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Diversification effects of China's carbon neutral bond on renewable energy stock markets: A minimum connectedness portfolio approach

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ABSTRACT

Socially responsible investment (SRI) is becoming increasingly popular in China, with the announcement of carbon dioxide peaking by 2030 and carbon neutrality by 2060 (30–60 targets). As a conventional underlying asset of SRI, renewable energy stocks are attractive, but with higher price volatility than many other traditional industrial stocks. This paper aims to investigate the interaction and diversification effects of China's Carbon Neutral Bond (CNB), a new SRI underlying asset just launched in 2021, on renewable energy stocks using a novel minimum connectedness portfolio approach recently proposed by Broadstock et al. (2020). The empirical results show that, first, China's CNB is weakly related to renewable energy stocks, whether in the time or frequency domain, and is the main recipient of the net linkage effect. Second, different renewable energy stocks benefit differently from the diversification effect of CNB. However, in extreme market conditions, the diversification effect of the CNB is reduced. Third, the newly developed minimum connectedness portfolio approach can outperform traditional minimum variance and correlation methods by achieving higher cumulative portfolio returns. Finally, the Sharpe ratios of renewable energy stock portfolios with CNB are significantly higher than those without it across different allocation methods. These findings have important implications for policy makers and SRI investors.

1. Introduction

Socially Responsible Investing (SRI) is becoming increasingly popular in China, largely due to the country's green and sustainable development strategy and its growing environmental challenges in recent years. SRI generally over-allocates or seeks industries with better socially responsible performance in environmental protection, public welfare and innovation. Although renewable energy stocks are ideal targets for investors to achieve these goals of SRI, they are observed to be more volatile than many other stocks in traditional industries for its prominent but uncertainly profitable perspectives (Attarzadeh and Balcilar, 2022; Chen et al., 2018; Dutta, 2017; Janda et al., 2022; Sadorsky, 2012; Su and Wang, 2022; Wang et al., 2022a; Wang et al., 2022b; Wei et al., 2022b; Zhang et al., 2019). Therefore, how to efficiently diversify the market risk of renewable energy stocks is of great significance for not only SRI investors, but also the policy makers of renewable energy industry.

Besides renewable energy stocks and many other SRI instruments, green bond (GB) is a fundamental and rapidly progressive one (Broadstock et al., 2020). The GB market in China experiences rapid growth since its introduction in 2015. Moreover, by the end of 2021, China has been ranked as the second largest GB market in the world. Especially, in 2020, China announced to the world with the targets of carbon dioxide peaking by 2030 and carbon neutrality by 2060 (30·60 targets). According to the measurements of Chinese National Center for Climate Change Strategy and International Cooperation (NCSC) and many other research institutions, China's "30·60 targets" will require green investment of 150 trillion to 300 trillion yuan, which means that China will invest an average of 3.75 trillion to 7.5 trillion yuan per year in green sector in the future. More importantly, on February 9, 2021, the China

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Interbank Market Dealers Association (CIMDA) innovatively launched carbon neutral bond (CNB). As a sub-species of green bond financing instruments, CNBs mainly raise funds for low-carbon emission reduction areas, which will have a huge contribution to the achievement of carbon neutrality and carbon peaking targets. In the following day, the first batch of CNBs were successfully issued in the interbank bond market. Six companies, namely, China Southern Power Grid, Three Gorges Group, Huaneng International, State Power Investment, Sichuan Airport Set and Yalong River Basin Company, issued medium and long-term carbon neutral bonds with 2 years and above, with a total issue amount of 6.4 billion yuan. According to the "China Green Bond Market Report 2021", published jointly by the Climate Bonds Initiative (CBI) and China Central Depository & Clearing Research Centre (CCDC Research), a carbon neutrality bond (CNB) is an innovative label in green bond. Compared with other green bonds in China, the use of proceeds of CNBs is more precisely targeted towards carbon reduction and requires carbon reduction disclosure under dedicated guidelines. CNBs accounted for over 40% of the total labelled green bonds issued in China in 2021. Based on analysis from Climate Bonds, CNBs had closer alignment with Climate Bonds green definition than general labelled Chinese green bonds.[1] Therefore, China's newly developed CNBs have a strong appeal not only to domestic but also to foreign SRI investors.

For investors, including SRI investors, when facing increasing uncertainties from global economy fluctuation, financial market turmoil, and geopolitical conflict, etc., they usually reduce their investment in high-risk assets (e.g., stocks) and allocate more low-volatile assets (e.g., bonds) to diversify the market risk in their portfolio, which is well recognized as "fly-to-quality" phenomenon (Baur and Lucey, 2010; Baur and McDermott, 2010; Connolly et al., 2005). However, to the best knowledge of the authors, there is no researches focusing on the diversification effects of China's CNB on renewable energy stocks, which are definitely of great significance for SRI investors and relative policy makers. For the common SRI attributes of CNB and renewable energy stock, this paper, thus, aims to quantify the interactions between CNB and renewable energy stocks in China, and then investigate whether and how CNB can be used as a diversification (hedging) instrument for renewable energy stocks from the perspective of SRI portfolio. This research can be very significant for not only the regulatory policies in renewable energy industry and green finance, but also the designments of portfolio and risk management strategies in renewable energy stock and CNB markets.

By now, although some researches have studied the interactions between green bonds, stocks and other assets (Arfaoui et al., 2023; Bai et al., 2021; Benlagha et al., 2022; Billah et al., 2022; Chai et al., 2022; Chen et al., 2022; Farid et al., 2023; Hassan et al., 2022; Hung, 2021; Mensi et al., 2022a; Mensi et al., 2022b; Naeem et al., 2022a; Naeem et al., 2022b; Nguyen et al., 2021; Pham and Nguyen, 2022; Reboredo et al., 2022; Tiwari et al., 2022a; Tiwari et al., 2022b; Wei et al., 2019; Xi and Jing, 2022; Yan et al., 2022), no literature directly examines the connectedness effects among CNB and renewable energy markets, let along the possible diversification effects of CNB on renewable energy markets in China. Many existing researches have proved that GBs can offer high diversification effects on equities, commodities, clean energy, and traditional bonds for the low or negative correlations of GBs with other assets. For example, by the rolling window wavelet correlation approach, Nguyen et al. (2021) examine the interrelationships between green bonds and other asset markets, including equities, commodities, clean energy, and traditional bonds, over the 11-year period from 2008 to 2019. They find that the diversification benefits of green bonds are clearly demonstrated as they have low or negative correlations with equities and commodities. Mensi et al. (2022a) investigates the dynamic and frequency spillover effects between global green bonds, WTI oil, and G7 stock markets using the time-frequency spillover index and wavelet coherence methods. They also find that green bonds provide G7 investors with higher diversification benefits than oil in the short term. Mensi et al. (2022b) further investigate the quantile interactions between eight green bonds and the S&P 500 index using the methodology of Ando et al. (2022), and demonstrate that green bonds and the S&P 500 exhibit stronger connectedness during crises (e.g., GFC, COVID-19). Reboredo et al. (2022) document a considerable diversification advantage for green bonds when included in low-carbon portfolios in the Chinese, European, and U.S. markets, by considering a de-risking metric based on expected shortfalls. Tiwari et al. (2022a) study the time-varying connectedness among S&P Green Bonds, Solactive Global Solar, Solactive Global Wind, S&P Global Clean Energy and carbon price. They point out that clean energy dominates all other markets and is the main net transmitter of shocks across the network, while green bonds and Solactive Global Wind become the main recipients of shocks in the system. Then, Tiwari et al. (2022b) adopt the novel quantile cross-spectral coherence methodology of quantile spectral coherency model, cross-quantilogram correlation approach, windowed time-lagged cross-correlation, and windowed scalogram difference models to quantify the tail risk dependence, co-movement and predictability between green bond and green stocks. They further confirm that green bonds do act as a hedge, diversifier or safe-haven for environmental portfolios in bear market.

It is worth noting that, although common bonds are generally considered as hedging instruments for stocks (Abul Basher and Sadorsky, 2016; Ciner et al., 2013; Dutta et al., 2021; Ma et al., 2021), there is only one paper that investigates the hedging (diversification) effects of green bond on renewable energy stocks by using the dynamic connectedness information among them (Tiwari et al., 2022a). The existing literature does not answer the question of whether and how the newly launched Carbon Neutral Bond (CNB) can diversify the market risks of renewable energy stocks in China, which are certainly of great importance to China's policy makers and SRI investors in formulating their regulatory policies and portfolio allocation strategies.

Therefore, we contribute to the existing literature in three major aspects: *firstly*, as noted above, CNBs have closer alignment with Climate Bonds green definition than general labelled Chinese GBs. Thus, CNBs are more attractive than general GBs for SRI investors, while they are not examined thoroughly in recent researches for the reason that they are just launched in February 2021 in China. To the best of our knowledge, this is the first paper focusing on the interactions and diversification effects between China's newly launched CNB and renewable energy stock markets, which are urging issues for CNB issuers and SRI investors in China to understand. *Secondly*, we adopt a novel portfolio allocation method, namely the minimum connectedness portfolio approach proposed by Broadstock et al. (2020), to test the diversification effects of China's CNB on renewable energy stocks, and compare it with two commonly used allocation models (i.e., the minimum variance and minimum correlation). This minimum connectedness portfolio approach provides investors with a new option for portfolio allocation strategy, which is shown in this paper to outperform the minimum variance and minimum correlation methods by achieving higher cumulative returns in most cases. *Thirdly*, Third, the original Broadstock et al. (2020) method uses the pairwise connectedness index (PCI), i.e., the total connectedness between two assets, as the optimal portfolio allocation criterion. However, we argue that in a multi-asset system (as in this paper), net pairwise directional connectedness (NPDC) may be a better choice than PCI to describe the pairwise interaction between two assets without losing the possible impact of other assets. Therefore, we construct the CNB and renewable energy stock portfolios using not only PCI but also NPDC as the optimization criterion (Chen et al., 2023). We find that the NPDC method can achieve higher cumulative portfolio returns than that based on the PCI method, which extends a new optimal approach in the minimum connectedness portfolio model.

The rest of this paper is as follows: Section 2 introduces the

[1] https://www.climatebonds.net/resources/reports/china-green-bond-market-report-2021.

connectedness effect measurements by on a TVP-VAR model. Section 3 describes the data used in this paper. Section 4 illustrates the empirical results, and the robustness checks for the major conclusions are listed in Section 5. Finally, we discuss the conclusions and policy implications in Section 6.

2. Methodology

2.1. Connectedness measurements based on TVP-VAR model

Following the static connectedness measurement developed by Diebold and Yilmaz (2012) and its TVP-VAR extension proposed by Antonakakis et al. (2020), for simplicity we firstly define a n-variable TVP-VAR(p) model as

$$Y_t = A_t Z_{t-1} + \varepsilon_t \quad \varepsilon_t|\Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t \quad \xi_t|\Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

where $Y_t = \left(y_{1,t}, y_{2,t}, \dots, y_{n-1,t}, y_{n,t}\right)'$ is an $n \times 1$ vector of interested variables at time t, and $Z_{t-1} = \left(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}\right)'$. A_t is the $n \times np$ parameter matrix at time t, and $vec(A_t)$ is the vectorized form of A_t. ε_t and ξ_t are the error items, and Ω_{t-1} denotes the information set available at time t-1. Then, Σ_t and Ξ_t are the variance-covariance matrix for ε_t and ξ_t, respectively. This TVP-VAR model can be estimated by a multivariate Kalman filtering method of Koop et al. (1996), and more technical details of this estimation can be found in Antonakakis et al. (2020).

