Do green economy stocks matter for the carbon and energy markets? Evidence of connectedness effects and hedging strategies

Abstract

Purpose - We phrase our analysis around the connectedness effects and portfolio allocation in the "Carbon-Energy-Green economy" system.

Design/methodology/approach - This paper utilizes the TVP-VAR method provided by Antonakakis et al. (2020) and Chatziantoniou et al. (2021), and portfolio back-testing models, including bivariate portfolios and multivariate portfolios.

Finding - Firstly, the connectedness within the "Carbon-Energy-Green economy" system is strong, and is mainly driven by short-term (weekly) connectedness. Notably, the COVID-19 pandemic leads to a vertical increase in the connectedness of this system. Secondly, in the "Carbon-Energy-Green economy" system, most of the sectors in the green economy stocks tend to be the transmitters of shocks to other markets (particularly the energy efficiency sector), while the carbon and energy markets are always the recipients of shocks from other markets (particularly the crude oil market). Thirdly, Green economy sector stocks have satisfactory hedging effects on the market risk of carbon and energy assets. Interestingly, hedging risks in relatively 'dirty' assets requires more green economy stocks than in relatively 'clean' assets. Finally, the results indicate that portfolios that include green economy stocks significantly outperform portfolios that do not contain green economy stocks, further demonstrating the crucial role of green economy stocks in this system.

Originality/value - Understanding the interactions and portfolio allocation in the "Carbon-Energy-Green economy" system, especially identifying the role of the green economy performance in this system, is important for investors and policymakers.

Keywords Green economy stocks, Carbon market, Energy market, Connectedness, Portfolio allocation

Paper type Research paper

1. Introduction

Increasingly severe extreme weather events and environmental hazards are posing serious challenges to global economic development. Countries are gradually reaching a consensus on a green transformation of their economies (Wang et al., 2023; Wei et al., 2023; Wei et al., 2022b). Particularly, the outbreak of conflict between Russia and Ukraine, which triggered a global energy crisis in February 2022, has highlighted the importance of greening the economy and energy. The green economy is an emerging economic model that promotes low-carbon energy. It creates new market opportunities as a low-carbon, resource-efficient and socially inclusive economy. The results will not only markedly reduce environmental risks and improve human well-being and social equity, but will also stimulate the development of green investments (Amato and Korhonen, 2021; Pham, 2019). In fact, between 2011 and 2021, the total global investment in the low-carbon energy transition expanded from $264 billion to $755 billion [1]. Arguably, global green investment and financing is continuing to grow. Among these, green economy stocks have become an attractive asset for investors' portfolio allocation (Chen et al., 2023). Also, because of their special "green" qualities, it is not surprising to note that green economy stock assets comply with Environmental, Social and Governance (ESG) characteristics and are an essential tool for socially responsible investment (SRI). Admittedly, SRI may lead to additional costs, but since the growing public acceptance of cleaner production and sustainable consumption, the demand for SRI by investors has increased clearly (Ortas et al., 2013; Díaz et al., 2022).

However, the development of socially responsible investments such as green economy stocks is disruptive to traditional asset investment situations. Apparently, the incremental costs of socially responsible investing can influence the costs that would otherwise be incurred by individual and institutional investors managing asset portfolios, and thus green economy stocks may create a shock to other assets, including energy and carbon assets. Additionally, carbon and energy prices are the main drivers of investment and profitability of green economy projects, because they can affect the limited costs of companies, leading companies to constantly adjust their resource allocation, such as improving energy efficiency, using renewable energy sources (Reboredo et al., 2017). With all these in mind, there is a distinct transfer of risk between the carbon market, the energy market, and the green economy stocks (hereafter "Carbon-Energy-Green economy" system). Consequently, in the "Carbon-Energy-Green economy" system, understanding the connectedness and exploring the portfolio strategies of assets is crucial for risk management, asset allocation, and decision-making.

Furthermore, the literature on the carbon market, energy market, or green economy has recently attracted considerable attention. On the one hand, there have been a large number of studies that have explored the potential relationship between the carbon market and the energy market (Duan et al. 2021; Jiang and Chen, 2022a, b; Tian et al., 2022). Of these, Zheng et al. (2015) concluded that the carbon and energy markets are cross-correlated, and that there is a physical relationship between carbon emissions and energy production. The results of Dai et al. (2021) showed that the long-term spillover effect in the carbon and energy markets is strong, and demonstrated that carbon assets can hedge the risk of energy assets. On the other hand, as the green economy development strategy and the transition from the traditional economic development model to a green economy have become inevitable (Ali et al., 2021), the upgrading of the energy mix has become a priority for the economic development of countries, which has pushed researchers to focus on the energy market and the green economy (Dutta et al. 2020a; Chen et al., 2023; Gao et al., 2021; Reboredo et al., 2020; Shahbaz et al., 2021; Wei et al., 2022a; Wei et al., 2017; Wei et al., 2019). Dutta et al. (2020b) confirmed that green economy investments are associated with oil price shocks. And Sharma et al. (2023) discovered that the green economy is very sensitive to price changes in the energy market. Moreover, it was not difficult to find that the carbon market is important for building a green economy, given the increasingly broad scope of decarbonization programs (Dunlap, 2023). So the characteristics of the connection between the green economy and the carbon market are also the topics of academic research (Jin et al., 2020; Shahbaz et al., 2021; Tian et al., 2022; Zheng et al., 2022). Castro et al. (2021) asserted that green technologies help to reduce carbon emissions. Li et al. (2022) contended that in the short and medium term, the green market has a positive impact on carbon prices. Conclusively, the existing literature confirmed the potential connection between the carbon market and the energy market, and the inevitable association of the energy market and the green economy, which is dependent on the carbon market for its development. Therefore, the effects of the carbon market, the energy market and green economy stocks are transmitted to each other, and there may exist a closed-loop interacting mechanism. Unequivocally, we believe that there may be a dynamic linkage in the "Carbon-Energy-Green economy" system.

At the same time, global crisis events have been prone to asset price instability in recent years, owing to modern technological advances that have broken down barriers to the flow of information across markets. As a result, portfolio allocation that includes carbon, energy and green economy assets becomes more complex and diversified given the risk correlation between carbon markets, energy markets and green economy (Asl et al., 2021; Chen et al., 2022; Dutta et al., 2020b; Ren and Lucey, 2022; Tiwari et al., 2022). Particularly, in the context of very severe environmental risks, socially responsible investment is gradually becoming more and more accepted as a mainstream investment product, despite the added expenses associated with such initiatives (Broadstock et al., 2020). As expected, the role and positioning of green economy stocks as one of the main instruments for socially responsible investment, in mainstream investment products is unclear. To this end, we first analyze the connectedness characteristics of the "Carbon-Energy-Green economy" system, and then discuss the portfolio performance under this system, especially the performance of the green economy.

