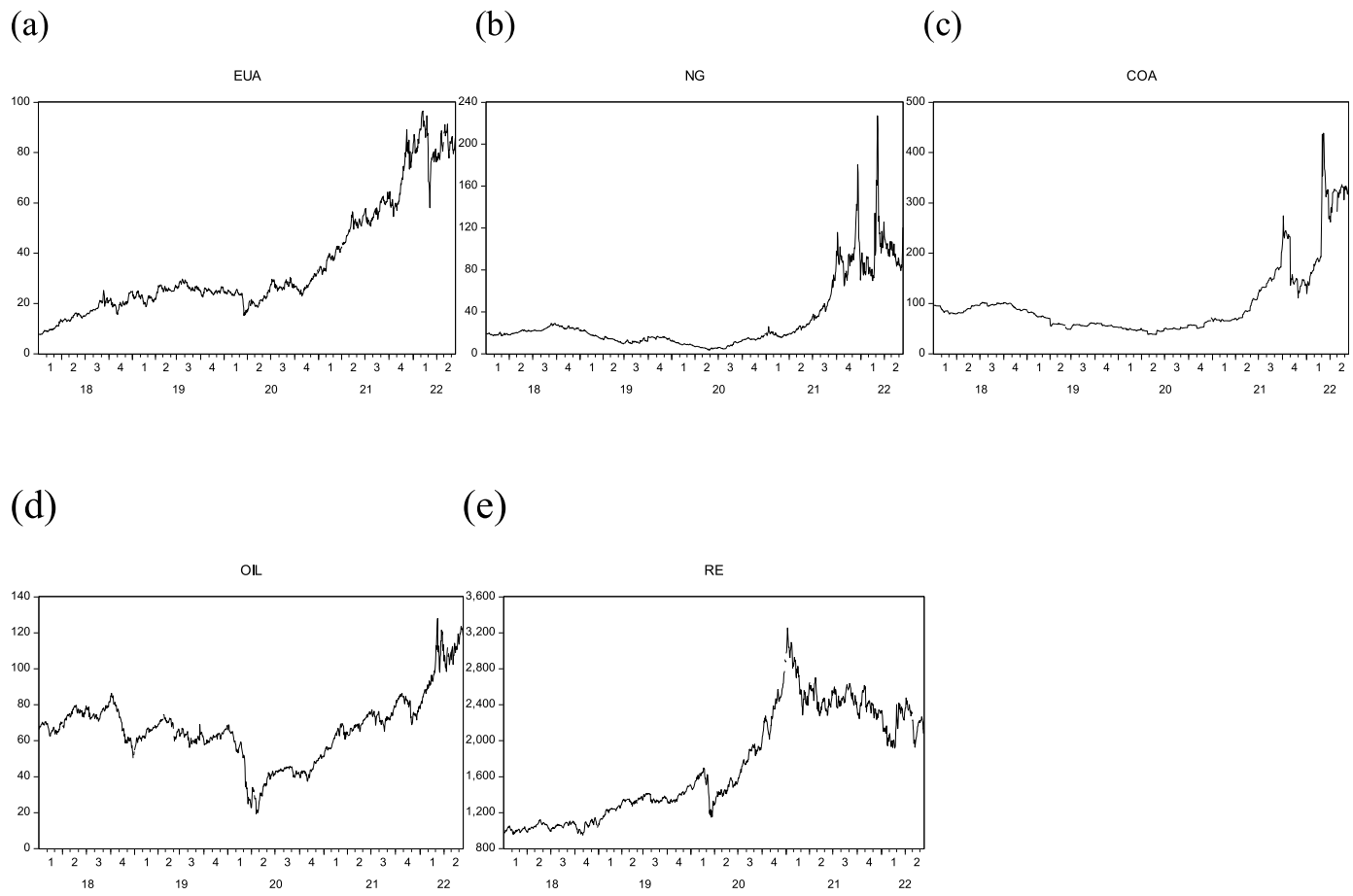


Fig. 1. The trends of the related series.

Table 1
Descriptive statistics for each index.

	Carbon market	Traditional market			Renewable market
	EUA	COA	OIL	NG	RE
Observations	1137	1137	1137	1137	1137
Mean	0.207	0.123	0.063	0.159	0.068
Median	0.286	0.048	0.218	0.034	0.126
Maximum	16.194	32.666	20.049	41.278	10.030
Minimum	−19.444	−54.059	−29.019	−35.242	−12.972
Std.Dev	3.062	3.313	2.892	5.295	1.814
Skewness	−0.680	−2.546	−1.486	0.563	−0.310
Kurtosis	8.068	85.813	25.027	13.574	7.818
Jarque-Bera	1304.544***	326124.4***	23403.930***	5356.72***	1118.020***
ADF	−35.507***	−32.459***	−31.927***	−24.729***	−21.641***
PP	−35.806***	−32.611***	−31.927***	−30.571***	−32.984***
KPSS	0.102	0.548	0.226	0.375	0.111

Note: Std.Dev. is Stand Deviation, and *** represents significance at the 1% level.

decomposition. The lag length is set to 1 based on the Schwartz information criterion (SIC).³

5.1. Static connectedness of spillovers

Table 2 provides the evaluation of connectedness at the median quantile ($\tau = 0.5$). The TCI (10.6%) in the bottom right corner of the

Table 2
Static full-sample spillovers ($\tau = 0.5$).