Consequently, A_t and ε_t are adopted to compute the Wold representation form of this TVP-VAR model as:

$$Y_t = A_t Z_{t-1} + \varepsilon_t = \sum_{i=0}^{\infty} B_{i,t}\varepsilon_{t-i} \tag{3}$$

where the response function $B_{i,t} = \sum_{l=1}^{p} A_{l,t}B_{i-l,t}$, $B_{0,t}$ is a one-dimensional unit matrix and $B_{i,t} = 0$ when $i < 0$. Following Eq. (3), the H-step-ahead generalized forecast error variance decomposition (GFEVD), which measures the impact a shock in series k has on series j, can be expressed as

$$\Phi_{jk,t}(H) = \frac{\sigma_{kk,t}^{-1}\sum_{h=0}^{H-1}\left(\theta_j' B_{h,t}\Sigma_t\theta_k\right)^2}{\sum_{h=0}^{H-1}\left(\theta_j' B_{h,t}\Sigma_t B_{h,t}'\theta_j\right)} \tag{4}$$

where $\sigma_{kk,t} = (\Sigma)_{kk,t}$, and θ_j (θ_k) is a $n \times 1$ vector with the j-th (k-th) item being 1 and the remaining ones being 0. To make ensure that the sum of the elements in each row of $\Phi_{jk,t}(H)$ equals to 1, i.e., all variables totally contribute 100% of forecast error variance of variable j, we may normalize each entry by the row sum as:

$$\widetilde{\Phi}_{jk,t}(H) = \frac{\Phi_{jk,t}(H)}{\sum_{j=1,k=1}^{n}\Phi_{jk,t}(H)} \times 100 \tag{5}$$

with $\sum_{k=1}^{n}\widetilde{\Phi}_{jk,t}(H) = 1$ and $\sum_{j=1,k=1}^{n}\widetilde{\Phi}_{jk,t}(H) = N$. Therefore, the total connectedness index (TCI), which assess the overall intensity of interaction among all the variables in this TVP-VAR(p) system is calculated as:

$$TCI_t(H) = \frac{\sum_{j,k=1,j\neq k}^{n}\widetilde{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^{n}\widetilde{\Phi}_{jk,t}(H)} \times 100 \tag{6}$$

According the definition in Broadstock et al. (2020), the pairwise connectedness index (PCI) is calculated as the TCI on the bilateral level illustrating the degree of interaction just between two variables. Following Broadstock et al. (2020), this PCI is adopted as the optimization criterion in a minimum connectedness portfolio in the next step. Then the directional connectedness received by variable j from all the others is defined as:

$$FROM_{j\leftarrow *,t}(H) = \frac{\sum_{k=1,j\neq k}^{n}\widetilde{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^{n}\widetilde{\Phi}_{jk,t}(H)} \times 100 \tag{7}$$

and the directional spillover transmitted from variable j to all the others as estimated as:

$$TO_{j\rightarrow *,t}(H) = \frac{\sum_{k=1,k\neq j}^{n}\widetilde{\Phi}_{kj,t}(H)}{\sum_{j=1,k=1}^{n}\widetilde{\Phi}_{jk,t}(H)} \times 100 \tag{8}$$

After this, it is a natural way to compute the net directional connectedness of variable j as the difference between TO and FROM connectedness as:

$$NET_{j,t}(H) = TO_{j\rightarrow *,t}(H) - FROM_{j\leftarrow *,t}(H) \tag{9}$$

Therefore, a positive (negative) NET index shows that variable j is a net connectedness sender (receptor) in this TVP-VAR system, which means that variable j plays the role of information leader (lagger) in the system. Lastly, we calculate net pairwise directional connectedness index (NPDC) as the directional connectedness between j and k as:

$$NPDC_{j\rightarrow k,t}(H) = \left(\frac{\widetilde{\Phi}_{kj,t}(H)}{\sum_{j=1,k=1}^{n}\widetilde{\Phi}_{jk}(H)} - \frac{\widetilde{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^{n}\widetilde{\Phi}_{jk}(H)}\right) \times 100 \tag{10}$$

Similarly, a positive NPDC denotes that the connectedness effect of j on k is stronger than that of k on j, implying that j dominates the change of k, and vice versa. Moreover, we can see that NPDC measures the interactions between two variables of j and k in a multi-variable environment, while PCI calculates these effects in a bivariate system, which may lead this PCI indicator to ignore the impacts of third parties on the relationship between variables of j and k. Therefore, we think that NPDC is a more suitable index than PCI in measuring not only the intension but also the direction of the influence of variable j on k.

2.2. Portfolio allocation methods

In this paper, we first adopt three commonly used portfolio allocation methods, i.e., equal weighted portfolio, minimum variance portfolio (MVP) proposed by Markovitz (1959), and minimum correlation portfolio (MCP) by Christoffersen et al. (2014) to calculate the performances of China's renewable energy portfolios. The MVP and MCP allocation approaches aim to minimize the overall variance and correlation of the portfolio, respectively, and the portfolio weights are estimated as follows:

$$\text{MVP}: \quad \mathbf{w}_{\Sigma_t} = \frac{\Sigma_t^{-1}\mathbf{I}}{\mathbf{I}\Sigma_t^{-1}\mathbf{I}} \tag{11}$$

where $\mathbf{w}_{\Sigma_t}$ is the $n \times 1$ weights vector, $\mathbf{I}$ is a $n \times 1$ vector of ones, and Σ_t denotes the $n \times n$ dimensional conditional variance-covariance matrix at time t. Then, we define

$$\text{MCP}: \quad \mathbf{w}_{\mathbf{R}_t} = \frac{\mathbf{R}_t^{-1}\mathbf{I}}{\mathbf{I}\mathbf{R}_t^{-1}\mathbf{I}} \tag{12}$$

where $\mathbf{R}_t$ is the conditional correlation coefficient matrix at time t.

Moreover, as noted in Broadstock et al. (2020), pairwise connectedness index (PCI) is an alternative measure of interactions between two assets, and thus may also be adopted as a optimization criterion for portfolio allocation. Thus, they propose a new minimum connectedness portfolio (MCoP2) as follows:

$$\text{MCoP2}: \quad \mathbf{w}_{\mathbf{PCI}_t} = \frac{\mathbf{PCI}_t^{-1}\mathbf{I}}{\mathbf{I}\mathbf{PCI}_t^{-1}\mathbf{I}} \tag{13}$$

Similarly, $\mathbf{PCI}_t$ is the matrix of the pairwise connectedness index. Furthermore, we argue that pairwise directional connectedness index

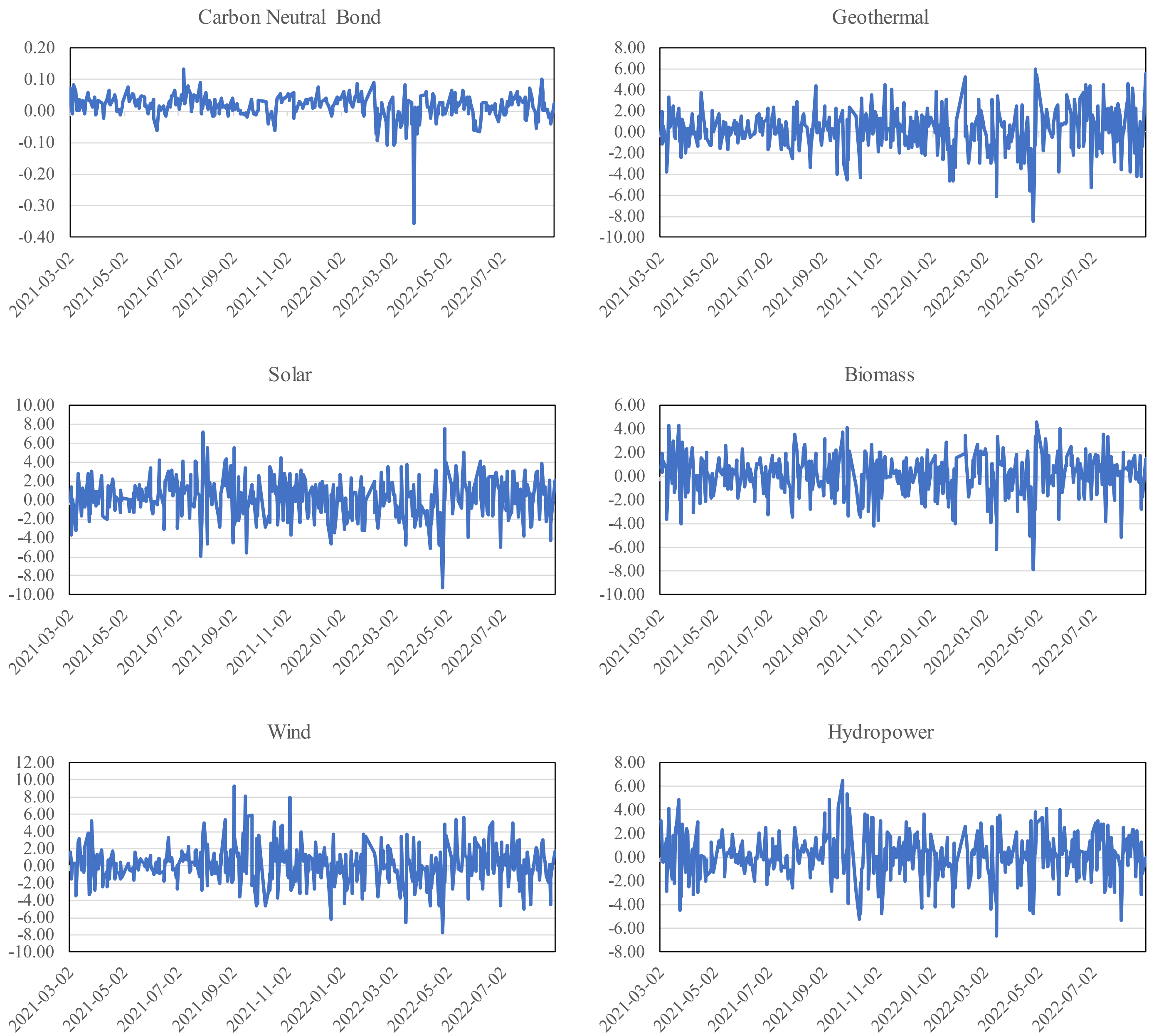

Fig. 1. Time series plots of the Chinese carbon neutral bond and renewable energy stock returns.

(NPDC) can measure the interactions between two variables of j and k in a multi-variable environment, while PCI only estimates these effects in a bivariate system. This means that PCI may ignore the impacts of third parties on the relationship between variables of j and k in a multi-variable environment. Therefore, we think that NPDC is a more proper measurement than PCI in assessing not only the intension but also the direction of the influence of variable j on k. Following this consideration, we propose a new minimum connectedness portfolio (MCoP1) in this paper as follows:

$$\text{MCoP1}: \quad \mathbf{w}_{\mathbf{NPDC}_t} = \frac{\mathbf{NPDC}_t^{-1}\mathbf{I}}{\mathbf{INPDC}_t^{-1}\mathbf{I}} \tag{14}$$

where $\mathbf{NPDC}_t$ denotes the matrix of the pairwise directional connectedness index.

2.3. Portfolio evaluation approaches

After the various allocations of China's renewable energy stock portfolios, we evaluate the performances of them through three major ways. Firstly, the hedge effectiveness of the Ederington (1979) is employed to compare the percentage of risk reduction from single renewable energy stock by different portfolio allocation methods. This hedge effectiveness (HE) is defined as:

$$\text{HE} = 1 - \frac{var\left(R_{portfolio}\right)}{var(R_i)}, \tag{15}$$

where $var\left(R_{portfolio}\right)$ is the return variance of different portfolios, and $var(R_i)$ is the return variance of a specific renewable energy stock. It is easy to understand that a larger HE denotes a better diversification (hedging) effect of a portfolio, and vice versa. Secondly, we choose time-varying cumulative returns to measure the profitable ability of different portfolio allocation methods. Thirdly, Sharpe ratio, a commonly used criterion by fund manager (Sharpe, 1966), to assess the integrated performance of both risk and return of these portfolios, which is defined as:

Table 1
Descriptive statistics for the returns of China's carbon neutral bond and renewable energy stocks.