In conclusion, we make contributions on three fronts. Firstly, it is the first explicit consideration of the risk-linked characteristics and the roles of three markets in the "Carbon-Energy-Green economy" system. In point of fact, most of the extant studies lack a comprehensive discussion of how these three types of markets are connected. Secondly, we shed light for the first time on the position of green economy stocks in the "Carbon-Energy-Green economy" system and how various markets are hedged. Unequivocally, little evidence exists on the effect to which green economy stocks hedge carbon and energy assets. Thirdly, the major methods adopted in the above literature often rely on rolling window techniques at their core part (Jiang and Chen, 2022b; Sharma et al., 2023; Tian et al., 2022; Wei et al., 2022c; Zhang et al., 2019), and are prone to parameter instability (Chatziantoniou et al., 2021). In light of this, this paper utilizes the TVP-VAR method provided by Antonakakis et al. (2020) and Chatziantoniou et al. (2021) to test the connectedness performance of the "Carbon-Energy-Green economy" system, and further to verify the robustness of the results. Additionally, we employ portfolio back-testing models, including bivariate portfolios and multivariate portfolios, which takes into account portfolio allocation in the system.

The remainder of the essay is structured as follows: Section 2 for the research methodology, Section 3 for the data employed, Section 4 for the empirical findings, and Section 5 for the conclusions and suggests relevant counter-measures.

2. Methodology

This section consists of two main parts. First, we use the time-domain TVP-VAR model proposed by Antonakakis et al. (2020) to estimate the connectedness of the "Carbon-Energy-Green economy" system and to analyze the role played by each of the three types of markets in this system. Further, we validate the robustness of this part of the results by employing the frequency domain TVP-VAR approach introduced by Chatziantoniou et al. (2021). Second, we apply the portfolio back-testing approach to investigate the investment performance of carbon, energy and green economy assets. In this context, we discuss the specific contribution of green economy stocks in the portfolios of the "Carbon-Energy-Green economy" system.

2.1. TVP-VAR based time-varying and frequency connectedness approach

To investigate the time-frequency relationships between the carbon, energy and green economy, we utilize the TVP-VAR frequency connectedness method recently established by Chatziantoniou et al. (2021). This method combines the TVP-VAR connectedness approach offered by Antonakakis et al. (2020) with the frequency connectedness approach proposed by Baruník and Křehlík (2018). Among these, the TVP-VAR connectedness method, was an integration of the work of Diebold and Yilmaz (2012) with Koop and Korobilis (2014). Following this, Chatziantoniou et al. (2021) used the spectral decomposition technique of

Stiassny (1996) to extend the dimensionality of connectedness exploration to different frequency domains.

This approach is chosen not only because it has the same two main advantages as the TVP-VAR connectedness method: (i) it compensates for the problem of parameter instability due to the arbitrary choice of the rolling window size, and (ii) it avoids the problem of losing some valuable parameters, but it also broadens the observation perspective to be able to assess the connectedness in different frequency domains. We first estimate the TVP-VAR (p) model.

$$y_t = \Phi_{it} y_{t-i} + \epsilon_t \qquad\qquad \epsilon_t \sim (0, \Sigma_t), \tag{1}$$

where y_t, y_{t-1} and ϵ_t are all N × 1 dimensional vectors. Φ_{it} and Σ_t are N × N dimensional matrices, the former represents the time-varying coefficients of VAR for day *t,* and the latter is time-varying variance-covariance matrix. i stands for the value of the lag order *p* and accepts values in the range $i = 1, 2, \cdots, p$. Moreover, we let the *N* × *N* dimensional matrix lag polynomial $\Phi(L) = [I_N - \Phi_{it} L^i]$, with I_N denoting the identity matrix. Subsequently, we can write Eq. (1) as $\Phi(L) y_t = \epsilon_t$. If the TVP-VAR process is stable, we can apply the Wold representation theorem to convert it into the TVP-VMA (∞) form: $y_t = \Psi(L)\epsilon_t$, $\Psi(L)$ is an infinite lag polynomial (i.e., coefficient), and it can be calculated recursively from $\Phi(L) = [\Psi(L)]^{-1}$ in the TVP-VMA (∞) form. And, $\Psi(L)$ can be represented by an approximation Ψ_h computed at the horizons of $h = 1, 2, \cdots, H$. Then, we calculate the generalized forecast error variance decomposition (GFEVD) using Ψ_h (Koop et al., 1996; Pesaran and Shin, 1998; Wiesen et al., 2018).

The GFEVD expresses the impact of shocks in sequence *b* on the predicted error variance of sequence a, it can be stated as follows:

$$\gamma_{abt}(H) = \frac{(\Sigma_t)_{bb}^{-1} \sum_{h=0}^{H} ((\Psi_h \Sigma_t)_{abt})^2}{\sum_{h=0}^{H} (\Psi_h \Sigma_t \Psi_h')_{aa}}, \tag{2}$$

$$\tilde{\gamma}_{abt}(H) = \frac{\gamma_{abt}(H)}{\sum_{k=1}^{N} \gamma_{abt}(H)}, \tag{3}$$

where H denotes the prediction horizon, and we normalize Eq. (3) to obtain the following equations: $\sum_{a=1}^{N} \tilde{\gamma}_{abt}(H) = 1$ and $\sum_{b=1}^{N} \sum_{a=1}^{N} \gamma_{abt}(H) = N$. Then, we will measure different connectedness, respectively. First, the total directional connectedness to others (i.e., TO),

$$TO_{at}(H) = \sum_{a=1, a \neq b}^{N} \tilde{\gamma}_{bat}(H). \tag{4}$$

Eq. (4) expresses the effect of shocks in variable *a* on all others *b*. Second, the total directional connectedness from others (i.e., FROM).

$$FROM_{at}(H) = \sum_{b=1, a \neq b}^{N} \tilde{\gamma}_{abt}(H). \tag{5}$$

Eq. (5) means the effect of shocks of variable a from all other variables b. Next, based on Eq. (4) and Eq. (5), the net total directional connectedness (i.e., NET) as follows:

$$NET_{at}(H) = TO_{at}(H) - FROM_{at}(H). \tag{6}$$

Eq. (6) is interpreted as the effect of shocks of variable *a* on the connectedness of the system. If $NET_{at} > 0$, it signifies that variable *a* has a stronger impact on all other variables than any others have on it., i.e., variable *a* acts as a net transmitter in the whole connectedness network. If $NET_{at} < 0$, the result is the opposite. The net pairwise directional connectedness index (i.e., NPDC) of two sequences:

$$NPDC_{abt}(H) = \tilde{\gamma}_{abt}(H) - \tilde{\gamma}_{bat}(H). \tag{7}$$

Eq. (7) is interpreted as the net pairwise connectedness between variable *a* and variable *b*. If $NPDC_{abt} > 0$, it means that variable *a* has more influence on variable *b*, that is, variable *a* dominates variable *b*. If $NPDC_{abt} < 0$ implies the inverse result. Finally, we quantify the total connectedness index (i.e., TCI) to gauge the degree of association and the level of risk in the system:

$$TCI_t(H) = N^{-1} \sum_{a=1}^{N} TO_{at}(H) = N^{-1} \sum_{a=1}^{N} FROM_{at}(H). \tag{8}$$