	EUA	RE	COA	OIL	NG	From
EUA	89.7	2.3	0.7	3.5	3.8	10.3
RE	2.5	91.6	2.7	2.9	0.3	8.4
COA	0.1	0.1	89.9	2.7	7.1	10.1
OIL	2.9	2.8	2.6	89	2.6	11
NG	3.1	0.6	6.8	2.6	87	13
TO	8.6	5.8	12.9	11.6	13.8	52.8
NET	−1.7	−2.5	2.8	0.6	0.8	TCI
NPDC	1	1	2	3	3	10.6

³ In this paper, we consider altering the forecast horizon and the width of the rolling window to test the robustness and accuracy of our results (see Appendix), all estimates follow a similar trend.

table reflects the total connectedness. It means that about 1/10 of the prediction errors in the system are the results of market interactions [77]. Although they are not entirely independent of each other, the spillover effects are pretty minimal. This finding is aligned with Nie et al. [63], who contend the weak interaction among the carbon trading market, fossil fuels, and clean energy stock. The values on the diagonal represent their shocks, while the off-diagonal values record the directional volatility spillover between each market pair [78]. We can note that NG has the most significant influence on the other markets, as it accounts for the least proportion (87%) of shocks on its subsequent volatility. In addition, EUA and RE are the net information receivers in the system, while the traditional energy market is the net transmitter. Among them, COA is the most significant contributor (2.8%) to others, which reflects its dominance in the network of connectedness. In recent years, most EU member states have implemented a series of policy packages to phase out coal in power generation [3]. The most cost-effective way to mitigate CO₂ emissions is to move away which is the most carbon-intensive fossil fuel and the principal energy carrier in the power sector.

Given that the median settings cannot identify spillover intensity in situations of extreme positive and negative shocks [77], we then estimate the connectedness at the left ($\tau = 0.05$) and right tails ($\tau = 0.95$). The spillover results are detailed in Tables 3 and 4, respectively. The spillover effects values appear symmetrical for the lower and upper quantiles. Furthermore, compared to the mean quantile, the impact of the extreme market on the connectedness network of underlying assets proves to be more pronounced. The findings align with Naeem et al. [61], who claim that there is a rise in connectedness among the underlying markets throughout the GFC and the shale oil revolution. More specifically, the strong spillover of the EUA to RE in extreme shocks reveals that carbon assets constitute a risk factor for clean market fluctuations [12]. In addition, the coal market is observed to be the largest transmitter in the system under the mean quantile, while it transforms into a receiver under extreme conditions. When it comes to EUA and RE, the results are verified to be the opposite. This can be explained by the fact that a key role of these two markets is to reduce coal use. For the NG, the spillover effects are always positive, with the biggest transmitter (4.9%) in the extreme right tail.

Fig. 2(a–c) presents the network of connectedness corresponding to the three different quantiles mentioned above. These diagrams intuitively visualise the direction and magnitude of the spillover from one variable to another. The arrows between nodes indicate the transmission paths of information spillover, and the thickness of the connecting line segments represents the degree [26]. We find the strongest bidirectional spillover effects between COA and RE in normal market conditions, whereas the other interconnections are modest. The OIL is relatively independent, with a rather weak connectedness to the carbon market, which indicates the potential ability of the oil market to hedge price fluctuations in other assets. According to the results of the lower quantile ($\tau = 0.05$), the COA occupies a central position and is closely linked to the other classes. The other four markets are weakly or barely connected. Fig. 2(c) presents the network of return connectedness at the upper quantile ($\tau = 0.95$). The COA continues to be strongly connected to others. Furthermore, all five markets have established and

Table 3
Static full-sample spillovers ($\tau = 0.05$).

	EUA	RE	COA	OIL	NG	From
EUA	32.1	19.9	10.9	18.5	18.6	67.9
RE	20.2	33.6	10.4	19.1	16.7	66.4
COA	13.2	12.8	42	15	17.1	58
OIL	19.1	19.1	11.5	33.2	17.1	66.8
NG	18.9	16.9	13.5	17.3	33.4	66.6
TO	71.4	68.7	46.3	69.8	69.5	325.7
NET	3.5	2.3	−11.8	3	2.9	TCI
NPDC	4	3	0	2	1	65.1

Table 4
Static full-sample spillovers ($\tau = 0.95$).