	CNB	Solar	Wind	Geothermal	Biomass	Hydropower
Mean	0.015	0.183	0.116	0.165	0.099	0.112
Standard deviation	0.038	2.227	2.320	2.014	1.821	1.928
Skewness	−2.789	−0.196	0.290	−0.287	−0.592	−0.160
Kurtosis	26.532	3.722	4.275	4.130	4.012	3.664
Jarque-Bera	8919.168***	10.307**	29.933***	24.466***	37.022***	8.277**
Q(5)	84.137***	1.609	3.828	2.100	5.829	2.962
Q(20)	153.685***	12.575	15.485	15.575	20.085	20.973
ADF	−12.560***	−18.386***	−20.096***	−18.816***	−20.515***	−20.091***
P-P	−13.900***	−18.482***	−20.117***	−18.919***	−20.550***	−20.124***

Notes: This table reports the descriptive statistics for returns of the Chinese green bond and stock sector indices. Jarque-Bera is the statistics for normal distribution. $Q(n)$ is the Ljung-Box Q statistics with lag length of n. ADF and P—P are statistics of Augmented Dickey-Fuller and Phillips-Perron unit root test, respectively. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

$$SR = \frac{\overline{R}_{portfolio}}{\sqrt{var\left(R_{portfolio}\right)}}, \tag{16}$$

where $\overline{R}_{portfolio}$ denotes the average return of a portfolio, and $\sqrt{var(R_{portfolio})}$ represents the square root of portfolio return variance. Obviously, a bigger Sharpe ratio indicates a better return in this portfolio than that of another one, which has the same risk (variance) as the former.

3. Data

As noted above, compared with other green bonds in China, CNBs are more precisely targeted towards carbon reduction and require carbon reduction disclosure under dedicated guidelines. In 2021, CNBs accounted for over 40% of the total labelled green bonds issued in China. Thus, we adopt the ChinaBond Carbon-Neutral Green Bond Index to denote the overall performance of CNBs in China, which is launched on February 26, 2021.[2] In terms of different categories of renewable energy, we follow the "Renewables 2022 Global Status Report" published by REN21, the only global renewable energy community of stakeholders from academia, governments, NGOs and industry, and select biomass, geothermal, solar, hydro and wind power as they represent the majority of modern renewable energy.[3] Therefore, to describe the stock market performances of different renewable energy sectors, we choose five renewable energy stock indices developed by Wind Co., Ltd., which is the largest and most authoritative provider of capital market information in China.[4] These renewable energy stock indices are: (1) Solar Power Generation Concept Index, including 79 listed companies focusing on power generation, equipment, solar cells and materials and other related fields. (2) Wind Power Generation Concept Index, containing 39 listed companies related to wind farm operations, wind turbines and wind towers, blades and other equipment accessories related fields. (3) Geothermal Energy Concept Index, including 7 companies developing and manufacturing equipment related to geothermal energy. (4) Biomass Energy Concept Index, which covers 19 companies related to straw power generation, garbage power generation, biogas power generation, corn, bagasse, wood bran power generation, etc. Finally, (5) Hydropower Concept Index, containing 22 related companies in the field of hydropower.

We select daily price data from March 1, 2021 to August 30, 2022, totally 368 observations, in our empirical examination. All the price data are converted to logarithm returns by first-order difference of the logarithm prices. Fig. 1 shows the return series plots of CBN and renewable energy stocks. It can be seen that the returns of renewable energy stocks are much larger than that of CNB, implying that renewable energy stock markets are more volatile than CNB markets with bigger risks. Moreover, we also find quite different return patterns in these five renewable energy stock returns, indicating that different renewable energy stocks may have various responses to external shocks, and they may play mixed roles in information transmissions among them.

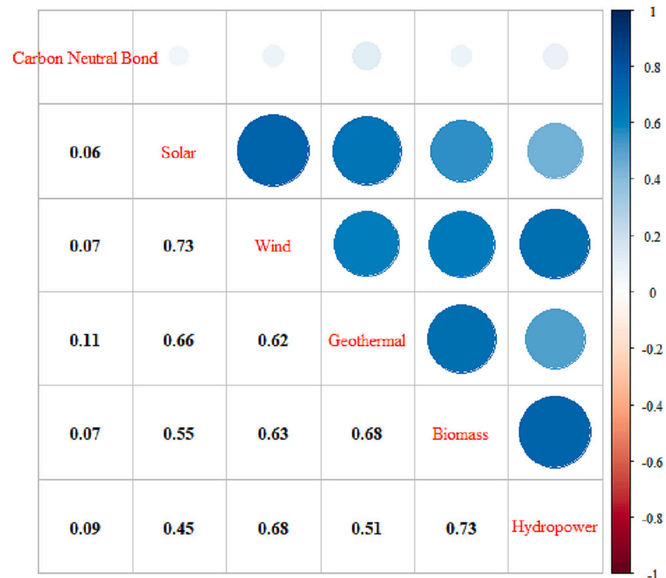

Fig. 2. Pearson correlation coefficient matrix for the Chinese carbon neutral bond and renewable energy stock returns.

Table 1 furthermore demonstrates the descriptive statistics of the these returns series. Similar to the results in Fig. 1, firstly, we find that CNB has the smallest return mean than those of renewable energy stocks, and all these returns have positive means, suggesting the profitable investments in China's CNB and renewable energy stock markets. Across them, solar stocks have the largest return mean of 0.183%, while CNB has the smallest one of 0.015%. Secondly, the standard deviations of renewable energy stocks are much larger than the one of CNB, implying bigger market risks in renewable energy stocks than CNB. Thirdly, the skewness, kurtosis and Jarque-Bera statistics show that most of these series are not normally distributed with left-skewed and leptokurtic distributions. Fourthly, the Ljung-Box Q statistics prove that CNB returns are autocorrelated up to 20 days, while renewable energy stock returns have no such autocorrelations. This finding may suggest that renewable energy stock market is more efficient than CNB market for its much larger number of investors than the latter. Finally and most importantly, the Augmented Dickey-Fuller and Phillips-Perron unit root tests show that all the returns series are stationary, and can be modelled

[2] https://yield.chinabond.com.cn/cbweb-mn/indices/single_index_query.
[3] https://www.ren21.net/wp-content/uploads/2019/05/GSR2022_Full_Report.pdf.
[4] https://www.wind.com.cn/NewSite/windIndex.html?id=30.

Table 2
Averaged connectedness for the returns of China's carbon neutral bond and renewable energy stocks.

	CNB	Solar	Wind	Geothermal	Biomass	Hydropower	FROM
CNB	87.50	3.11	2.53	3.00	1.84	2.03	12.50
Solar	0.63	42.46	20.78	15.98	11.68	8.46	57.54
Wind	0.38	17.76	36.64	12.45	14.92	17.84	63.36
Geothermal	0.90	15.56	13.60	41.10	18.48	10.36	58.90
Biomass	0.89	10.20	14.76	16.84	38.06	19.24	61.94
Hydropower	0.70	7.38	19.29	10.33	21.37	40.93	59.07
TO	3.50	54.02	70.96	58.60	68.29	57.93	**TCI**
NET	−9.00	−3.52	7.61	−0.30	6.36	−1.14	**62.66**

Notes: This table reports the directional connectedness indices among the returns of China's carbon neutral bond (CNB) and renewable energy stocks by the TVP-VAR method of Antonakakis et al. (2020). The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL connectedness index (TCI) of all the markets.

with further transforms.

Then Fig. 2 illustrates the Pearson correlation coefficient matrix of China's CNB and renewable energy stock indices. First, we can see that CNB has very small and positive correlation with those renewable energy stocks, which may provide initial evidence that CNB may be adopted as diversification for renewable energy stocks. Second, Fig. 2 also demonstrates that, although those correlations among renewable energy stocks are much larger than the one for CNB, they are highly variable from 0.45 to 0.73, suggesting the heterogenous interactions across renewable energy stocks. This fact may also imply that different renewable energy sectors (i.e., Solar, Wind, Geothermal, Biomass, and Hydropower) responses heterogeneously to external shocks and their stock market performances can be quite different due to their distinct technological, production and consumption fundamentals. Therefore, we deduce that the highly variable correlations among CNB and renewable energy stocks may generate separate diversification effects of CNB on renewable energy stocks.

4. Empirical results

4.1. Connectedness analysis of CNB and renewable energy stock markets

Before detecting the diversification effects of CNB on renewable energy stock markets, we firstly investigate the connectedness effects among them. The reason for doing so is twofold: on the one hand, the connectedness analysis based on the TVP-VAR model can help us understand not only the net connectedness but also the time-varying interactions between China's CNB and renewable energy stock markets, which is of great value to policymakers in designing the regulation of green bond and renewable energy stock markets. On the hand, the quantitative connectedness measurements are also key inputs in portfolio allocation for SRI investors. To get a basic idea of the overall connectedness effects among China's CNB and renewable energy stock markets, we firstly report in Table 2 the averaged (time-mean) directional connectedness indices among the returns of China's carbon neutral bond (CNB) and renewable energy stock indices by the TVP-VAR method of Antonakakis et al. (2020). Table 2 shows that, first of all, the averaged total connectedness is 62.66%, suggesting a relatively close interaction among China's carbon neutral bond (CNB) and renewable energy stock markets. Then, we find that CNB has smaller directional connectedness with the five renewable energy stock indices (varying from 0.38% to 3.11%) than those among renewable energy stock indices themselves. This evidence is in line with the results revealed in Fig. 2, suggesting the possible diversification role of CNB on renewable energy stocks. Moreover, the NET connectedness measurements show that CNB is the largest connectedness effect receiver with net connectedness of −9.00%, while Wind is the biggest net connectedness transmitter. This finding further confirms that CNB is a strong information receptor in this system, and it can be used as a hedge for renewable energy stocks.

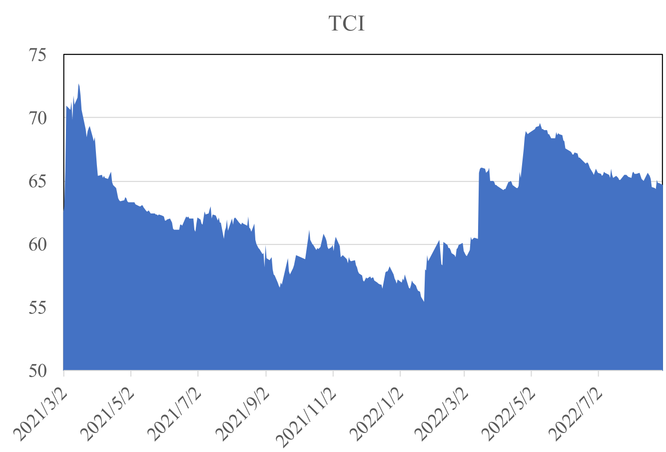

Fig. 3. Time-varying total connectedness index (TCI) for the Chinese carbon neutral bond and renewable energy stock returns.

Furthermore, we present the time-varying total, net, and net pairwise directional connectedness (NPDC) measurements in Figs. 3 to 5, respectively. Fig. 3 shows that the total connectedness index (TCI) fluctuates wildly through March 2021 to August 2022. It reaches the highest level of about 73% at the beginning of the data sample, suggesting that China's CNBs markets connect tightly with renewable energy stocks in the early days of the CNB issuing. However, after that the TCI drops clearly to about 60% till October 2021. Then from October 31 to November 12, 2021, the 26th Conference of the Parties (COP26) of the UNFCCC takes place in Glasgow, UK. The issue of global climate change is once again attracting public attention, which may cause the temporary increasing TCI during that time. In February 2022, China's National Development and Reform Commission and National Energy Administration issued the "Options on Improving Institutional Mechanisms and Policy Measures for Green and Low-Carbon Energy Transition", proposing that by 2030, China will basically establish a complete basic system and policy system for green and low-carbon energy development, forming an energy production and consumption pattern in which non-fossil energy sources both basically meet the incremental energy demand and replace the fossil energy stock on a large scale, and the energy security guarantee capacity is comprehensively enhanced. Inspired by this action, we find that the total connectedness among China's CNB and renewable energy stock markets increase obviously to about 65% to 70% after that.