All of the above are connectedness measures in the time domain, and to develop the connectedness analysis in the frequency domain, Chatziantoniou et al. (2021) considered the frequency response function according to the spectral analysis method of Stiassny (1996):

$$\Psi(e^{-a\omega}) = \sum_{h=0}^{\infty} e^{-a\omega h} \Psi_h. \tag{9}$$

In Eq. (9), ω denotes the spectral density of y_t at frequency ω, which can be defined as the Fourier transform of TVP-VMA (∞):

$$S_y(\omega) = \sum_{h=-\infty}^{\infty} E(y_t y'_{t-h}) \, e^{-a\omega h} = \Psi(e^{-a\omega h})\Sigma_t \Psi'(e^{+a\omega h}). \tag{10}$$

The combination of spectral density and GFEVD is called frequency GFEVD, and we normalize the frequency GFEVD as follows:

$$\gamma_{abt}(\omega) = \frac{(\Sigma_t)_{bb}^{-1} |\sum_{h=0}^{\infty} (\Psi(e^{-a\omega h})\Sigma_t)_{abt}|^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h})\Sigma_t \Psi(e^{i\omega h}))_{ii}}, \tag{11}$$

$$\tilde{\gamma}_{abt}(\omega) = \frac{\gamma_{abt}(\omega)}{\sum_{k=1}^{N} \gamma_{abt}(\omega)}, \tag{12}$$

where Eq. (12) is a within-frequency indicator, meaning that, for a given frequency ω, the effect of the spectral part of the a_{th} variable can be attributed to a shock in the b_{th} variable. However, the frequency ω in Eq. (11) and Eq. (12) is single, and the calculated connectedness is based on a single frequency only. In order to evaluate the connectedness in different frequency cases, Chatziantoniou et al. (2021) aggregated the frequencies to a specific range such that $\theta = (j,k){:}\, j < k,\ j,k \in (-\pi,\pi)$. This led to the calculation of the connectedness at different frequencies as follows:

$$\tilde{\gamma}_{abt}(\theta) = \int_j^k \tilde{\gamma}_{abt}(\omega) d\omega. \tag{13}$$

According to Eq. (13), we can calculate the connectedness measures for a certain frequency range θ. Thus, all the connectedness of Eq. (4) to (8) can be expressed in different frequency cases:

$$TO_{at}(\theta) = \sum_{a=1,a\neq b}^{N} \tilde{\gamma}_{bat}(\theta), \tag{14}$$

$$FROM_{at}(\theta) = \sum_{b=1,a\neq b}^{N} \tilde{\gamma}_{abt}(\theta), \tag{15}$$

$$NET_{at}(\theta) = TO_{at}(\theta) - FROM_{at}(\theta), \tag{16}$$

$$NPDC_{abt}(\theta) = \tilde{\gamma}_{abt}(\theta) - \tilde{\gamma}_{bat}(\theta), \tag{17}$$

$$TCI_{t}(\theta) = N^{-1} \sum_{a=1}^{N} TO_{at}(\theta) = N^{-1} \sum_{a=1}^{N} FROM_{at}(\theta). \tag{18}$$

Eq. (14) to (18) show some connectedness measures for a specific frequency range. Baruník and Křehlík (2018) argued that the degree of connectedness contribution within each frequency band needs to be weighted with respect to all connectedness contributions of the whole system by $\Xi(\theta) = \frac{\sum_{a,b=1}^{N} \tilde{\gamma}_{bat}(\theta)}{N}$. Based on this weighting, Eq. (14) to (18) are transformed into:

$$\widetilde{TO_{at}}(\theta) = \Xi(\theta) \cdot TO_{at}(\theta), \tag{19}$$

$$\widetilde{FROM}_{at}(\theta) = \Xi(\theta) \cdot FROM_{at}(\theta), \tag{20}$$

$$\widetilde{NET_{at}}(\theta) = \Xi(\theta) \cdot NET_{at}(\theta), \tag{21}$$

$$\widetilde{NPDC_{abt}}(\theta) = \Xi(\theta) \cdot NPDC_{abt}(\theta), \tag{22}$$

$$\widetilde{TCI_{t}(\theta)} = \Xi(\theta) \cdot TCI_{t}(\theta). \tag{23}$$

Finally, we compare the frequency-domain connectedness and the time-domain connectedness, as follows:

$$TO_{at}(H) = \sum_{\theta} TO_{at}(\theta), \tag{24}$$

$$FROM_{at}(H) = \sum_{\theta} FROM_{at}(\theta), \tag{25}$$

$$NET_{at}(H) = \sum_{\theta} NET_{at}(\theta), \tag{26}$$

$$NPDC_{abt}(H) = \sum_{\theta} NPDC_{abt}(\theta), \tag{27}$$

$$TCI_t(H) = \sum_{\theta} TCI_{at}(\theta). \tag{28}$$

In the following, the TVP-VAR time-varying connectedness method is referred to as the TVP-VAR-DY method, and the TVP-VAR frequency connectedness method is referred to as the TVP-VAR-BK method.

2.2. Portfolio back-testing models

To identify the hedging potential between markets in the "Carbon-Energy-Green economy" system and to test the financial implications of the findings, we utilize portfolio back-testing to review the investment performance of carbon, energy, and green economy assets. On the one hand, we observe bivariate portfolios and assess the hedging effectiveness of green economy stocks on energy and carbon assets. On the flip side, to study the multivariate portfolio performance among carbon assets, energy assets and green economy stocks assets, we consider three approaches (MVP, MCP, MCoP) to constructing multivariate portfolios. Our analysis requires some assumptions. For instance, i) investors are only interested in investing in assets in the "Carbon-Energy-Green economy" system. ii) investors can directly purchase the indices in the system. iii) investors are open to investing in assets that include carbon, energy and green economy assets.

The reason for selecting these methods is directly correlated to the research objectives of this paper. Not only is it feasible to recognize the performance of green economy stocks as a hedge against assets of different "clean" nature (carbon and energy assets), but it is also possible to explore the risk diversification effects of green economy stocks in the "Carbon-Energy-Green economy" system. We begin by looking at the bivariate portfolios.

2.2.1. Bilateral hedge ratios and portfolio weights

To evaluate the performance of bivariate portfolios, we compute the hedge ratio of Kroner and Sultan (1993) and the optimal portfolio weights of Kroner and Ng (1998). First, the hedge ratio is given by the following equation:

$$\beta_{ab,t} = {h_{ab,t}}/{h_{bb,t}}, \tag{29}$$

where $h_{ab,t}$ is the conditional covariance of series a and b at moment t, and $h_{bb,t}$ is the conditional covariance of series b at moment t. Second, the optimal bilateral portfolio weights, which are the results that this paper will discuss. And the optimal bilateral portfolio weights between sequences a and b are calculated as:

$$w_{ab,t} = \frac{h_{aa,t} - h_{ab,t}}{h_{aa,t} - 2h_{ab,t} + h_{bb,t}}, \tag{30}$$

with

$$w_{ab,t} = \begin{cases} 0 & if\ w_{ab,t} < 0 \\ w_{ab,t} & if\ 0 < w_{ab,t} < 1, \\ 1 & if\ w_{ab,t} > 1 \end{cases} \tag{31}$$

where $w_{ab,t}$ is the weight of sequence a in a 1\$ combination of sequences a and b. In the 1\$ combination of sequence a and b, the weight of sequence b is denoted as $1 - w_{ab,t}$. Then, the three portfolio approaches we use are described below.