	EUA	RE	COA	OIL	NG	From
EUA	33.7	19.1	11.9	16.9	18.4	65.3
RE	19.4	33.8	12.5	17.3	17.1	66.2
COA	13.6	14.2	38.5	14.6	19.1	61.5
OIL	18.4	18.3	13.1	33.4	16.7	66.6
NG	17.9	16.5	16.2	15.8	33.6	66.4
TO	69.3	68.1	53.7	64.6	71.2	326.9
NET	3	1.9	−7.8	−2	4.9	TCI
NPDC	3	2	0	1	4	65.4

strengthened their connectedness compared to the scenario at the extreme right tail ($\tau = 0.95$).

Although static spillover analysis can quantify the overall connectedness among markets, it does not consider the time-varying features of spillovers [79]. In this regard, we adopt a rolling window strategy (the 200 rolling-window estimations) to explore the dynamic spillover effects between variables, which allows us to capture more comprehensive information [26,67].

5.2. Dynamic total connectedness

Fig. 3 presents the dynamics of the total connectedness index, covering the analysis for the mean ($\tau = 0.5$), lower ($\tau = 0.05$), and upper quantile ($\tau = 0.95$). The results indicate that asset returns are sensitive to positive and negative shocks since the total spillovers across markets at both the left and right tails are substantially greater than the mean quantile [80]. Likewise, we find many spikes and drops in the system, demonstrating the time-varying characteristics of the return connectedness network. Specifically, all three scenarios show a decreasing trend of total spillover in 2019. Such consequences may be attributed to NG asset, as it plays an essential role in the European energy structure. A low price might lead to the decoupling of investor sentiment and the energy market. The COVID-19 pandemic has witnessed a dramatic rise in the TCI, reaching 25% for the first time. This finding is more pronounced at the lower quantiles ($\tau = 0.05$). While the pandemic is responsible for an economic downturn and a decline in energy demand, the external crisis stimulated the co-movement among the markets. As a result, investors tend to respond more swiftly to the spread of unfavourable information, which pushes up the spillover effects [12]. Subsequently, the total spillovers gradually declined as the epidemic subsided. Since the beginning of 2021, the average TCI has shifted from 14% to 20%. The same upward tendency also can be captured in the upper quantile ($\tau = 0.95$). During this period, European energy markets have suffered an unprecedented shock, and significant changes have occurred in the fossil fuels, renewables, and carbon markets. The enormous energy shortfalls and climate targets have accelerated the deployment of clean energy. The recent spike in the TCI is driven by the War between Russia and Ukraine in February 2022, which shows significant volatility on the extreme left and right tails compared to the mean spillovers. The geopolitical risks exacerbate uncertainty in the supply of fossil energy sources, resulting in a high connectedness among markets.

5.3. Dynamic net directional volatility connectedness

Fig. 4(a–c) exhibits the connectedness of dynamic net volatility for three conditions (i.e., mean, lower and upper). Based on this test, we can evaluate whether a particular market in the system is a net transmitter or receiver of shocks at certain periods. The dynamic net spillover effects are normally asymmetric, with positive and negative swings of different scales [81].

According to the results, the EUA is the transmitter of spillovers during most of the sample period. Nevertheless, all three analyses indicate a significant net negative spillover from the beginning of 2022. Since the geopolitical risk of the Russia-Ukraine conflict increases the