Fig. 4 illustrates the net connectedness indices (NET) of CNB and five renewable energy stocks. We find that Biomass and Wind stocks are two absolute connectedness senders to others, while CNB is a significant connectedness receptor across the whole data sample. This finding is also confirmed by the NPDC evidence revealed in Fig. 5. In particular,

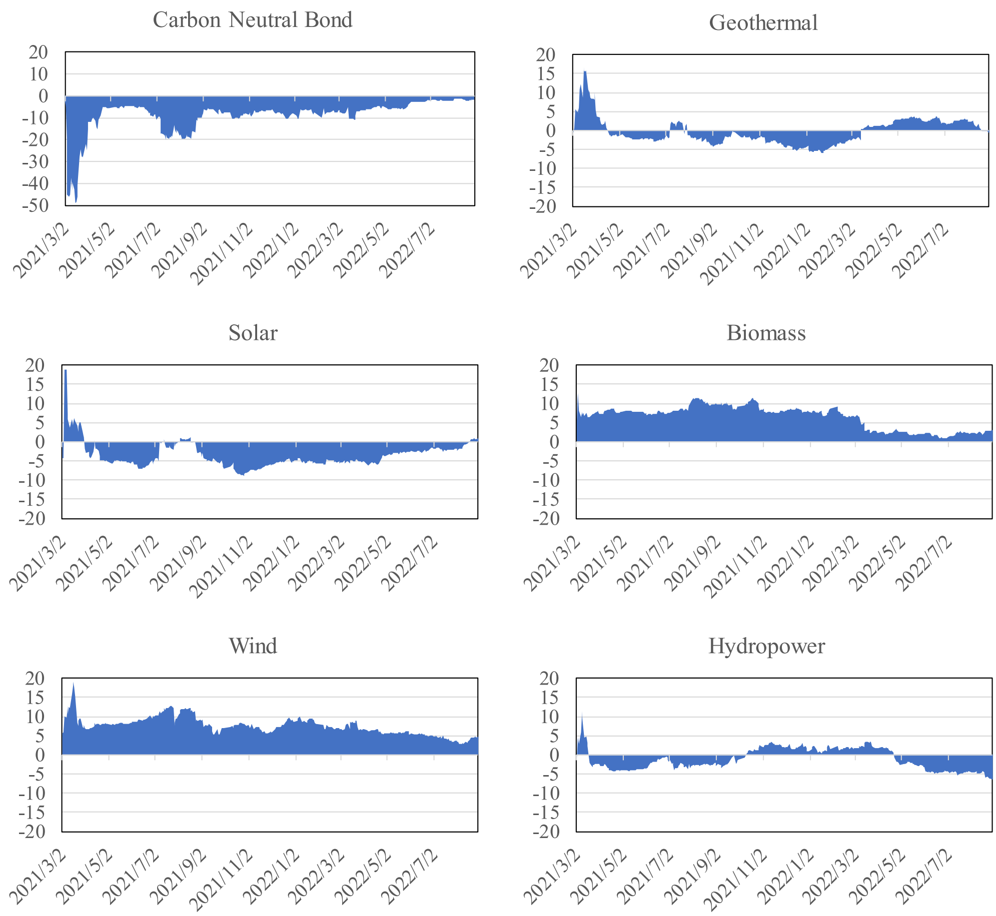

Fig. 4. Time-varying net connectedness index (NET) for the Chinese carbon neutral bond and renewable energy stock returns.

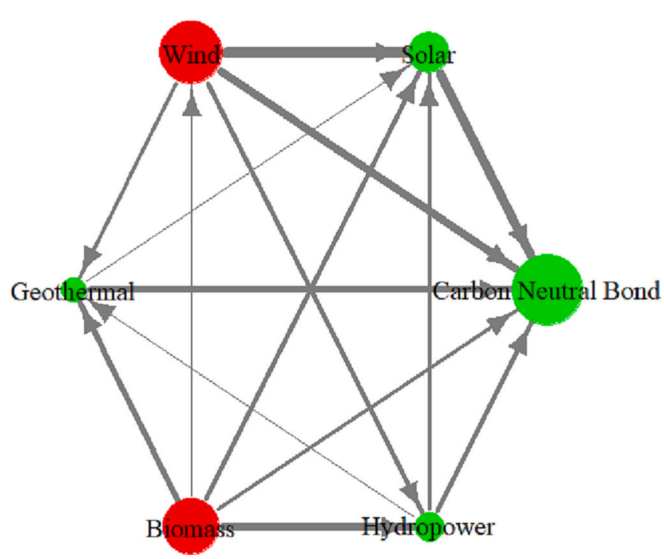

Fig. 5. Averaged net pairwise directional connectedness index (NPDC) between China's carbon neutral bond and renewable energy stock indices. Red and green nodes denote the connectedness senders and receptors, respectively. The thickness of the arrow line indicates the intensity of the connection. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

CNB market is the only recipient of information spillover from the other five markets. In summary, the above analysis proves that the total and net connectedness effects among China's CNB and renewable energy stock markets vary wildly with time, and CNB is the major connectedness receptor, while Biomass and Wind stocks are two main transmitters. These results remind us CNB may be a proper diversification asset for SRI investors to hedge the market risks of their renewable energy stock portfolios.

4.2. *Diversification effects of CNB on renewable energy stock portfolio*

In this sub-section, we present the diversification effects of China's CNB on renewable stock markets by using four different portfolio allocation methods, i.e., the minimum variance portfolio (MVP) of Markovitz (1959), the minimum correlation portfolio (MCP) of Christoffersen et al. (2014), the minimum connectedness portfolio based on PCI criterion (MCoP2) by Broadstock et al. (2020), and finally the minimum connectedness portfolio based on NPDC criterion (MCoP1) proposed in this paper. The rationale for examining the diversification effects of China's CNB on renewable stock markets is mainly based on the conclusion of several recent studies (Broadstock et al., 2020; Chen et al., 2023; Tiwari et al., 2022a; Tiwari et al., 2022b). They find that the main recipient of net connectedness in a multi-asset system tends to be weakly correlated with other assets and can thus be used as a diversification tool for other assets in the system.

4.2.1. *Allocation weights and hedge effectiveness*

Firstly, the time-varying portfolio weights for CNB and the five renewable energy stocks are demonstrated in Fig. 6.

We find in Fig. 6 that the portfolio weights for CNB and renewable

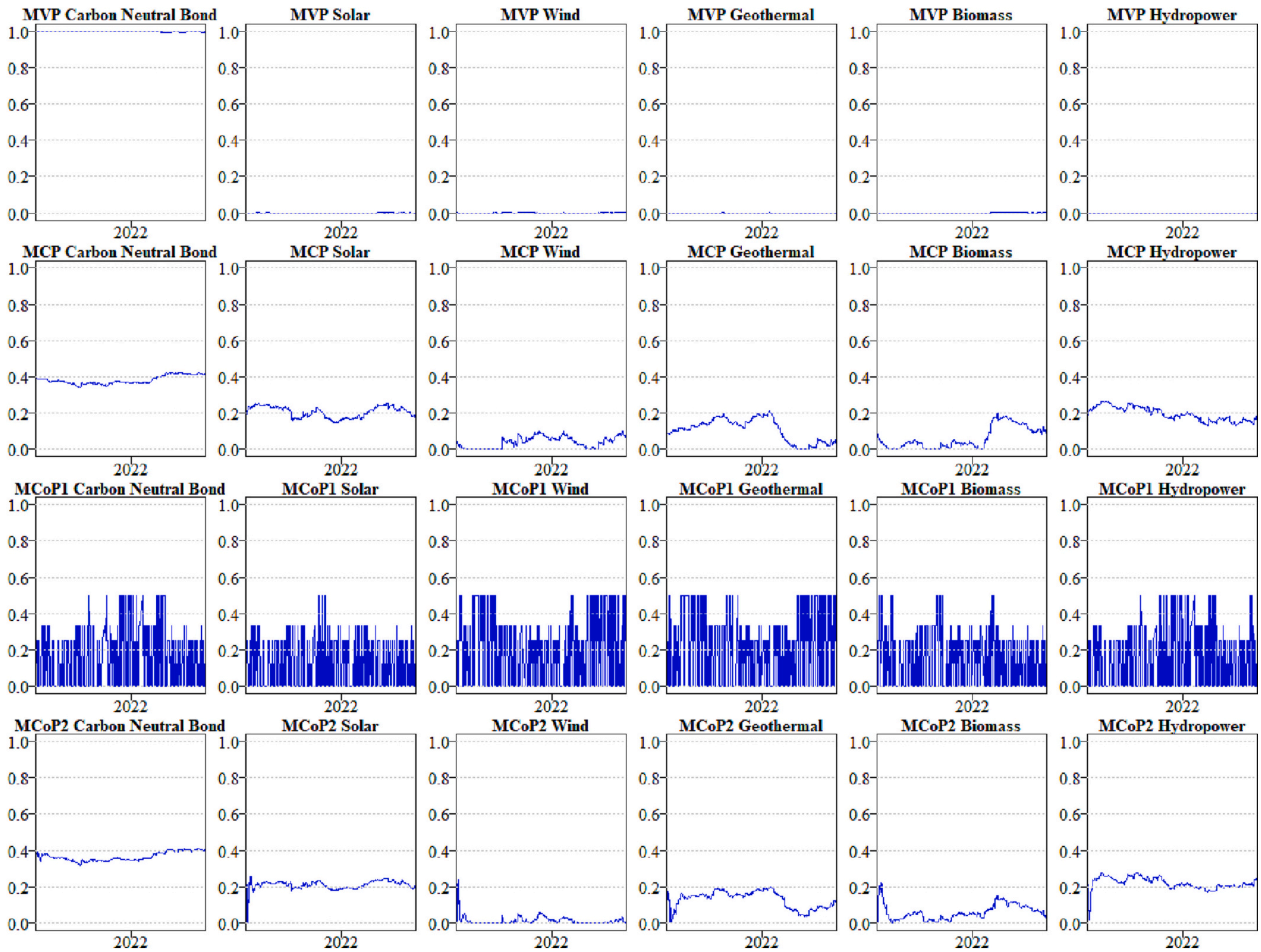

Fig. 6. Portfolio weights for the Chinese carbon neutral bond and renewable energy stocks under the four portfolio allocation methods.

Table 3
Averaged portfolio weights and hedge effectiveness for China’s carbon neutral bond and renewable energy stocks.

	MVP		MCP		MCoP1		MCoP2	
	Mean	HE	Mean	HE	Mean	HE	Mean	HE
CNB	1.00	–	0.38	–	0.15	–	0.37	–
Solar	0.00	1.00	0.21	0.78	0.12	0.51	0.21	0.77
Wind	0.00	1.00	0.04	0.80	0.21	0.55	0.01	0.79
Geothermal	0.00	1.00	0.11	0.74	0.22	0.40	0.13	0.72
Biomass	0.00	1.00	0.06	0.68	0.15	0.27	0.06	0.66
Hydropower	0.00	1.00	0.20	0.71	0.15	0.34	0.22	0.70

Notes: This table reports the averaged portfolio weights and hedge effectiveness for China’s carbon neutral bond and renewable energy stocks. Mean columns show the average portfolio weights of the CNB and renewable energy stocks. HE columns demonstrate the hedge effectiveness of one individual renewable energy stock compared to the portfolio constructed. The bigger the HE, the larger the risk (variance) reduction is obtained and vice versa.

energy stocks are quite different in these four portfolio methods. Firstly, due to the very small variance of CNB compared to those of renewable energy stocks, MVP method, which optimizes the portfolio by minimizing the portfolio variance, allocates almost all the weights to CNB as shown in the first row of Fig. 6. Secondly, we see that MCP and MCoP2 methods obtain similar portfolio weights for CNB and renewable energy stocks (i.e., the second and last rows in Fig. 6), indicating that the optimization criteria in these two methods are similar to each other. That means correlation estimation and pairwise connectedness index (PCI) among CNB and renewable energy stocks are very comparable, and thus the diversification effects of CNB on renewable energy stocks are similar based on the MCP and MCoP2 methods. This conclusion is also verified in the next steps of this section. Thirdly, we observe very divergent portfolio weight allocations in CNB and renewable energy stocks by the MCoP1 method, which optimize portfolio by minimizing the NPDC across CNB and renewable energy stocks. However, it is worth noting that the investment weights for CNB and renewable energy stocks by MCoP1 approach seem to be more *balanced* than those in other portfolio allocation methods. That are no assets with dominant weights included in this MCoP1 portfolio, which may be a preferred attribute of *balanced* investment for SRI investors.