2.2.2. Minimum variance portfolio (MVP)

The minimum variance portfolio (MVP) method developed by Markowitz (1959) is one of the commonly used methods in constructing portfolios, which attempts to construct a portfolio based on the lowest volatility of multiple assets with the following formula for the weights:

$$w_{H_t} = \frac{H_t^{-1} I}{I H_t^{-1} I'}, \tag{32}$$

where w_{H_t} is an $n \times 1$ dimensional portfolio weight vector, H_t denotes the $n \times n$ dimensional conditional variance-covariance matrix for period *t*, and *I* is an *n*-dimensional vector.

2.2.3. Minimum correlation portfolio (MCP)

In addition, Christoffersen et al. (2014) introduced a minimum correlation portfolio (MCP). The MCP approach seeks to frame portfolios according to the minimized conditional correlation of multiple assets rather than volatility. The investment weights are calculated as follows:

$$C_t = diag(H_t)^{-0.5} H_t diag(H_t)^{-0.5}, \tag{33}$$

where C_t is an $n \times n$ dimensional matrix, based on which the weights of the MCP method are:

$$w_{C_t} = \frac{C_t^{-1} I}{I C_t^{-1} I}. \tag{34}$$

2.2.4. Minimum connectedness portfolio (MCoP)

Recently Broadstock et al. (2020) have identified a minimum connectedness portfolio approach (MCoP1), where weights are calculated by minimizing pairwise connectedness rather than correlation or volatility. The MCoP1 approach aims to reduce interconnectedness and spillover effects between variables, providing a portfolio that is not heavily influenced by network shocks. Therefore, assets that have less influence on others and are less influenced by others will be given higher weights in the portfolio, as shown below,

$$w_{PCI_t} = \frac{PCI_t^{-1} I}{I PCI_t^{-1} I'}, \tag{35}$$

where PCI_t is the pairwise connectedness index matrix, and *I* is the identity matrix. Besides, we apply a new minimum connectedness portfolio approach (MCoP2) from Chen et al. (2023), which differs from the MCoP1 approach in that the weights of MCoP2 are calculated by minimizing net pairwise connectedness rather than pairwise connectedness.

$$w_{NPDC_t} = \frac{NPDC_t^{-1} I}{INPDC_t^{-1} I'}, \tag{36}$$

where $NPDC_t$ is the net pairwise connectedness index matrix.

2.2.5. Portfolio evaluation

To capture the performance of the three portfolios, we calculate the Sharpe ratio (Sharpe, 1998) and the hedge effectiveness (Ederington, 1979). One is hedge effectiveness (HE), which is defined as follows:

$$HE = 1 - \frac{var(r_{portfolio})}{var(r_a)}. \tag{37}$$

The formula means the percentage reduction in the variance of the unhedged position. The larger the HE, the greater the risk reduction and the more effective the portfolio is at hedging. where $var(r_{portfolio})$ denotes the variance of the portfolio and $var(r_a)$ denotes the variance of the unhedged assets.

As for the Sharpe ratio,

$$SR = \frac{\bar{r}_{portfolio}}{\sqrt{var(r_{portfolio})}}. \tag{38}$$

The risk-free rate is assumed to be zero, where r_p denotes the returns of the portfolio. A higher SR value indicates that there is a higher return relative to the level of risk in the portfolio. Worded differently, the higher the SR value, the more advantageous the portfolio is.

3. Data

In this paper, we focus on discussing the connectedness of the "Carbon-Energy-Green economy" system and analyze the portfolio allocation of this system. To do so, we will take three asset prices that reflect the carbon market, the energy market and the green economy stocks respectively: carbon futures prices, energy prices and green economy stock prices.

In terms of the carbon market, referring to the existing literature (Ji et al., 2018), we use the EUA carbon futures price of the European Climate Exchange (EUA) [2]. In terms of the energy market, we collect Brent crude oil futures prices (OIL), Rotterdam coal futures prices (hereafter COAL), and UK natural gas futures prices (GAS) to represent three main energy markets (Duan et al., 2021) [2]. In terms of the green economy stocks, we utilize the NASDAQ OMX Green Economy Sector stock indexes to track the performance of the green economy across the major sectors (Chen et al., 2023; Pham, 2019; Ren and Lucey, 2022) [3]. Currently, there are 12 primary sector indices, namely NASDAQ OMX Advanced Materials Index (GRNAM) representing the advanced materials sector, NASDAQ OMX Bio/Clean Fuels Index (GRNBIO) representing the bio/clean fuels sector, NASDAQ OMX Energy Efficiency Index (GRNENEF) representing the energy efficiency sector. NASDAQ OMX Green Building Index (GRNGB) for the green building sector. NASDAQ OMX Healthy Living Index (GRNHL) for the healthy living sector, and NASDAQ OMX Lighting Index (GRNLIGHT) for the lighting sector. NASDAQ OMX Natural Resources Index (GRNNR) for the natural resources sector. NASDAQ OMX Pollution Mitigation Index (GRNPOL) for the pollution mitigation sector. NASDAQ OMX Recycling Index (GRNREC) for the recycling sector. NASDAQ OMX Renewable Energy Generation Index (GRNREG) for the renewable energy generation sector. NASDAQ OMX Transportation Index (GRNTRN) for the transportation sector. NASDAQ OMX Water Index (GRNWATER) for the water resources sector. Table 1 contains the precise definitions of the various indexes.

[Insert Table 1 about here]

Since the NASDAQ OMX Green Economy Index can only be traced back to the end of 2010 at the earliest, we choose 14th October 2010 to 29th February 2024 as the sample period, and calculate the log returns to describe the changes in the markets. Descriptive statistics for all variables are presented in Table 2.

[Insert Table 2 about here]

Table 2 reveals that, with the exception of the crude oil and bio/clean fuels sectors, which have a weak negative mean case, all other returns have positive mean values, indicating an overall upward trend in the asset prices of carbon, energy and green economy stocks. Moreover, the variance of carbon and energy returns is markedly larger than the variance of green economy stock returns. This implies that the carbon and energy markets are more volatile than the green economy stocks market. In addition, looking at the kurtosis and skewness values, we can see that all variables are kurtosis and fat-tailed. From the normality test, the J-B statistic discloses the non-normal distribution of all variables. From the stationarity test, the ERS statistic displays that all variables are stationary time series. Finally, the Ljung-Box test statistics demonstrate the existence of autocorrelation. In summary, we can construct econometric models based on the above data.

4. Empirical results

In this study, we first measure the connectedness of the “Carbon-Energy-Green economy” system and ensure the robustness of the results by applying time-frequency domain parameter vector autoregressions (TVP-VAR-DY and TVP-VAR-BK). Then, we discuss the performance of portfolio returns and risks within the “Carbon-Energy-Green economy” system by using a portfolio back-testing approach.

4.1. Averaged dynamic connectedness analyses

In this section, we present the static findings derived from the TVP-VAR-DY approach to assess the transmission mechanisms in the “Carbon-Energy-Green economy” system. And we further verify the reliability of the results in this paper by using the TVP-VAR-BK method. We start by reporting the average connectedness listed in Table 3 and Table 4.