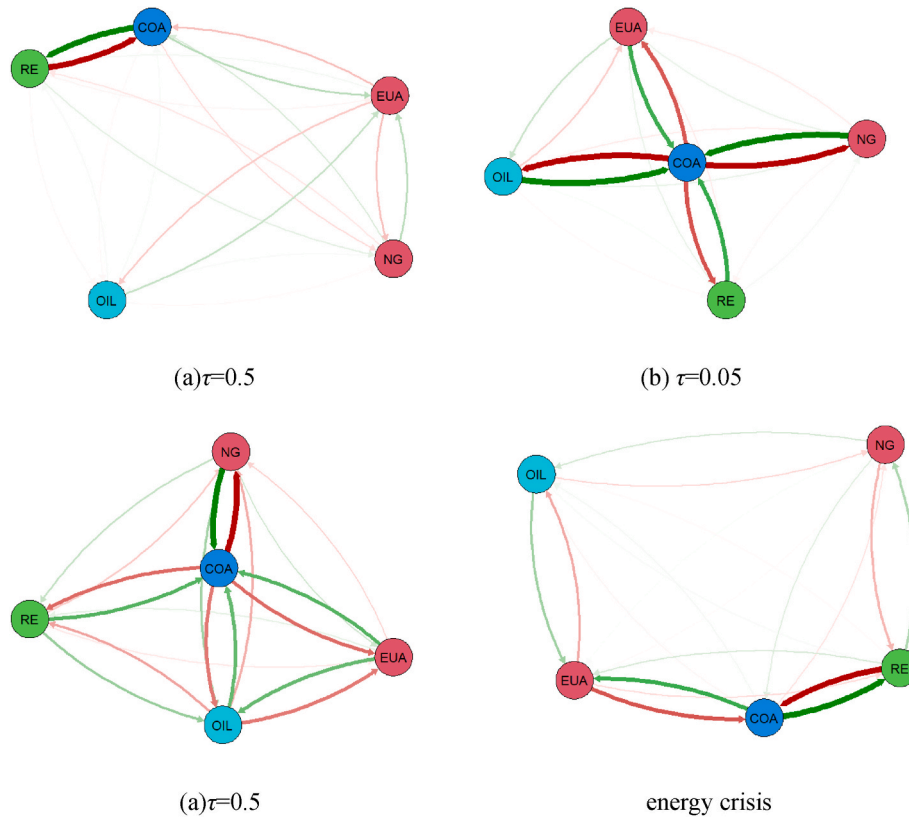


Fig. 2. Connectedness networks among the markets in different quantiles and energy crises.

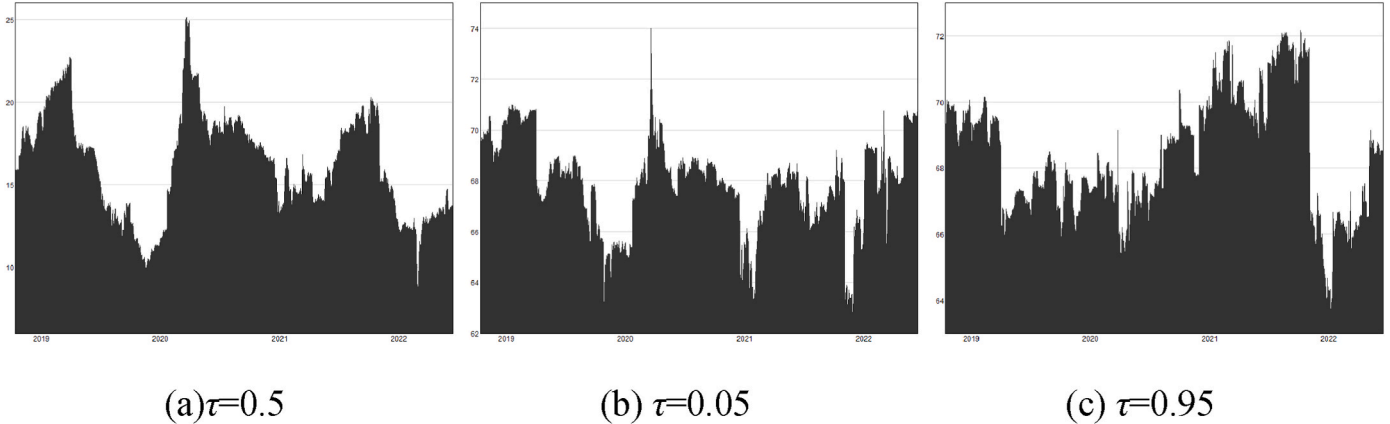


Fig. 3. Dynamic total connectedness index (TCI) in different quantiles.

uncertainty of energy supply, which worsens Europe's energy dilemma. As a result, the aura of the carbon market to reducing fossil fuels use has greatly dimmed due to the energy shortage, resulting in the EUA shifting from a transmitter to a receiver of spillover effects. By contrast, COA is a recipient of the information in times of extreme shocks, attributing to a shift from coal-based power generation and efforts to reduce the dependence on coal. As an emerging market, the RE is still in its infancy [82], which is more likely to be affected by the other markets. In particular, some extreme shocks, such as energy security threats and legislative incentives for structural transition, have propelled the clean market to become a transmitter periodically at the left and right tails. In addition, there is a great deal of instability in the oil market, and their roles are constantly changing as they are often subject to external shocks from demand and supply [78]. In the case of NG, it is dominated by positive net spillovers for almost the entire sample period in different

quantiles. This can be explained by the importance of European production and consumption, which is considered strategic energy and has been widely praised for its high liquidity and extensive trade [83].

5.4. Dynamic net pairwise directional connectedness

This section is evidence of the system's dynamic net pairwise directional connectedness, which provides a feasible pathway to analyse the evolution of the interrelationship between variables over time [72]. In light of the extensive research conducted on correlations in other markets, we focus exclusively on connectedness involving carbon assets [78].