Then Table 3 summarizes the portfolio weights and hedge

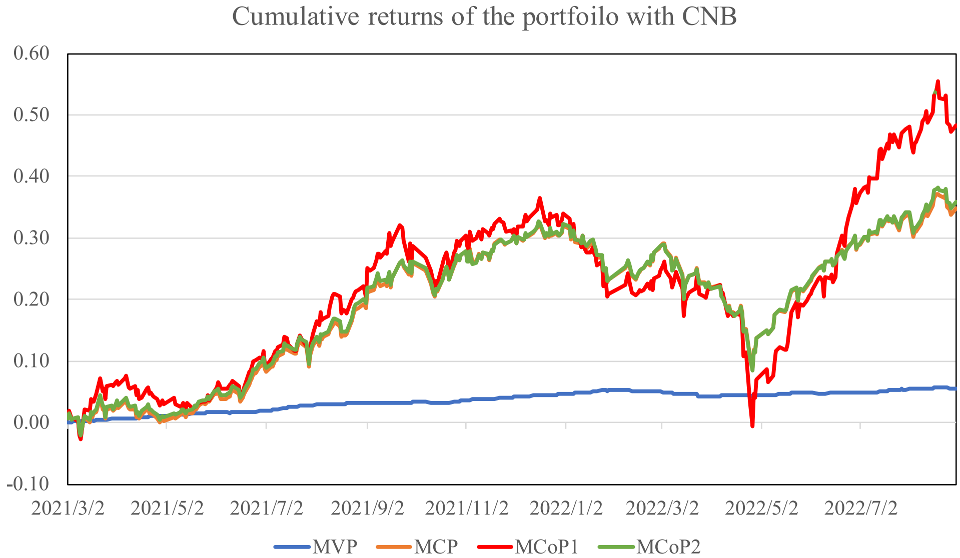

Fig. 7. Cumulative returns of renewable energy stock portfolios with China's carbon neutral bond under the four portfolio allocation methods.

effectiveness (HE) of the MVP, MCP, MCoP1 and MCoP2 allocation methods. The mean columns in Table 3 show the average portfolio weights of the CNB and renewable energy stocks. We can see that in the MVP portfolio, almost all the investment weight is allocated to CNB for its much smaller variance than those of renewable energy stocks. Therefore, it is no surprise that the hedge effectiveness measured for these individual renewable energy stocks are very close to 1, a perfect result for hedging action. In practice, however, this MVP portfolio is not desirable to SRI investors for the reason that CNBs are usually adopted as diversification assets for existing renewable energy stock portfolio. In the consequence, a portfolio with dominant weight of only CNBs does not work well for SRI investors.

Besides MVP, we further find that the portfolio weights and hedge effectiveness for MCP and MCoP2 methods are quite similar, indicating a strong analogy in the optimization approaches between these two methods. That means minimization correlation and pairwise connectedness index (PCI) may obtain comparable asset weight allocations and thus analogous results in hedging performances. Nevertheless, we also find that the asset weights designed by MCP and MCoP2 vary greatly across CNB and different renewable energy stocks. For example, in the MCP portfolio, Wind and Biomass stocks are only allocated with 4% and 6% investment weights, while CNB and Solar stock obtain as high as 38% and 21% weights respectively, which are also observed in the MCoP2 portfolio. As noted above, these *unbalanced* allocation outcomes in MVP, MCP and MCoP2 methods may be not desirable for SRI investors.

Furthermore, it is worth noting that MCoP1 method provide quite *balanced* portfolio weights for CNB and renewable energy stocks. The average allocation weight for CNB is 15%, and those for renewable energy stocks vary mildly from 12% to 22%. Since various renewable energy sectors are promising in development perspective but all with high uncertainty, a balanced investment allocation among different types of renewable energy stocks is very significant for SRI investors. Therefore, we think that this *balanced* portfolio achieved by MCoP1 is more attractive for SRI investors than those by MVP, MCP and MCoP2 methods. Finally, the hedge effectiveness (HE) results shown across MCP, MCoP1 and MCoP2 methods are highly consistent, that is, Wind stocks benefit most in CNB diversification and Biomass stocks get relatively smaller hedging effects.

4.2.2. *Cumulative returns of different portfolios*

In this sub-section, we further investigate the results of another criterion (i.e., cumulative return) to evaluate the performances of different portfolios. Firstly, Fig. 7 presents the time evolutions of the cumulative returns under MVP, MCP, MCoP1, and MCoP2 methods.

We can see in Fig. 7 that, cumulative returns in MVP are clearly much smaller than those in MCP, MCoP1, and MCoP2, due to the fact that in this MVP portfolio most investment weight is allocated to CNB. Then, in line with the results found in Section 4.2.1, the cumulative returns in MCP (minimum correlation portfolio) and MCoP2 (minimum PCI portfolio) are very close to each other. Finally, we find that MCoP1 (minimum NPDC portfolio) produces the largest cumulative returns over those in other three methods during most of the sample date. To quantitatively access the performance of different portfolios regarding to the cumulative returns, we present the simple statistics of these cumulative returns in Table 4.

Table 4
Simple statistics for the cumulative returns of portfolios for China's carbon neutral bond and renewable energy stocks.

	MVP	MCP	MCoP1	MCoP2
Mean	0.035	0.194	0.216	0.197
Minimum	0.001	−0.019	−0.027	−0.020
Maximum	0.057	0.372	0.555	0.382
Standard deviation	0.016	0.109	0.133	0.108
$Q(1)$	362.167***	360.673***	357.493***	360.062***
$Q(5)$	1750.619***	1735.738***	1689.490***	1728.369***
$Q(20)$	6097.511***	5903.541***	5192.636***	5827.696***
Hurst	0.933	0.918	0.926	0.918

Notes: This table reports the simple statistics for the cumulative returns of portfolios for China's carbon neutral bond and renewable energy stocks. $Q(n)$ is the Ljung-Box Q statistics with lag length of n. Hurst denotes the Hurst exponent of Hurst (1951). A Hurst exponent larger than 0.5 indicates that the time series is persistent, indicating a long-memory process existing in it.

Table 4 indicates firstly the largest mean cumulative returns is in MCoP1 (i.e., 0.216), while the smallest one is in MVP (i.e., 0.035). In addition, MCP and MCoP2 have the close cumulative returns of 0.194 and 0.197, respectively. Secondly, the largest maximum cumulative return is also found in MCoP1 as 0.555, while this value for MVP is only 0.057. The minimum cumulative returns for these four portfolios are however found to be close to each other, ranging from −0.027 to 0.001. Thirdly, the standard deviation statistics indicate that MVP has the smallest fluctuation in cumulative return, suggesting its stable performance in portfolio gain. Moreover, MCP, MCoP1, and MCoP2 share similar standard deviations in their cumulative returns as 0.109, 0.133,

Table 5
Sharpe ratios for MVP, MCP, and MCoP portfolios with or without China's carbon neutral bond.

	Sharpe ratio				
	Equal weighted	MVP	MCP	MCoP1	MCoP2
With CNB	0.080	0.394	0.092	0.084	0.092
Without CNB	0.078	0.085	0.084	0.077	0.085

Notes: This table reports the Sharpe ratios for five renewable energy stock portfolios with or without China's carbon neutral bond. Equal weighted denotes the portfolio constructed with equal weights for each asset. MVP and MCP are minimum variance and minimum correlation portfolios. MCoP1 and MCoP2 indicate the minimum connectedness portfolios based on NPDC and PCI criteria, respectively.

and 0.108, respectively. Lastly, we argue that the predictability or persistence in cumulative returns is an important metric that investors greatly appreciate. This means that greater predictability (or persistence) in the portfolio cumulative returns can help investors to adjust their portfolios more gracefully and thus better manage portfolio risk (Fama, 1965; Greene and Fielitz, 1979; Lo, 1991). Therefore, we further report the Ljung-Box Q statistics, as well as Hurst exponent calculated by rescaled range (R/S) analysis of Hurst (1951) to evaluate the predictability (or persistence) of the four cumulative return series. Table 4 shows that Ljung-Box Q statistics up to lags of 1 day, 5 days (one week) and 20 days (one month) are all significant at 1% level, implying that all these cumulative return series are highly autocorrelated (persistent) with great predictability. Then to compare the degree of predictability, the Hurst exponents are reported in the last row of Table 4. As noted in many researches (Hurst, 1951; Jacobsen, 1996; Lo, 1991), the Hurst exponent of a time series can be obtained by R/S analysis. If Hurst exponent = 0.5, it indicates that the time series is random walk, and the closer a Hurst exponent is to 0.5, the more unstable the trend of the series is. If 0 < Hurst exponent < 0.5, it denotes that the series is anti-persistence, which implies that if the series is going up (down) in the previous period, then the possibility of the series going down (up) in the next period is high. However, if 0.5 < Hurst exponent < 1, the time series is persistent or long-range correlated, suggesting that if the series is running up (down) in the previous period, there is a high probability that the sequence will go up (down) in the next period, and the closer a Hurst exponent is to 1, the higher this probability is. Therefore, investors may greatly appreciate a larger Hurst exponent in the cumulative returns of a portfolio, which will result in more stable returns in that portfolio and provide investors with more consistent expectations of their investment. Table 4 shows that, the Hurst exponents estimated for the cumulative returns of MVP, MCP, MCoP1 and MCoP2 portfolios are 0.933, 0.918, 0.926, and 0.918, respectively, indicating high persistence or great predictability in these four series. Among them, we can see that MVP has the largest Hurst exponent of 0.933, which is no surprise that this MVP portfolio is allocated almost by CNB. Except for MVP, MCoP1 obtains larger Hurst exponent of 0.926 than those of MCP and MCoP2 methods, indicating more persistent pattern and better predictability for SRI investors in its cumulative returns by using MCoP1 allocation method (i.e., more consistent performance of portfolio returns).

In summary, both Fig. 7 and Table 4 indicate the superior performance of the MCoP1 portfolio in terms of cumulative returns compared to the MCP and MCoP2 methods, with the exception of the MVP portfolio, which contains almost the entire investment weight in CNB.

4.2.3. *Sharpe ratios of different portfolios*

Moreover, we present the Sharpe ratios of the MVP, MCP, MCoP1, MCoP2 portfolios, as well as equal weighted portfolio in Table 5 to get another assessment of them, and display these ratios with or without CNB in the renewable energy stock portfolio.

Firstly, Table 5 shows that through the five different portfolio methods, renewable energy stock portfolios with CNB get larger Sharpe ratios than those without CNB, indicating significant diversification effects of CNB on renewable energy stocks in China. Thus, using CNB to hedge the market risk in holding renewable energy stocks in China is efficacious for SRI investors. Secondly, almost all the Sharpe ratios for MVP, MCP, MCoP1 and MCoP2 portfolios are larger than those of equal weighted portfolio, suggesting that no matter the traditional portfolio allocations (e.g., minimum variance and minimum correlation methods), or the novel optimizations of minimum connectedness approaches (MCoP1 and MCoP2) can outperform the equal weighted portfolio. In other words, active portfolio management is necessary and valid for renewable energy stock portfolio in China. Finally, regarding to the portfolio with CNB, MVP produces the largest Sharpe ratio of 0.394, about four times over other ratios. We think that this particular large ratio does not mean that this MVP method is much preferable than other methods for SRI investors. When considering the investment weights in these portfolios, as shown in Fig. 9 and Table 3, we can find that the large Sharpe ratio in MVP is mainly due to the fact that MVP allocates

Table 6
Averaged frequency connectedness for the returns of China's carbon neutral bond and renewable energy stocks.