[Insert Table 3 about here]

[Insert Table 4 about here]

Table 3 and Table 4 provide the findings of the TVP-VAR-DY and the TVP-VAR-BK methods. Table 3 and Table 4 state that, for the “Carbon-Energy-Green Economy” system, the average value of the Total Connectedness Index (TCI) is 67.91%. These discoveries suggest that an average of 67.91% of the forecast error variance in the “Carbon-Energy-Green economy” system can be attributed to the system itself, implying that 67.91% of the connectedness is due to the diffusion of shocks in the system across markets, and that there is strong connectedness in the system. Also, it is necessary to stress that the total connectedness (TCI) over the sample period is mainly driven by short-term connectedness (i.e., the high-frequency component, 55.00%), followed by medium-term connectedness (i.e., the medium-frequency component, 10.78%) and the long-term connectedness (i.e., the low-frequency component, 2.73%).

From the diagonal elements in Table 3, in the case of the carbon market, only 32.23% of the index fluctuations are attributable to network connectedness, with intra-index shocks accounting for 67.77% of the index evolution. In the case of the energy market, we can see that

50.58% of the crude oil market, 71.83% of the coal market, and 76.44% of the natural gas market are driven by intra-index shocks, while 49.42% of the crude oil market, 28.17% of the coal market and 23.56% of the natural gas market have index movements caused by network connectedness. The features of carbon and energy markets described above are similar to the results of (Tan et al., 2020), who found that more than 65% of the movements in the carbon and other energy markets, except for the crude oil market, are self-induced. Actually, the share of crude oil consumption in total energy consumption has been between 40% and 50%, far exceeding the consumption of coal and natural gas [4], so the crude oil market may be more susceptible to shocks from other factors and behave more sensitively. In the case of the green economy stocks, only 15-30% of the evolution of the index is explained by intra-index shocks. It follows that in the "Carbon-Energy-Green economy" system, the crude oil sector and green economy stocks are relatively more tightly associated with other market shocks. This finding is also confirmed by the frequency connectedness results in Table 4.

Turning to the "NET" values of each market in the "Carbon-Energy-Green economy" system, it is also clear from Table 3 that the energy efficiency sector in the green economy stocks represents the largest net sender to this network (28.41%), followed by water sector (25.51%) and recycling sector (19.66%). And carbon (−14.83%), crude oil (−23.86%), coal (−12.58%) and natural gas (−9.24%) sectors are all the net recipients. On a parallel note, the results of the TVP-VAR-BK approach (Table 4) support this observation, which illustrates the robustness of the paper's conclusions. It is worth pointing out that the net shocks received by the carbon and energy markets are substantially more pronounced than those received by the sectors in the green economy market (except for the bio/clean fuels sector, which also performs the role of the primary net recipient of shocks). In effect, Pham (2019) argued that biofuels and oil price movements are closely related since biofuels are often perceived as a closer alternative to fossil fuels. Similarly, we contend that there should be a highly correlated relationship between biofuels and energy markets. Given that prices and demand move in the same direction among substitutes, the bio/clean fuels sector performs analogously to the energy market. In summary, in terms of the "Carbon-Energy-Green economy" system, the carbon and energy markets are inevitably exposed to shocks of different sectors, while the majority of green economy sector stocks tend to dominate other markets. For simplicity, Figure 1 visualizes the net pairwise connectedness in the "Carbon-Energy-Green economy" system through a chord diagram based on the interrelationship between the carbon market, energy market, and green economy stocks variables based on the results in Tables 3 and 4.

[Insert Figure 1 about here]

In Figure 1, these variables are arranged radially along a circle and connected by arcs. The contribution of each variable to the overall system is represented by the width of the node for that variable. In this case, there are two kinds of arcs under the same node, with arcs close to the node indicating shocks that the variable delivers to other variables, and arcs not close to the node expressing shocks that the variable receives from other variables. Consider subfigure (a) as an example, at one end of the spectrum, it is convenient to notice from the width of each node that the crude oil sector and the energy efficiency sector have a large effect on the system. From the opposite end of the spectrum, it can be seen from the two types of arcs under the same node that the three sectors with the largest net contribution are the energy efficiency sector, the water sector, and the recycling sector in the green economy stocks, while the carbon and energy markets have virtually no shocks to the rest of the system and are obvious shock recipients. This implies that green economy stocks are the emitters of shocks and risks in the system, while carbon and energy markets are the receivers of shocks and risks. As expected, the above results are also confirmed in subfigures (b), (c) and (d).

Although Tables 3, 4 and Figure 1 can show static information of the “Carbon-Energy-Green Economy” system connectedness, it fails to capture the heterogeneous performance of the system’s connectedness over time. Thus, we direct our attention toward dynamic connectedness.

4.2. Dynamic connectedness analyses

In this sub-section, we investigate dynamic connectedness in the “Carbon-Energy-Green economy” system. Figure 2 depicts the dynamics of the connectedness of this system for the period from 2010 to 2024 for different time and frequency scenarios.

[Insert Figure 2 about here]

According to Figure 2, we find that the total connectedness mainly fluctuates between 50% and 90% of the “Carbon-Energy-Green economy” system, and the connectedness is constantly changing over time. This is similar to the study by Tan et al. (2020), who suggested that the features of information spillovers in carbon, energy and financial markets are different over time. Indeed, it is widely perceived that market uncertainty, financial crises, policy changes and catastrophic events lead to compromised correlations between markets (Antonakakis et al., 2018; Bai et al., 2021; Chatziantoniou et al., 2022; Li et al., 2021; Li and Wei, 2018; Liu et al., 2022), and this perception is also reflected in Figure 2.

Comparing the four turbulent periods of rising connectedness (2011, 2014-2015, 2017, 2020), we observe that the growth in connectedness induced by the COVID-19 event in 2020 is more dramatic and larger than in 2011, 2014-2015 and 2017. This assertion is supported by the graph, which shows a vertical spike in 2020, from 62% to around 82%. In contrast, connectedness rises from 72% to about 82% in 2011 during the nuclear leak in Fukushima, Japan, increased from 65% to ~78% during the 2014-2015 oil crisis and grew from 52% to roughly 65% after the announcement of the U.S. withdrawal from the Paris Agreement in 2017. Interestingly enough, after COVID-19 pandemic, the gradual decline in the connectedness of the “Carbon-Energy-Green economy” system. This may be owing to the economic and financial distress following the COVID-19 pandemic, countries adopted expansionary monetary and fiscal policies to energize capital markets and the real economy, thus reducing the volatility of the “Carbon-Energy-Green economy” system (Antonakakis et al., 2023; Chadha et al., 2021).

Notably, Figure 2 also depicts the connectedness trend of the TVP-VAR-BK approach. The trend of connectedness at different frequencies is in consonance with the evolution of the total connectedness in TVP-VAR-DY method. It proves the robustness of our findings. Moreover, Figure 3 visualizes the time-varying net shocks for the carbon, energy, and green economy stocks over the sample period, clarifying the transmitter and recipient role of shocks switching in each market at different periods.

[Insert Figure 3 about here]

Figure 3 displays that in the “Carbon-Energy-Green economy” system, the carbon market and the energy market are consistently net recipients of shocks for the vast majority of the time, although there are brief instances of transmission. Rather, the energy efficiency, water resources and recycling sectors of the green economy stocks also act as net transmitters of shocks most of the time, especially the energy efficiency sector. This is in accordance with the results in Table 3, Table 4 and Figure 1, and similar to the conclusions of (Pham, 2019) and

(Chen et al., 2023). In light of the aforementioned, we think there may be a linkage in green economy stocks, carbon and energy assets that could serve as a risk-hedging mechanism. Therefore, we can initiate a discussion of portfolio management for the system.