As is shown in Fig. 5, the dynamic net pairwise spillover varies from asset category, and there are greater connectedness densities at the extreme conditions ($\tau = 0.05, 0.95$) compared to the intermediate

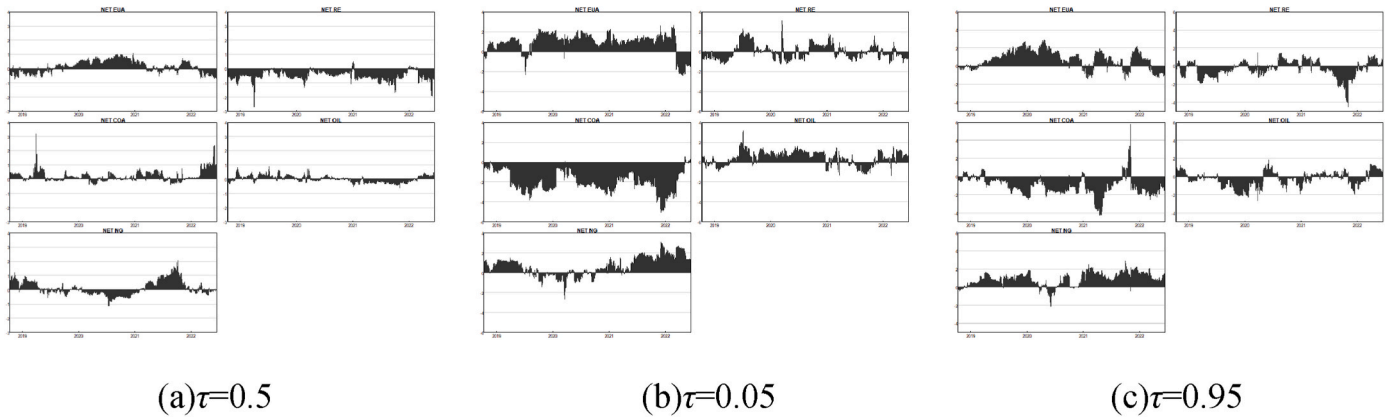


Fig. 4. Dynamic net connectedness index in different quantiles.

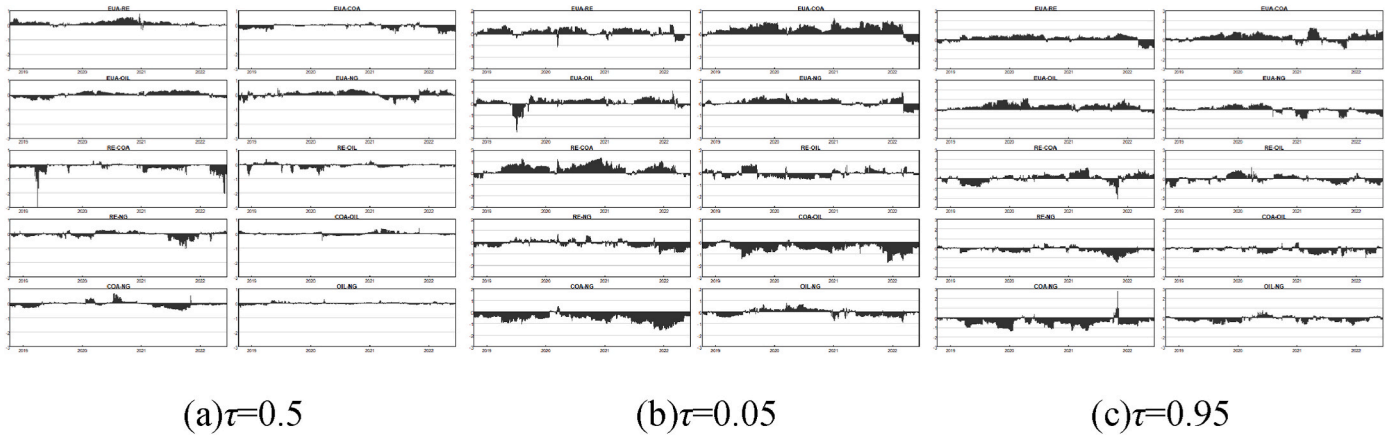


Fig. 5. Dynamic net pairwise directional connectedness in different quantiles.

quantile ($\tau = 0.5$). The net pairwise spillover effect between EUA and RE is overwhelmingly positive, indicating the ability of the carbon market to transmit the information. This is due to the possibility that the price fluctuations in the emissions trading system may indirectly affect the demand for RE, ultimately leading to changes in the renewable market. The EUA is susceptible to external shocks of COA at the middle quantile, but the role tends to be transformed at the left and right tails. The energy transition towards net-zero emissions has focused on coal, a major driver of CO₂ emissions and the changes to the carbon market. In turn, the demand is also significantly influenced by the EUA at highly positive or negative shocks [10]. In this regard, similar results can be captured from the natural gas market, indicating the time-varying spillover effects between carbon assets and NG. Since the introduction of the market reserve mechanism in 2019, EUA has been mainly a transmitter of information to the OIL. However, all three assessment analyses have witnessed a leadership position in the oil market since 2022. In mid-2019, we also note a significant increase in negative spillovers in the middle quartile. One potential explanation is the increase in oil prices triggered by the supply reduction [84]. In May 2019, the new round of sanctions imposed by the U.S. on Iran recommended that no exceptions be granted to certain countries and regions from importing Iranian oil. In addition, major world oil producers such as the Organization of the Petroleum Exporting Countries and Russia, commonly known as OPEC+, join forces to restrict production, all of which reduce the amount of oil available and drive up the prices. As a result, the price spike dampens investors' enthusiasm for holding carbon allowances.