	CNB	Solar	Wind	Geothermal	Biomass	Hydropower	FROM
Panel A: Short-term frequency, 1 to 22 days							
CNB	78.38	2.76	2.22	2.76	1.70	1.83	11.27
Solar	0.62	40.29	20.06	15.35	11.34	8.32	55.68
Wind	0.36	16.95	35.09	12.02	14.49	17.33	61.15
Geothermal	0.86	14.65	12.96	39.17	17.83	10.06	56.36
Biomass	0.89	9.61	14.15	16.09	36.54	18.45	59.2
Hydropower	0.70	7.06	18.56	10.00	20.70	39.16	57.00
TO	3.42	51.03	67.94	56.22	66.05	55.99	**TCI**
NET	−7.85	−4.64	6.79	−0.14	6.85	−1.01	**60.13**
Panel B: Long-term frequency, longer than 22 days							
CNB	9.12	0.35	0.31	0.24	0.14	0.19	1.23
Solar	0.01	2.17	0.73	0.63	0.35	0.15	1.86
Wind	0.02	0.81	1.55	0.43	0.43	0.51	2.21
Geothermal	0.04	0.91	0.64	1.93	0.66	0.3	2.55
Biomass	0.01	0.58	0.61	0.75	1.52	0.79	2.74
Hydropower	0.01	0.32	0.74	0.33	0.67	1.76	2.07
TO	0.08	2.99	3.03	2.38	2.24	1.94	**TCI**
NET	−1.15	1.12	0.81	−0.16	−0.50	−0.13	**2.53**

Notes: This table reports the directional connectedness indices among the returns of China's carbon neutral bond (CNB) and renewable energy stocks by the TVP-VAR method of Barunik and Ellington (2021). The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL connectedness index (TCI) of all the markets.

Table 7
Averaged quantile connectedness for the returns of China's carbon neutral bond and renewable energy stocks during extreme market conditions.

	CNB	Solar	Wind	Geothermal	Biomass	Hydropower	FROM
Panel A: quantile = 0.05, extreme bearish market							
CNB	29.14	14.05	14.95	14.29	13.49	14.08	70.86
Solar	10.47	21.62	18.1	17.54	16.76	15.51	78.38
Wind	9.75	17.96	21.46	16.31	16.88	17.65	78.54
Geothermal	10.62	17.69	16.27	21.21	18.05	16.16	78.79
Biomass	10.13	16.48	16.38	17.72	20.98	18.31	79.02
Hydropower	10.36	15.72	17.55	16.13	18.72	21.52	78.48
TO	51.33	81.91	83.24	82	83.89	81.71	**TCI**
NET	−19.53	3.53	4.69	3.21	4.86	3.23	**92.81**
Panel B: quantile = 0.95, extreme bullish market							
CNB	30.85	13.41	13.80	14.37	13.06	14.51	69.15
Solar	9.68	21.91	18.62	17.41	16.63	15.75	78.09
Wind	9.71	17.93	21.26	16.58	17.03	17.49	78.74
Geothermal	11.71	16.71	16.48	21.26	17.61	16.22	78.74
Biomass	9.35	16.09	17.12	16.95	22.09	18.39	77.91
Hydropower	10.59	15.34	17.96	15.69	18.54	21.88	78.12
TO	51.04	79.49	83.98	81.01	82.88	82.37	TCI
NET	−18.11	1.39	5.24	2.27	4.97	4.24	**92.15**

Notes: This table reports the quantile connectedness indices among the returns of China's carbon neutral bond (CNB) and renewable energy stocks by the quantile connectedness method of Ando et al. (2022). The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL connectedness index (TCI) of all the markets.

almost all the weight in CNB, which has obviously much smaller variance than those of renewable energy stocks, and thus produce this particularly big Sharpe ratios. However, in terms of renewable energy stock portfolios without CNB, the Sharpe ratios for MVP, MCP, MCoP1, MCoP2 portfolios, as well as equal weighted portfolio are very close (ranging from 0.077 to 0.085), suggesting that the advantage of the MVP portfolio therefore is less obvious without the help of CNB. To summarize, these Sharpe ratio results further confirm the significant diversification effects of China's CNB on renewable energy stocks, and further support that CNB is indeed a good choice for SRI investors to hedge market risks.

Table 8
Sharpe ratios for MVP, MCP, and MCoP portfolios with or without China's carbon neutral bond during extreme market conditions.

	Sharpe ratio				
	Equal weighted	MVP	MCP	MCoP1	MCoP2
Panel A: quantile = 0.05, extreme bearish market					
With CNB	0.0771	0.0761	0.0470	0.0891	0.0619
Without CNB	0.0755	0.0871	0.0859	0.0769	0.0772
Panel B: quantile = 0.95, extreme bullish market					
With CNB	0.0771	0.0710	0.0850	0.0586	0.0759
Without CNB	0.0755	0.0844	0.0759	0.0649	0.0678

Notes: This table reports the Sharpe ratios for five renewable energy stock portfolios with or without China's carbon neutral bond. Equal weighted denotes the portfolio constructed with equal weights for each asset. MVP and MCP are minimum variance and minimum correlation portfolios. MCoP1 and MCoP2 indicate the minimum connectedness portfolios based on NPDC and PCI criteria, respectively.

5. Robustness checks

5.1. Connectedness analysis of CNB and renewable energy stock markets in frequency domain

In Section 4.1, we illustrate the time-domain connectedness effects between CNB and renewable energy stock markets in China. Nevertheless, as pointed out in many relevant researches (Barunik and Krehlik, 2018; Dew-Becker and Giglio, 2016; Liu et al., 2022; Mensi et al., 2022a; Nguyen et al., 2021; Wei et al., 2022a; Wei et al., 2023), speculative markets, including fossil and renewable energy stock markets, respond heterogeneously to external shocks at different time frequencies. Therefore, following the method of Barunik and Ellington (2021), in this sub-section we further investigate the connectedness effects between CNB and renewable energy stock markets in China at different time frequencies.

Table 6 shows the results of connectedness in the frequency domain, where short-term frequency and long-term frequency are defined as 1 to 22 days (one month) and >22 days, respectively. We can see from Table 6 that, firstly, the largest total connectedness effect is centered on short-term frequency (TCI = 60.13% in Panel A of Table 6), suggesting that most of the information exchange between CNB and renewable energy stock markets takes place within 1 to 22 days. This means that investors' trading activities in Chinese CNB and renewable energy stocks are mostly short-term. Second, consistent with the results in Table 2, the CNB has very low pairwise directional connectedness with the five renewable energy stocks in both short and long frequencies, suggesting the weak interactions between the CNB and renewable energy stock markets in China. Finally, the net connectedness results in Panel A of Table 6 are fully consistent with those in Table 2, while the long-term frequency results in Panel B of Table 6 have some exceptions. In any case, CNB is always the largest recipient of net connectedness, whether in the time domain or at short and long frequencies. These results further confirm that CNB can be reliably used as a hedging instrument for renewable energy stocks in China.

5.2. Connectedness and diversification effects during extreme market conditions

Under extreme market conditions, assets tend to be more tightly correlated than under normal conditions, which will weaken the diversification utility of portfolio allocations (Ando et al., 2022; Hung, 2021; Wei et al., 2022a; Wei et al., 2022b). Therefore, in this subsection, we further test the connectedness and diversification effects between CNB and renewable energy stock markets in China under extreme market turbulence using the quantile connectedness method of Ando et al. (2022).

Table 7 shows that during extreme bearish and bullish market conditions (i.e. quantile at 0.05 and 0.95), the total connectedness index is measured at 92.81% and 92.15% respectively, which is much higher than the 62.66% in normal environment in Table 2. In addition, we find that the pairwise directional connectedness of CNB with renewable

Table 9
Averaged connectedness for the returns of China's carbon neutral bond and renewable energy stocks before and after the Russia-Ukraine conflict.

	CNB	Solar	Wind	Geothermal	Biomass	Hydropower	FROM
Panel A: before the Russia-Ukraine conflict (March 1, 2021 to February 23, 2022)							
CNB	84.07	4.27	2.96	3.42	2.65	2.64	15.93
Solar	1.53	48.31	19.01	13.14	10.64	7.36	51.69
Wind	0.88	14.63	40.09	9.37	15.94	19.1	59.91
Geothermal	1.06	12.57	11.05	47.64	18.93	8.75	52.36
Biomass	1.41	7.75	14.92	15.61	41.34	18.98	58.66
Hydropower	1.06	5.05	20.04	7.9	21.78	44.17	55.83
TO	5.94	44.27	67.98	49.43	69.94	56.83	**TCI**
NET	−10.00	−7.42	8.07	−2.93	11.28	1.00	**58.88**
Panel B: after the Russia-Ukraine conflict (February 24, 2022 to August 30, 2022)							
CNB	87.52	2.29	1.87	4.06	1.78	2.48	12.48
Solar	0.34	31.01	23.91	20.4	13.87	10.48	68.99
Wind	0.46	23	29.32	18.79	13.93	14.5	70.68
Geothermal	0.87	20.74	19.31	29.79	16.9	12.39	70.21
Biomass	0.76	14.96	14.98	17.89	31.55	19.87	68.45
Hydropower	0.66	11.62	16.98	14.54	21.71	34.49	65.51
TO	3.09	72.6	77.05	75.67	68.18	59.71	**TCI**
NET	−9.38	3.61	6.38	5.46	−0.27	−5.79	**71.26**

Notes: This table reports the directional connectedness indices among the returns of China's carbon neutral bond (CNB) and renewable energy stocks by the TVP-VAR method of Antonakakis et al. (2020). The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL connectedness index (TCI) of all the markets.

Table 10
Sharpe ratios for MVP, MCP, and MCoP portfolios with or without China's carbon neutral bond before and after the Russia-Ukraine conflict.

	Sharpe ratio				
	Equal weighted	MVP	MCP	MCoP1	MCoP2
Panel A: before the Russia-Ukraine conflict (March 1, 2021 to February 23, 2022)					
With CNB	0.1053	0.7099	0.1196	0.1164	0.0883
Without CNB	0.1026	0.1135	0.1064	0.1067	0.0892
Panel B: after the Russia-Ukraine conflict (February 24, 2022 to August 30, 2022)					
With CNB	0.0460	0.0735	0.0543	0.0470	0.0245
Without CNB	0.0456	0.0479	0.0581	0.0605	0.0508

Notes: This table reports the Sharpe ratios for four renewable energy stock portfolios with or without China's carbon neutral bond. Equal weighted denotes the portfolio constructed with equal weights for each asset. MVP and MCP are minimum variance and minimum correlation portfolios. MCoP1 and MCoP2 indicate the minimum connectedness portfolios based on NPDC and PCI criteria, respectively.

energy stocks also increases significantly. For example, the total connectedness received by CNB increases from 12.50% in Table 2 to 70.86% and 69.15% in Table 7 at quantiles of 0.05 and 0.95, respectively. These results suggest that during extreme market turbulence, the interactions between CNB and renewable energy stocks in China increase significantly, and the diversification effects of CNB may be ruined accordingly. Table 8 then reports the Sharpe ratios of different portfolios with and without CNB in extreme market conditions. In this table, we find mixed evidence that in extreme bearish markets (quantile = 0.05), the renewable energy stock portfolios with CNB have higher Sharpe ratios than those without CNB in two out of five cases. With respect to the extreme bull market (quantile = 0.95), there are three out of five cases in which the portfolios with CNB achieve higher Sharpe ratios. These results further confirm the stylized fact that in extreme market environments, the diversification benefits of hedging assets are significantly reduced. Therefore, portfolio managers should pay very close attention to the hedging performance of CNB on renewable energy stocks in extreme market environments, and promptly adjust the asset weights to compensate for the diminishing diversification effects that work well in normal market conditions.