4.3. Portfolio and hedging strategies analysis

[Insert Table 5 about here]

Table 5 provides the investment weights and hedging effectiveness (HE) of bivariate portfolios of carbon and energy assets for 12 green economy sector stocks. Firstly, we perceive that the weights of green economy stocks against coal and crude oil assets (21%-42%,13%-35%) are much larger than those against natural gas and carbon assets (9%-19%, and 7%-26%) in bivariate portfolios. To be more explicit, the hedging risk in more 'dirty' assets (coal and oil) requires more investment in green economy stocks than hedging exposure to more 'clean' assets (carbon and natural gas). Secondly, the weighting and hedging effects vary substantially across the different green economy sectors. For instance, in a bivariate portfolio of carbon assets, the average weight of water sector stocks (GRNWATER) is only 7%, while the average weight of biofuel sector stocks (GRNBIO) is as high as 26%. Likewise, in a bivariate portfolio of coal assets, the HE value of the COAL/GRNWATER portfolio is 90%, while the HE value of the COAL/GRNBIO portfolio is only 76%.

Finally, the HE values reveal that the green economy sector stocks can generate the highest hedging effect in the natural gas market (i.e., around 90% to 96%), followed by the carbon market (i.e., around 76% to 90%). In contrast, green economy stocks have lower hedging effects in the crude oil and coal markets (i.e., approximately 48% to 80% and 75% to 90%). Notwithstanding this, we cannot deny the hedging ability of green economy stocks in each bivariate portfolio. This also proves that green economy stocks are effective in hedging the market risk in the “Carbon-Energy-Green economy” system. Next, we will explain the portfolio performance in the “Carbon-Energy-Green economy” system using diversified portfolios, including minimum variance portfolios (MVP), minimum correlation portfolios (MCP), and minimum connectedness portfolios (MCoP1, MCoP2). The relative performance of the four types of portfolios is also evaluated by employing the Sharpe ratio.

[Insert Figure 4 about here]

Figure 4 draws the cumulative returns based on the diversified portfolios, MVP, MCP, MCoP1 and MCoP2. As can be seen in Figure 4, the cumulative returns of the MCoP2 approach have a distinct superiority, the cumulative returns of the MCoP1 and MCP approaches perform essentially the same, while the cumulative returns based on the MVP approach perform quite clearly different from the cumulative returns based on the MCP, MCoP1 and MCoP2 approaches. Furthermore, we continue to compare the Sharpe ratios of the four portfolio methods. To identify the importance of various markets in the “Carbon-Energy-Green economy” system, we report Sharpe ratios for different portfolios constructed from a mix of three assets (16 sectors). It is necessary to mention that among the green economy sector stocks, the advanced materials sector, the bio/fuel sector, the energy efficiency sector and the renewable energy generation sector make up the clean energy stock index. We regard the four clean energy sector stocks as a separate category, i.e., the clean energy stocks category (Pham, 2019), when discussing the different portfolios of the “Carbon-Energy-Green economy” system. In the following discussion, in order to ensure the robustness of the conclusions in this paper, apart from the Sharpe ratio, we also use two ratios, the sortino ratio and the omega sharpe ratio, to observe the performance of the diversified portfolios under the four methodologies (MVP, MCP, MCoP1, MCoP2).

[Insert Table 6 about here]

As depicted in figure 6, first, we illustrate that the different methods have a high heterogeneity across the portfolios. And more concretely, there is no very clear dominant performance of any method in the “EUA” base portfolios in Panel A. But in the Panels B and C, MVP and MCoP2 perform best. Then, each portfolio has a different Sharpe ratio. For instance, the Sharpe ratio of the “EUA+OIL+COAL+GAS” portfolio is 0.0093 and the Sharpe ratio of the “EUA+OIL+COAL+GAS+GREEN” portfolio is 0.307. This means that various portfolios are differentiated in yield and risk.

On a final note, the Sharpe ratio values demonstrate that the portfolios with added green economy stocks are able to beat all the portfolios without added green economy stocks. Particularly, the “EUA+GREEN”, “GAS+GREEN” and “EUA+OIL+COAL+GAS+GREEN” portfolios have a significant advantage, with Sharpe ratio values of 0.0351, 0.0310 and 0.0307, respectively. This indicates the importance of green economy stocks in hedging the carbon and energy market risks. On a parallel note, we opine that cleaner portfolios have notably larger Sharpe ratio values when looking only at portfolios with green economy stock assets added. By way of example, “EUA+GREEN” is 0.0351 and “GAS+GREEN” is 0.0310, while “OIL+GREEN” is 0.0269 and “COAL+GREEN” is 0.0252. This finding is also confirmed in the sornito ratio and omega sharpe ratio, meaning that the outcome of this paper is robust. And our observations are consistent with Pham (2019), which argued that clean energy stocks in different sectors can hedge against oil prices, and Chen et al. (2023), which thought that green economy stocks are a vital asset for hedging against the natural gas market risk. This result not only re-emphasizes the role of green economy stocks, but also provides investors with a new way of thinking about "sectoralizing" investments in green economy stocks. It is therefore important for investors to move away from the past practice of only investing in carbon and energy assets, and to add green economy stocks to hedge against market risk.

5. Conclusions

This paper examines the connectedness and portfolio management based on the framework of the "Carbon-Energy-Green economy" system, and set out to further examine the effect of green economy stocks on the carbon and energy markets. On the one hand, there is a high degree of connectedness inside the "Carbon-Energy-Green economy" system, and it is noteworthy that the COVID-19 pandemic produced an increase vertically in the connectedness of this system. Besides, the carbon and energy markets are invariably sensitive to shocks from others. Most sectors in the green economy stocks tend to dominate others. On the flip side, green economy stocks provide a satisfactory hedge against market risk in carbon and energy futures. It's worth stating early on that hedging risk in more 'dirty' assets requires more investment in green economy stocks than hedging exposure to more 'clean' assets. What is more, portfolios that do not include green economy stocks are significantly less advantageous than portfolios that contain green economy sector stocks. This emphasizes the positive impact of green economy stocks in the system on portfolio returns.

Our research has profound implications for investors and decision-makers. For investors, apparently, green economy stocks should be allocated more to 'dirty' assets than to 'clean' assets when considering the use of green economy stocks to hedge the risk of only one asset in the system. To put differently, in a bivariate portfolio, more green economy stock assets are needed to hedge the risk of crude oil assets and coal assets, and fewer green economy stock assets are in demand to hedge exposure to carbon and natural gas assets. Along a similar vein, when taking into account both carbon, energy and green economy assets, investors can use green economy sector stocks to hedge the market risk of carbon and energy assets, or they can solely utilize the clean energy category of green economy stocks to hedge their risk and avoid investing only in the carbon and energy markets to get higher returns and lower risk. For decision-makers, on a parallel note, can treat carbon, energy and green economy assets as interconnected assets in their policy frameworks, in light of the fact that the carbon and energy markets have been deeply influenced by the green economy market. And they should continue to support green economy markets.