5.5. Impact of the energy crisis on the connectedness network

The recovery of economic activity has been placed on the agenda after lifting restrictions on the COVID-19 pandemic. However, it comes with the energy crisis following a sharp rise in European fossil fuel prices and demand. The current geopolitical tensions in Ukraine have further aggravated its energy dilemma, which appears to slow down the net-zero transition of the EU. Therefore, we choose this period as a subsample⁴ to explore whether the energy crisis significantly reshapes the structure of the spillover network and the potential impact on net-zero ambitions.

Table 5

Static sub-sample spillovers (energy crisis, $\tau = 0.5$).

	EUA	RE	COA	OIL	NG	From
EUA	96.6	0.4	1.9	0.9	0.1	3.4
RE	0.1	96.2	2.5	0.8	0.5	3.8
COA	0.3	0.1	84.9	6.4	8.3	15.1
OIL	0.1	0.8	6.5	85	7.6	15
NG	0.1	1.2	8.0	7.2	83.4	16.6
TO	0.6	2.5	18.9	15.3	16.6	53.8
NET	-2.8	-1.4	3.8	0.4	0	TCI
NPDC	0	2	3	2	3	10.8

⁴ The subsample spans from April 1, 2021 to June 15, 2022, and the setting of the empirical parameters is exactly identical to the full sample test.

Table 5 presents the results of static sub-sample spillover. It reveals a virtually identical total spillover index (10.8) compared to the case of the normal market condition ($\tau = 0.5$) in Table 2, implying that the overall spillover effects are hardly affected by the energy crisis. This conclusion contradicts that of [35], who claim that the specific systemic risks intensify the network density and among examined energy market. Moreover, COA and OIL transmit spillover effects regardless of the time horizon, while EUA and RE tend to receive the information. In particular, the carbon market accounts for the largest recipient of shocks during the energy crisis. Therefore, the carbon market may not be able to provide strong hedging capacity against risks proceeding from other markets, as the relatively lower transmission compared to receive information [78]. This can be attributed to the market's ongoing metamorphosis and the inadequacy of the mechanisms to counter threats such as adverse economic outlook and geopolitical risks. Likewise, the net spillover index of the natural gas market is observed to be 0, it is an indicator of potential decoupling between gas and other markets [22]. In this regard, investing in the NG is the strategy investors can use to hedge against the energy crisis risks. This conclusion is further endorsed by Fig. 2, which shows no connectedness between the NG and EUA and only a modest association with other markets.

5.6. Robustness tests

In this paper, we consider altering the forecast horizon and the rolling window width to test our results' robustness and accuracy [65, 81]. Figs. A1–A2 in the Appendix present the results for assessments of 150- and 250-day rolling windows, with the forecast horizon set to 5 and 10 days, respectively. The findings reveal that these estimations follow a similar trend, confirming our results' robustness and validity over the different forecast horizons and rolling windows [10,26].

6. Conclusion

This paper explores the spillover effects and connectedness among fossil fuels, renewable energy, and carbon trade markets under different market conditions. The static and dynamic frameworks are analysed with the use of the QVAR method. According to the static analysis, all three quartiles ($\tau = 0.5, 0.05$, and 0.95) of the evaluation demonstrate that NG has positive spillover effects. The coal market is observed to be the largest transmitter in the system under mean-quantile analysis, while it is most vulnerable to extreme shocks. In contrast, the results of EUA and RE prove to be opposite. We then consider the dynamic framework to explore the time-varying features of connectedness. The dynamic total spillover results show the significant impact of some extreme events (e.g., COVID-19, Russia-Ukraine conflict) on the spillover effects. The dynamic net spillover results suggest that EUA is a transmitter during most of the sample period. In contrast, COA receives the information in times of extreme shocks. Furthermore, there is a great deal of volatility in the oil market; their roles are constantly changing as they are frequently subject to external shocks from demand and supply. Also, the dynamic net pairwise spillover properties among them are examined, and the results vary from the asset category. Overall, the impact of extreme conditions on the connectedness network of underlying assets proves to be more pronounced compared to the mean quantile. However, the density of spillovers between the markets during the energy crisis does not increase significantly in our static analysis. One potential reason is that the correlation network may result from multiple shocks acting together. Furthermore, there is no connectedness

between the NG and EUA and only a modest association with other markets during the crisis.