5.3. Connectedness and diversification effects before and after the Russia-Ukraine conflict

In Section 4, we examine the linkage and diversification effects of China's CNB on renewable energy stocks across the entire data sample. However, many recent studies have demonstrated that the outbreak of the Russia-Ukraine conflict in February 2022 has shaken the global energy markets in an unprecedented manner, which may affect the connectedness between green bonds and renewable energy stock markets (Adekoya et al., 2022; Ahmed et al., 2022; Chen et al., 2023; Qureshi et al., 2022; Umar et al., 2022). Therefore, we further investigate the connectedness and diversification effects of China's CNB on renewable energy stocks by dividing the full data sample into two subsamples: one is before the Russia-Ukraine conflict (i.e., from 1 March 2021 to 23 February 2022) and the other is after the Russia-Ukraine conflict (i.e., from 24 February 2022 to 30 August 2022). Tables 9 and 10 show the connectedness and diversification effects of China's CNB on renewable energy stocks, respectively.

In general, Table 9 shows very similar results to those in Tables 2. First, CNB has very low pairwise directional connectedness with renewable stocks, and it maintains the low level of connectedness in both subsamples before and after the Russia-Ukraine conflict. Second, the total connectedness increases from 58.88% before the conflict to 71.26% after the conflict, further confirming the stylized fact that interactions between speculative markets increase in turbulent environments. Finally, although the role of other assets in net connectedness differs before and after the conflict, CNB is still the largest net connectedness receiver in both subsamples, suggesting that it can still serve as a hedging instrument for renewable energy stocks in China.

Table 10 shows the Sharpe ratios of the renewable energy stock portfolios with and without CNB before and after the Russia-Ukraine conflict. We find some analogous results in Tables 2 and 10. On the one hand, Panel A of Table 10 suggests that under normal market conditions before the Russia-Ukraine conflict, four out of five portfolios with CNB have higher Sharpe ratios than those without CNB. However, Panel B of Table 10 shows that in the very turbulent environment following the Russia-Ukraine conflict, only two out of five portfolios with CNB have higher Sharpe ratios than those without CNB. These findings further confirm the results reported in Section 5.2 that although CNB has a significant diversification effect on Chinese renewable energy stocks, its diversification role may diminish during highly turbulent

Table 11
Averaged connectedness for the returns of China's green bond and renewable energy stocks.

	GB	Solar	Wind	Geothermal	Biomass	Hydropower	FROM
GB	91.82	2.03	1.29	2.22	1.24	1.40	8.18
Solar	0.23	42.75	20.96	15.99	11.64	8.43	57.25
Wind	0.18	17.82	36.63	12.46	15.02	17.89	63.37
Geothermal	0.90	15.52	13.64	41.22	18.43	10.29	58.78
Biomass	0.59	10.14	14.94	16.82	38.25	19.24	61.75
Hydropower	0.38	7.34	19.45	10.28	21.39	41.15	58.85
TO	2.28	52.85	70.29	57.77	67.74	57.25	**TCI**
NET	−5.91	−4.40	6.92	−1.01	5.99	−1.59	**61.64**

Notes: This table reports the directional spillover among the returns of China's green bond and renewable energy stock indices by the TVP-VAR method of Antonakakis et al. (2020). The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL connectedness index (TCI) of all the markets.

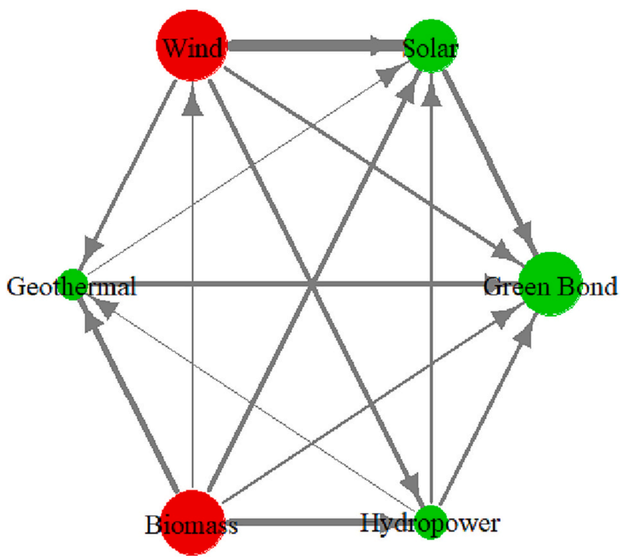

Fig. 8. Averaged net pairwise directional connectedness index (NPDC) between China's green bond and renewable energy stock indices. Red and green nodes denote the connectedness senders and receptors, respectively. The thickness of the arrow line indicates the intensity of the connection. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

market conditions.

5.4. Connectedness and diversification effects of China's green bond (GB) on renewable energy stock markets

In this sub-section, we further test the connectedness and diversification effects of China's green bond (GB) on renewable energy stock markets. This further examination is based on two major reasons: on the one hand, as a traditional green finance instrument, green bond (GB) has been widely adopted by SRI investors. However, the diversification effects of China's GBs on renewable energy stocks have not been examined by now. On the other hand, according to the "China Green Bond Market Report 2021", CNBs accounted for over 40% of the total labelled green bonds issued in China in 2021.[5] Therefore, comparing the diversification effects of general GB with those of CNB can not only help SRI investors to deeply understand the discrepancies between them, but also contribute to better choice of hedging instruments for SRI investors in renewable energy stock markets.

First, we present the average connectedness for the returns of China's GB and renewable energy stocks in Table 11. Very similar to the findings in Table 2, the total connectedness (TCI) between GB and renewable energy stocks is measured as 61.64% in Table 11, slightly smaller than the TCI between CNB and renewable energy stocks in Table 2 as 62.66%. Then the pairwise connectedness also shows that China's GBs are gently connected with renewable energy stocks for these pairwise connectedness indices are estimated only from 0.18% to 2.03%. Additionally, NET connectedness results indicate that GB is the major connectedness receptor, while Wind stock is the dominant contributor. These findings are further confirmed in Fig. 8, which is also highly consistent with those in Fig. 5.

Second, based on the above evidence in line with those revealed in CNB, we further demonstrate the time-varying portfolio weights for GB and the five renewable energy stocks in Fig. 9, and summarize the average portfolio weights and hedge effectiveness (HE) of the MVP, MCP, MCoP1 and MCoP2 allocation methods in Table 12.

Fig. 9 and Table 12 show a high degree of agreement in their conclusions with Fig. 6 and Table 3 as: firstly, due to the smaller variance of GB compared to those of renewable energy stocks, MVP method allocates almost all the investment weights to GB as shown in Fig. 9 and Table 12. Secondly, the MCP and MCoP2 produce similar portfolio weights and HE for GB and renewable energy stocks (i.e., the second and last rows in Fig. 9), suggesting that the estimated correlation and pairwise connectedness index (PCI) among GB and renewable energy stocks are very similar, and thus the diversification effects of GB on renewable energy stocks are close based on the MCP and MCoP2 methods. Thirdly, the portfolio weight allocated in GB and renewable energy stocks by the MCoP1 method, which looks more united, are quite different from those in other portfolios. It means that no assets with dominant weights are included in this MCoP1 portfolio, which may be a preferred attribute of balanced investment for SRI investors. Fourthly, we find that, besides MVP, the asset weights designed by MCP and MCoP2 vary greatly across GB and various renewable energy stocks. For example, in the MCP portfolio, Wind and Biomass stocks are only allocated with 8% and 10% investment weights, while GB and Solar stock obtain as high as 40% and 20% weights respectively, which are also observed in the MCoP2 portfolio. Furthermore, we find that MCoP1 method offers SRI investors with more *balanced* portfolio weights for GB and renewable energy stocks than other three methods. The average weight for GB in MCoP2 is 15%, and those for renewable energy stocks only change slightly from 14% to 22%. In summary, all the results shown in Fig. 9 and Table 12 are remarkably consistent with those in Fig. 6 and Table 3.

Then, we show the cumulative returns of renewable energy stock portfolios with China's GB in Fig. 10 and Table 13, and then the Sharpe ratios of these portfolios in Table 14. Fig. 10 demonstrate that the cumulative returns in MVP are clearly much smaller than those in MCP, MCoP1, and MCoP2. Then the cumulative returns in MCP (minimum

[5] https://www.climatebonds.net/resources/reports/china-green-bond-market-report-2021.

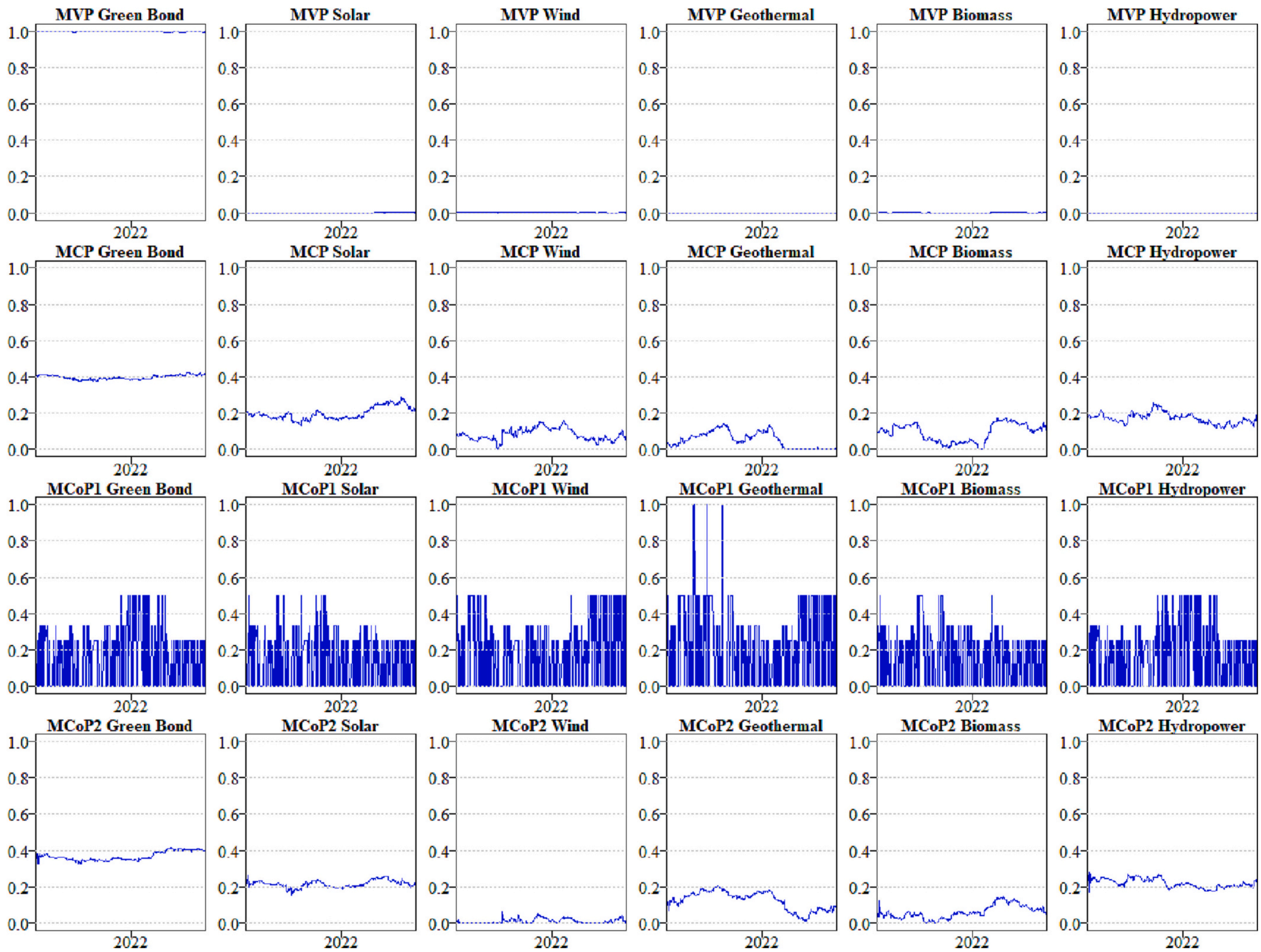

Fig. 9. Portfolio weights for the Chinese green bond and renewable energy stocks under the four portfolio allocation methods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 12
Averaged portfolio weights and hedge effectiveness for China's green bond and renewable energy stocks.