Notes

1. Specific data can be found in the "Energy transition investment trends 2022: Tracking global investment in the low-carbon energy transition" published by Bloomberg New Energy Finance.
2. See https://www.wind.com.cn/.
3. See Quandl and https://indexes.nasdaqomx.com/Index/Directory/Green.
4. Related reports and data can be found on the official website of the International Energy Agency (IEA): https://www.iea.org/subscribe-to-data-services/world-energy-balances-and-statistics.

References

Ali, E.B., Anufriev, V.P. and Amfo, B. (2021), "Green economy implementation in Ghana as a road map for a sustainable development drive: A review", *Scientific African*, Vol. 12, e00756.

Amato, D. D. and Korhonen, J. (2021), "Integrating the green economy, circular economy and bioeconomy in a strategic sustainability framework", *Ecological Economics*, Vol. 188, 107143.

Antonakakis, N., Chatziantoniou, I. and Gabauer, D. (2020), "Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions", *Journal of Risk and Financial Management*, Vol. 13, p. 84.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D. and de Gracia, F.P. (2023), "Dynamic connectedness among the implied volatilities of oil prices and financial assets: New evidence of the COVID-19 pandemic", International Review of Economics & Finance, Vol. 83, pp. 114-123.

Antonakakis, N., Gabauer, D., Gupta, R. and Plakandaras, V. (2018), "Dynamic connectedness of uncertainty across developed economies: A time-varying approach", *Economics Letters,* Vol. 166, pp. 63-75.

Asl, M.G., Canarella, G. and Miller, S.M. (2021), "Dynamic asymmetric optimal portfolio allocation between energy stocks and energy commodities: Evidence from clean energy and oil and gas companies", *Resources Policy,* Vol. 71, 101982.

Bai, L., Wei, Y., Wei, G., Li, X. and Zhang, S. (2021), "Infectious disease pandemic and permanent volatility of international stock markets: A long-term perspective", *Finance Research Letters*, Vol. 40, 101709.

Baruník, J.and Křehlík, T. (2018), "Measuring the frequency dynamics of financial connectedness and systemic risk", *Journal of Financial Econometrics*, Vol. 16, pp. 271-296.

Broadstock, D.C., Chatziantoniou, I. and Gabauer, D. (2020), "Minimum connectedness portfolios and the market for green bonds: Advocating socially responsible investment (SRI) activity", Available at SSRN 3793771.

Castro, P., Gutiérrez-López, C., Tascón, M.T. and Castaño, F.J. (2021), "The impact of environmental performance on stock prices in the green and innovative context", *Journal of Cleaner Production*, Vol. 320, 128868.

Chadha, J., Corrado, L., Meaning, J. and Schuler, T. (2021), "Monetary and fiscal complementarity in the Covid-19 pandemic", SSRN 3923209. available at SSRN: https://ssrn.com/abstract=3923209

Chatziantoniou, I., Gabauer, D. and de Gracia, F.P. (2022), "Tail risk connectedness in the refined petroleum market: A first look at the impact of the COVID-19 pandemic", *Energy Economics*, Vol. 111, 106051.

Chatziantoniou, I., Gabauer, D. and Gupta, R. (2021), "Integration and Risk Transmission in the Market for Crude Oil: A Time-Varying Parameter Frequency Connectedness Approach". Working Papers 202147, University of Pretoria, Department of Economics.

Chen, H., Xu, C. and Peng, Y. (2022), "Time-frequency connectedness between energy and nonenergy commodity markets during COVID-19: Evidence from China", *Resources Policy*, Vol. 78, 102874.

Chen, Y., Wei, Y., Bai, L. and Zhang, J. (2023), "Can Green Economy stocks hedge natural gas market risk? Evidence during Russia-Ukraine conflict and other crisis periods", *Finance Research Letters*, Vol. 53, 103632.

Christoffersen, P., Errunza, V., Jacobs, K. and Jin, X. (2014), "Correlation dynamics and international diversification benefits", *International Journal of Forecasting*, Vol. 30, pp. 807-824.

Dai, X., Xiao, L., Wang, Q. and Dhesi, G. (2021), "Multiscale interplay of higher-order moments between the carbon and energy markets during Phase III of the EU ETS", *Energy Policy*, Vol. 156, 112428.

Díaz, A., Esparcia, C. and López, R. (2022), "The diversifying role of socially responsible investments during the COVID-19 crisis: A risk management and portfolio performance analysis", *Economic Analysis Policy*, Vol. 75, pp. 39-60.

Diebold, F.X. and Yilmaz, K. (2012), "Better to give than to receive: Predictive directional measurement of volatility spillovers", *International Journal of Forecasting*, Vol. 28, pp. 57-66.

Duan, K., Ren, X., Shi, Y., Mishra, T. and Yan, C. (2021), "The marginal impacts of energy prices on carbon price variations: evidence from a quantile-on-quantile approach", *Energy Economics*, Vol. 95, 105131.

Dunlap, A. (2023), "The green economy as counterinsurgency, or the ontological power affirming permanent ecological catastrophe", *Environmental Science Policy*, Vol. 139, pp. 39-50.

Dutta, A., Bouri, E., Das, D. and Roubaud, D. (2020a), "Assessment and optimization of clean energy equity risks and commodity price volatility indexes: Implications for sustainability", *Journal of Cleaner Production*, Vol. 243, 118669.