Our findings provide implications for investors and policymakers seeking to formulate investment and development strategies. In light of the finding that a strengthening of connectedness frequently accompanies times of crisis, investors should pay greater attention to the spillovers of risk during severe economic market turmoil. Especially the coal market, which is the most susceptible to extreme shocks. Since the market condition may change over time, they are also supposed to develop dynamic and flexible portfolios to realise greater returns. During the energy crisis, a natural gas market is an appealing option that can be incorporated into the investment strategy to hedge against the risks due to its weak association with other markets. Concerning governments, they need to develop specific policy instruments and monitoring procedures in response to prevent potential risks among markets. In particular, the risk spillovers in extreme cases originate primarily from the renewable energy and carbon markets. Therefore, a well-defined framework for responding to crises should be established to shield relevant market participants from detrimental consequences. Under regular circumstances, fossil fuels are the greatest contributor to the risk of spillover. There ought to be continuous evolution in EU ETS to prevent the possible spread of risks caused by traditional energy markets. Likewise, accelerating the energy transition is the feasible solution to Europe's dual dilemma in light of energy security and the climate emergency. In this regard, the current situation should not impede the pursuit of sustainable development targets but instead persist in moving toward a future that eliminates the dependence on traditional energy.

This paper concentrates on the spillover effects of fossil fuels, renewable energy and carbon markets under different market scenarios. However, there is still more work that can be done, such as exploring the effect of external shocks (e.g., geopolitical risk) on the spillover effects. In addition, based on the analysis of big data and the combination of relevant techniques to further investigate the precise weighting of each asset in the portfolio, which will also be the focus of our research in the near future.

Author statement

Chi Wei Su: Conceptualization, Methodology, **Lidong Pang:** Data curation, Writing- Original draft preparation. **Meng Qin:** Writing- Reviewing and Editing, Visualization. **Oana-Ramona LOBONT:** Software, Investigation. **Muhammad Umar:** Methodology, Writing - review & editing.

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.