	MVP		MCP		MCoP1		MCoP2	
	Mean	HE	Mean	HE	Mean	HE	Mean	HE
GB	1.00	–	0.40	–	0.15	–	0.38	–
Solar	0.00	1.00	0.20	0.78	0.14	0.51	0.21	0.78
Wind	0.00	1.00	0.08	0.80	0.18	0.54	0.01	0.80
Geothermal	0.00	1.00	0.05	0.73	0.22	0.39	0.12	0.73
Biomass	0.00	1.00	0.10	0.67	0.15	0.26	0.06	0.67
Hydropower	0.00	1.00	0.17	0.71	0.16	0.34	0.22	0.70

Notes: This table reports the averaged portfolio weights and hedge effectiveness for China's green bond and renewable energy stock sector indices. Mean column shows the mean portfolio weights of the renewable energy stocks and HE column demonstrates the hedge effectiveness of one individual renewable energy stock compared with the portfolio constructed. The bigger the HE, the larger is the risk (variance) reduction and vice versa.

correlation portfolio) and MCoP2 (minimum PCI portfolio) are very close to each other. Moreover, the MCoP1 (minimum NPDC portfolio) obtains the largest cumulative returns over others in most of the time. Then Table 13 provides the simple statistics for these cumulative returns. It shows that the largest mean cumulative return is in MCoP1 (i.e., 0.267), while the smallest one is in MVP (i.e., 0.019). The minimum and maximum statistics indicate that there are no clear discrepancies in the minimum cumulative returns, while MCoP1 method produces the largest one of 0.614, suggesting the superior profitability of MCoP1 to other allocation approaches. Then the standard deviation statistics show that MVP has the smallest volatility in its cumulative returns, and MCP, MCoP1, and MCoP2 get similar standard deviations in their cumulative returns. Moreover, the results of Ljung-Box Q statistics and Hurst exponent suggest that the cumulative returns of the four portfolios are strongly autocorrelated and persistent (predictable). Except for MVP, MCoP1 has larger Hurst exponent of 0.927 than those of MCP and MCoP2, suggesting that SRI investors can benefit better from using MCoP1 method to get more persistence and predictability in their portfolio cumulative returns. All in all, the results of cumulative returns for China's GB and renewable energy stock portfolios are very close to

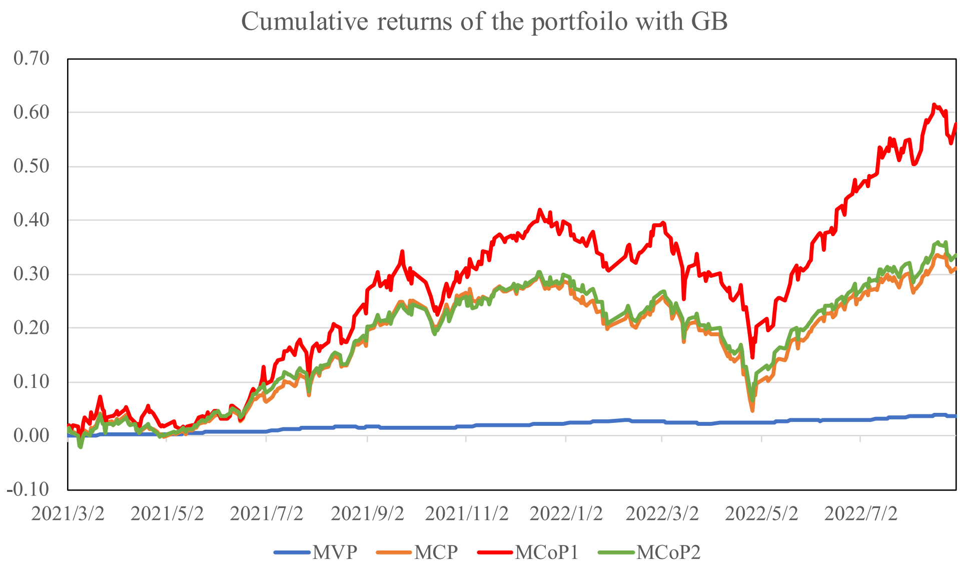

Fig. 10. Cumulative returns of renewable energy stock portfolios with China's green bond under the four portfolio allocation methods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 13
Simple statistics for the cumulative returns of portfolios for China's green bond and renewable energy stocks.

	MVP	MCP	MCoP1	MCoP2
Mean	0.019	0.172	0.267	0.180
Minimum	0.000	−0.018	−0.011	−0.022
Maximum	0.038	0.337	0.614	0.359
Standard deviation	0.010	0.099	0.161	0.102
Q(1)	362.372***	360.178***	359.100***	359.919***
Q(5)	1750.730***	1728.900***	1720.216***	1725.690***
Q(20)	6010.038***	5811.670***	5717.722***	5777.885***
Hurst	0.943	0.923	0.927	0.919

Notes: This table reports the simple statistics for the cumulative returns of portfolios for China's green bond and renewable energy stocks. $Q(n)$ is the Ljung-Box Q statistics with lag length of n. Hurst denotes the Hurst exponent of Hurst (1951). A Hurst exponent larger than 0.5 indicates that the time series is persistent, indicating a long-memory process existing in it.

Table 14
Sharpe ratios for MVP, MCP, and MCoP portfolios with or without China's green bond.

	Sharpe ratio				
	Equal weighted	MVP	MCP	MCoP1	MCoP2
With GB	0.079	0.353	0.081	0.101	0.088
Without GB	0.078	0.085	0.084	0.077	0.085

Notes: This table reports the Sharpe ratios for four renewable energy stock portfolios with or without China's green bond. Equal weighted denotes the portfolio constructed with equal weights for each asset. MVP and MCP are minimum variance and minimum correlation portfolios. MCoP1 and MCoP2 indicate the minimum connectedness portfolios based on NPDC and PCI criteria, respectively.

those revealed in Section 4.

Finally, we present the Sharpe ratios of the MVP, MCP, MCoP1, MCoP2 portfolios, as well as equal weighted portfolio in Table 14. These results in Sharpe ratios for China's GB and renewable energy stock portfolios are also in line with those for CNB in Table 5. We can see that, almost all the renewable energy stock portfolios with GB get larger Sharpe ratios than those without GB. Then almost all the Sharpe ratios for MVP, MCP, MCoP1 and MCoP2 portfolios are larger than those of equal weighted portfolio. Moreover, comparing the results in Tables 14 and 5, we can find that except for MCoP1, the Sharpe ratios revealed in Equal weighted, MVP, MCP, and MCoP2 for CNB portfolios are clearly larger than those for GB portfolios, indicating strong evidence that China's CNB have better diversification effects than GB on the renewable energy stocks. This finding reminds us that although CNBs are newly developed in China green finance markets, they are more effective than other traditional GBs in hedging the market risks of China's renewable energy stocks for the reason that the use of proceeds of CNBs is more precisely targeted towards carbon reduction and requires carbon reduction disclosure under dedicated guidelines than general GBs.[6]

In summary, the robustness checks in this section provide evidence not only for the potent hedging effects of China's GBs on renewable energy stocks, but also for superior roles of the newly developed CNBs than general GBs in Chinese green finance markets. In the consequence, we advocate not only the continued development of traditional green bond market, but also the expansion of the carbon neutral bond market in China. This will provide SRI investors with recognition of China's green bond market by providing an overall degree of international convergence in the Chinese GB market, thus providing strong green financial support for China to achieve its dual carbon goal by 2060.

6. Conclusions

With China's announcement of carbon dioxide peaking by 2030 and carbon neutrality by 2060 (30·60 targets), SRI in green finance projects is more and more significant for not only policy makers, but also various investors. This paper, therefore, investigates the interaction and diversification effects of CNBs on renewable energy stocks in China by using a TVP-VAR based connectedness index approach and a minimum connectedness portfolio allocation method. Our major findings show that: firstly, China's CNB interacts with renewable energy stocks slightly, and it is the major receiver of net connectedness effect from renewable energy stocks, providing the possible diversification role of CNB in renewable energy stocks. Secondly, we find that different renewable energy stocks profit distinctly from CNB with diversification effects for their different production fundamentals and revenue prospects. Among them, wind and solar energy stocks benefit mostly in

[6] https://www.climatebonds.net/resources/reports/china-green-bond-market-report-2021.

diversification effectiveness with the help of CNB. Thirdly, the MCoP1 allocation method, which adopt NPDC as optimization criterion, produces more *balanced* investment weights across CNB and renewable energy stocks, which may be a preferred attribute for SRI investors. Fourthly, evidence in cumulative return comparisons shows that, although MVP has the smallest fluctuation in its portfolio cumulative returns, MCoP1 produces the largest cumulative returns over the other three methods during most of the sample date. Moreover, the Hurst exponents estimated show that MCoP1 also has higher persistence or greater predictability in this return series than those of MCP and MCoP2. Finally, the Sharpe ratio results demonstrate again renewable energy stock portfolios with CNB get larger Sharpe ratios than those without CNB.

These findings have very important implications for both policy makers and SRI investors. For example, the verified diversification effectiveness of CNBs on renewable energy stocks suggests that, on the one hand, policymakers should further strengthen the development of China's CNB market and expand the capacity of the CNB market, while further improving the alignment of China's CNBs with international green standards. On the other hand, SRI investors can use China's CNBs to hedge the risk of their renewable energy stock portfolios with confidence. However, they should also be careful in using CNBs during extreme turmoil market environments. Then, the different roles of CNBs in renewable energy stocks remind SRI investors that when holding different renewable energy stocks, they can consider different portfolio allocation strategies and allocate flexible weights to CNBs to hedge the risks in the renewable energy stocks of the portfolio. For example, SRI investors may use CNBs primarily to hedge their risks if the majority of a portfolio's investments are in the wind and solar sectors. Otherwise, investors may use other tools besides CNBs to allocate their renewable energy stock portfolios. Moreover, in terms of portfolio applications, MVP allocation may not be a desirable method for SRI investors because the extraordinarily low variance of CNBs compared to renewable energy stocks may result in an extremely high investment weight in CNBs, thus creating a very unbalanced portfolio. Therefore, minimum correlation portfolio (MCP) and minimum connectedness portfolio (MCoP) approaches are more suitable than MVP for investors to create balanced portfolios with CNBs and renewable energy stocks. Finally, MCoP based on the NPDC criterion (MCoP1) is a better option for SRI investors because of its superior performance in portfolio profit (i.e., cumulative returns) and comparable ability in risk-return trade-off (i.e., Sharpe ratio) to other commonly used methods. Therefore, SRI investors should develop and adopt new allocation methods in managing their CNB and renewable energy stock portfolios instead of traditional methods designed for common bond portfolios.

CRediT authorship contribution statement

Lan Bai: Software, Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **Yu Wei:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Funding acquisition, Visualization, Writing – review & editing, Project administration. **Jiahao Zhang:** Investigation, Writing – original draft, Writing – review & editing. **Yizhi Wang:** Data curation, Software, Investigation, Conceptualization, Formal analysis, Methodology, Resources, Validation, Visualization, Writing - original draft, Writing - review & editing. **Brian M. Lucey:** Supervision, Project administration, Resources, Writing – review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106727.

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