Dutta, A., Jana, R. and Das, D. (2020b), "Do green investments react to oil price shocks? Implications for sustainable development", *Journal of Cleaner Production*, Vol. 266, 121956.
Ederington, L.H. (1979), "The hedging performance of the new futures markets", *The Journal of Finance*, Vol. 34, pp. 157-170.
Gao, Y., Li, Y. and Wang, Y. (2021), "Risk spillover and network connectedness analysis of China's green bond and financial markets: Evidence from financial events of 2015–2020", *The North American Journal of Economics and Finance*, Vol. 57, 101386.
Ji, Q., Zhang, D. and Geng, J. (2018), "Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets", *Journal of Cleaner Production*, Vol. 198, pp. 972-978.
Jiang, W. and Chen, Y. (2022a), "The time-frequency connectedness among carbon, traditional/new energy and material markets of China in pre-and post-COVID-19 outbreak periods", *Energy*, Vol. 246, 123320.
Jiang, W. and Chen, Y. (2022b), "The time-frequency connectedness among metal, energy and carbon markets pre and during COVID-19 outbreak". *Resources Policy*, Vol. 77, 102763.
Jin, J., Han, L., Wu, L. and Zeng, H. (2020), "The hedging effect of green bonds on carbon market risk", *International Review of Financial Analysis*, Vol. 71, 101509.
Koop, G. and Korobilis, D. (2014), "A new index of financial conditions", *European Economic Review*, Vol. 71, pp. 101-116.
Koop, G., Pesaran, M.H. and Potter, S.M. (1996), "Impulse response analysis in nonlinear multivariate models", *Journal of Econometrics*, Vol. 74, pp. 119-147.
Kroner, K.F. and Ng, V.K. (1998), "Modeling Asymmetric Comovements of Asset Returns", *Review of Financial Studies*, Vol. 11, pp. 817-844.
Kroner, K.F. and Sultan, J. (1993), "Time-Varying Distributions and Dynamic Hedging with Foreign Currency Futures", *Journal of Financial and Quantitative Analysis*, Vol. 28, pp. 535 - 551.
Li, H., Zhou, D., Hu, J. and Guo, L. (2022), "Dynamic linkages among oil price, green bond, carbon market and low-carbon footprint company stock price: Evidence from the TVP-VAR model", *Energy Reports*, Vol. 8, pp. 11249-11258.
Li, X., Li, B., Wei, G., Bai, L., Wei, Y. and Liang, C. (2021), "Return connectedness among commodity and financial assets during the COVID-19 pandemic: Evidence from China and the US", *Resources Policy*, Vol. 73, 102166.
Li, X. and Wei, Y. (2018), "The dependence and risk spillover between crude oil market and China stock market: New evidence from a variational mode decomposition-based copula method", *Energy Economics*, Vol. 74, pp. 565-581.
Liu, Y., Wei, Y., Wang, Q. and Liu, Y. (2022), "International stock market risk contagion during the COVID-19 pandemic", *Finance Research Letters*, Vol. 45, 102145.
Markowitz, H.M. (1959), "Portfolio Selection: Efficient Diversification of Investment", John Wiley, NY.
Ortas, E., Burritt, R.L. and Moneva, J.M. (2013), "Socially Responsible Investment and cleaner production in the Asia Pacific: does it pay to be good"? *Journal of Cleaner Production*, Vol. 52, pp. 272-280.
Pesaran, H.H. and Shin, Y. (1998), "Generalized impulse response analysis in linear multivariate models", *Economics Letters*, Vol. 58, pp. 17-29.
Pham, L. (2019), "Do all clean energy stocks respond homogeneously to oil price"? *Energy Economics*, Vol. 81, pp. 355-379.
Reboredo, J.C., Rivera-Castro, M.A. and Ugolini, A. (2017), "Wavelet-based test of co-movement and causality between oil and renewable energy stock prices". *Energy Economics*, Vol. 61, pp. 241-252.
Reboredo, J.C., Ugolini, A. and Aiube, F.A.L. (2020), "Network connectedness of green bonds and asset classes", *Energy Economics*, Vol. 86, 104629.
Ren, B. and Lucey, B. (2022), "A clean, green haven?—Examining the relationship between clean energy, clean and dirty cryptocurrencies", *Energy Economics*, Vol. 109, 105951.
Shahbaz, M., Trabelsi, N., Tiwari, A.K., Abakah, E.J.A. and Jiao, Z. (2021), "Relationship between green investments, energy markets, and stock markets in the aftermath of the global financial crisis", *Energy Economics*, Vol. 104, 105655.
Sharma, G.D., Shahbaz, M., Singh, S., Chopra, R. and Cifuentes-Faura, J. (2023), "Investigating the nexus between green economy, sustainability, bitcoin and oil prices: Contextual evidence from the United States", *Resources Policy*, Vol. 80, 103168.
Sharpe, W.F. (1998), "The sharpe ratio", *Journal of Portfolio Management*, Vol. 3, pp. 169-185.

Stiassny, A. (1996), "A spectral decomposition for structural VAR models", *Empirical Economics*, Vol. 21, pp. 535-555.
Tan, X., Sirichand, K., Vivian, A. and Wang, X. (2020), "How connected is the carbon market to energy and financial markets? A systematic analysis of spillovers and dynamics", *Energy Economics*, Vol. 90, 104870.
Tian, T., Lai, K.-h. and Wong, C.W. (2022), "Connectedness mechanisms in the “Carbon-Commodity-Finance” system: Investment and management policy implications for emerging economies", *Energy Policy*, Vol. 169, 113195.
Tiwari, A.K., Abakah, E.J.A., Gabauer, D. and Dwumfour, R.A. (2022), "Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: Implications for hedging and investments strategies", *Global Finance Journal*, Vol. 51, 100692.
Wang, X., Wang, Z. and Wang, R. (2023), "Does green economy contribute towards COP26 ambitions? Exploring the influence of natural resource endowment and technological innovation on the growth efficiency of China's regional green economy", *Resources Policy*, Vol. 80, 103189.
Wei, Y., Bai, L. and Li, X. (2022a), "Normal and extreme interactions among nonferrous metal futures: A new quantile-frequency connectedness approach", *Finance Research Letters*, Vol. 47, 102855.
Wei, Y., Liu, J., Lai, X. and Hu, Y. (2017), "Which determinant is the most informative in forecasting crude oil market volatility: Fundamental, speculation, or uncertainty"? *Energy Economics*, Vol. 68, pp. 141-150.
Wei, Y., Qin, S., Li, X., Zhu, S. and Wei, G. (2019), "Oil price fluctuation, stock market and macroeconomic fundamentals: Evidence from China before and after the financial crisis", *Finance Research Letters*, Vol. 30, pp. 23-29.
Wei, Y., Zhang, J., Bai, L. and Wang, Y. (2023), "Connectedness among El Niño-Southern Oscillation, carbon emission allowance, crude oil and renewable energy stock markets: Time- and frequency-domain evidence based on TVP-VAR model", *Renewable Energy*, Vol. 202, pp. 289-309.
Wei, Y., Zhang, J., Chen, Y. and Wang, Y. (2022b), "The impacts of El Niño-southern oscillation on renewable energy stock markets: Evidence from quantile perspective", *Energy*, Vol. 260, 124949.
Wei, Y., Zhang, Y. and Wang, Y. (2022c), "Information connectedness of international crude oil futures: Evidence from SC, WTI, and Brent", *International Review of Financial Analysis*, Vol. 81, 102100.
Wiesen, T.F., Beaumont, P.M., Norrbin, S.C. and Srivastava, A. (2018), "Are generalized spillover indices overstating connectedness"? *Economics Letters*, Vol. 173, pp. 131-134.
Zhang, Y., Wei, Y., Zhang, Y. and Jin, D. (2019), "Forecasting oil price volatility: Forecast combination versus shrinkage method", *Energy Economics*, Vol. 80, pp. 423-433.
Zheng, W., Zhang, L. and Hu, J. (2022), "Green credit, carbon emission and high quality development of green economy in China", *Energy Reports*, Vol. 8, pp. 12215-12226.
Zheng, Z., Xiao, R., Shi, H., Li, G. and Zhou, X., (2015), "Statistical regularities of Carbon emission trading market: Evidence from European Union allowances", *Physica A: Statistical Mechanics*, Vol. 426, pp. 9-15.

Corresponding author

Yu Wei can be contacted at: weiyusy@126.com

Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Yingyue Sun, Yizhi Wang, and Yu Wei. The first draft of the manuscript was written by Yingyue Sun and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Ethics statement

- *Ethical approval*

Not applicable.

- *Consent to participate*

This article does not contain any studies of human participants or animals by any of the authors.

- *Consent for publication*

Not applicable.

- *Competing interests*

The authors have no relevant financial or non-financial interests to disclose.

Funding statement

This work is supported by National Natural Science Foundation of China (Grant number 71971191), and Humanities and social science fund of ministry of education of China (Grant number 19YJC630136).