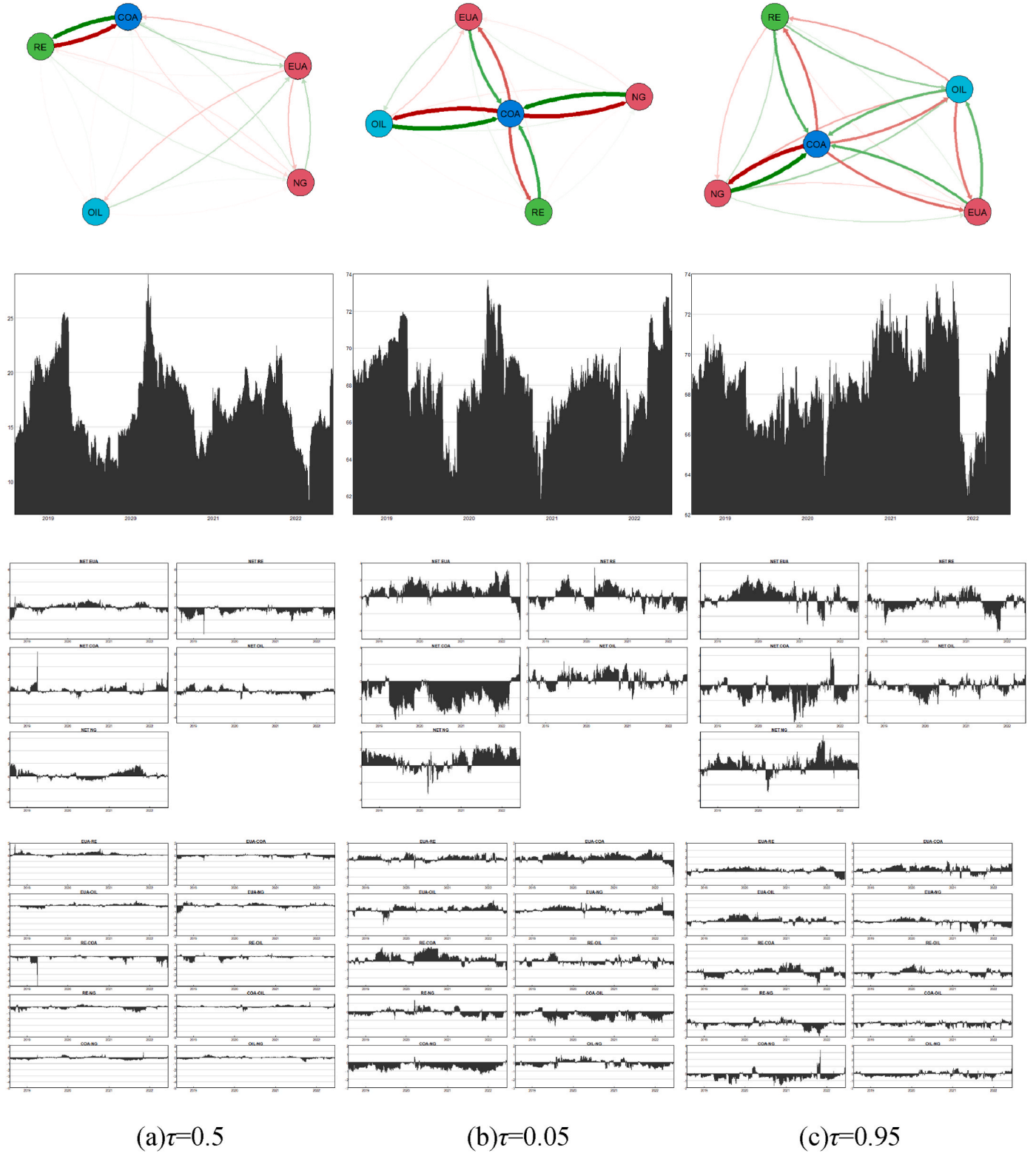
Data availability

Data will be made available on request.

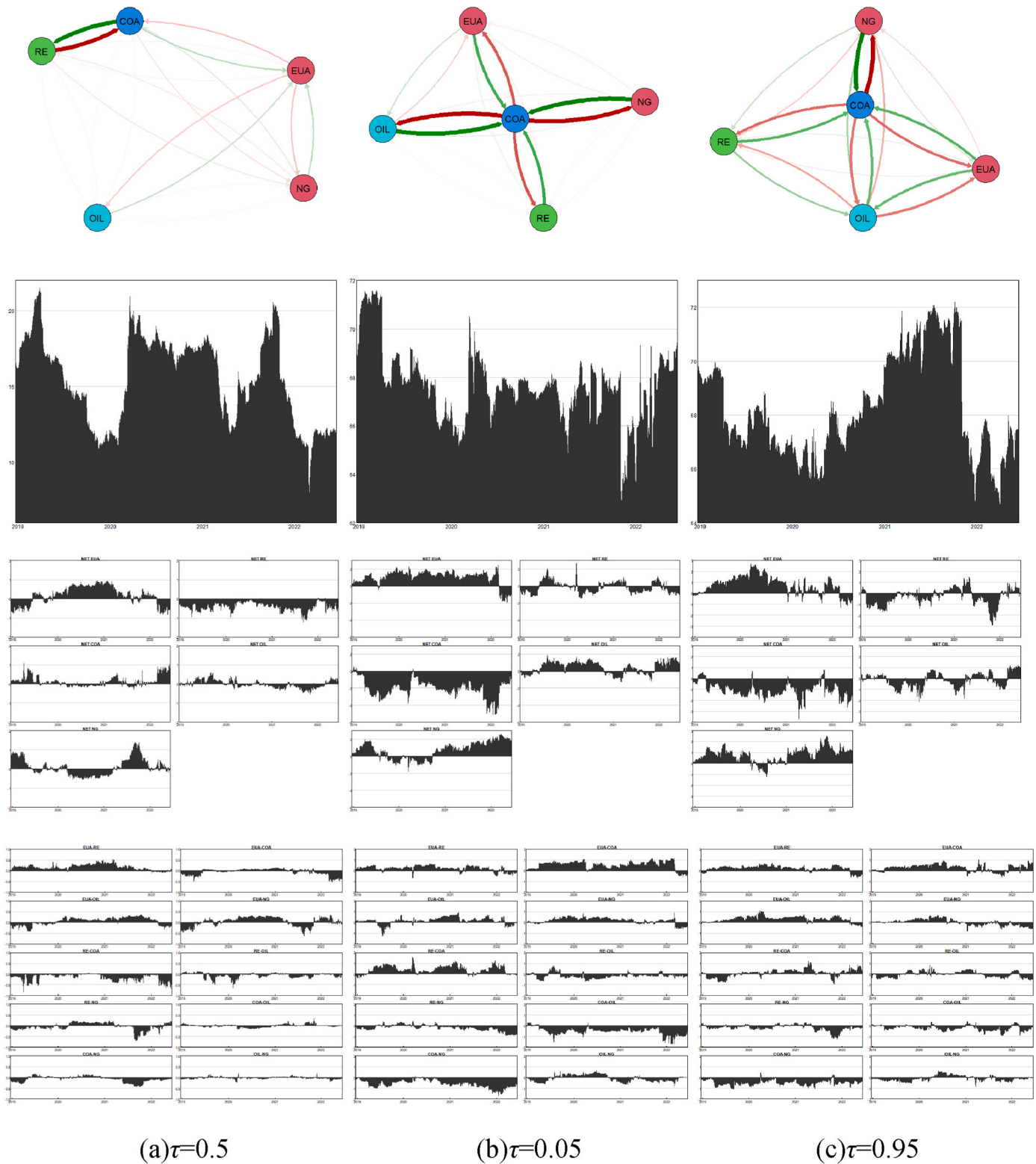
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Appendix



Appendix A1: (the rolling window is 150 days, forecast horizon is set to 5).



Appendix A2: (the rolling window is 250 days, forecast horizon is set to 10).

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