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Research article

Does carbon asset add value to clean energy market? Evidence from EU

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Abstract: This paper examines if clean energy stocks help investors in managing carbon risk. We use the price of the European Union Allowance (EUA) and European clean energy index (ERIX) for the three phases of the EU-Emission Trading Scheme. Analyzing the time-varying correlation and volatility of EUA stock and ERIX through generalized orthogonal GO-GARCH model, the empirical results reveal relative independence of the European renewable energy market from the carbon market providing diversification benefits and value addition by including carbon assets in clean energy stock portfolio. Furthermore, three portfolios with different weight allocation strategies reveal that the carbon asset provides risk and downside risk benefits when mixed with a clean energy stock portfolio. These results are useful for investors who enter the market for value maximization and the regulators striving to make strategies for managing carbon risk.

Keywords: European Union Allowance (EUA); European clean energy index (ERIX); GO-GARCH; carbon risk; portfolio diversification

JEL Codes: C40, G11, G15, D81

1. Introduction

Climate change has always been one of the most challenging environmental issues of recent times. Climate change concerns, like global warming, have challenged human communities for sustainable development due to the large amounts of greenhouse gas emissions (GHG). CO_2 emissions are the eminent cause of climate change (Lashof & Ahuja, 1990), contributing approximately 80% of the GHGs responsible for global warming. An international agreement addressed these and other growing concerns about global warming—the Kyoto Protocol in 2005 (International Energy Agency, 2012). To keep the climate intact various tactics were used to mitigate climate change. Among all, the European Union Emission Trading Scheme (EU-ETS), which was launched in 2005, represents the biggest carbon trading system in the world. It provides EU members with incentives to mitigate emissions and has become an essential tool for managing CO_2 reduction (Bing et al., 2015). The EU-ETS operates through a cap-and-trade program on the total volume of carbon emission allowances allocated per year; companies not corresponding to their CO_2 allowances face severe sanctions. A firm may emit less carbon than is allowed resulting in a surplus. This surplus can be sold to companies whose emission is greater than the allowance, making EU allowances a tradable commodity and carbon market as a mimic of the financial market (Benz et al., 2006; Uddin & Holtedahl, 2013).

In addition to the carbon market, Governments are promoting the clean energy sector all around the globe (Kazemilari et al., 2017) to minimize the adverse environmental effects caused by GHG emissions. Previous studies by Balcılar et al. (2016) and Reboredo et al. (2019) suggest that the main reason for the growth in renewable energy is increasing CO_2 emissions. Thus, one can say that carbon emission prices may affect the investments of renewable energy stocks. According to Creti et al. (2012), there is a linkage between energy commodities and carbon assets. Several authors have studied this linkage (Convery & Redmond, 2007; Bunn & Fezzi, 2007; Gronwald et al., 2011; Keppler & Mansanet-Bataller, 2010; Kumar et al., 2012; Marimoutou & Soury, 2015; Reboredo, 2014; Reboredo, 2015; Sadorsky, 2012; Tian et al., 2016; Wen et al., 2017; Zhang & Du, 2017; Zhang and Sun, 2016) and found significant effects.

Earlier studies have focused on the relationship between CO_2 and fossil fuels, yet the linkage between CO_2 allowances and the renewable energy market remains understudied. The effects of the EUA market on renewable energy stocks are initially specified by Kumar et al. (2012). Further, Koch et al. (2014) and Dutta (2018) focused on the return and volatility linkages between carbon emissions and renewable energy stock prices. The existing studies are limited to examine the return and volatility patterns among EUA and clean energy markets; however, it is crucial for investors to seek investment opportunities in alternative asset classes (carbon to clean energy market or vice versa) to reduce their risk. Hence, the main objective of this study is to measure the impact on risk and returns of clean energy stocks if carbon asset is included in the portfolio and examine diversification benefits. This paper contributes to the standing literature in the following ways.

To the best of our knowledge, this is the first study that employs the Generalized Orthogonal-GARCH model to examine the time-varying relationship between the markets under consideration. This model is computationally simpler and has no dimensionality constraints. In addition to GO-GARCH, the symmetric and asymmetric DCCs are applied with a multivariate student-t distribution to check non-normality in the distribution. Then we estimate GO GARCH with a multivariate affine negative inverse Gaussian (MANIG) distribution.

Secondly, it is pioneer research to investigate whether the carbon assets add to the value of clean energy stock portfolios. As earlier studies have indicated, both the clean energy sector and carbon market have seen significant growth and are expected to grow even more in the future, thus, the need for more attention. In addition, it will help investors decide whether to add carbon assets to their portfolios to increase return or not and to what extent these assets can be added for portfolio optimization (Arouri et al., 2015). Thus, these findings will assist investors during portfolio optimization and weight allocation.

Third, this research comparatively measures the diversification benefits of the alternate market (clean energy markets) for the carbon market.

Fourth, this paper is a source of information for policymakers to design energy policies: promoting portfolios comprised of carbon assets and clean energy stocks to reduce GHG emissions further.

Finally, the three phases of carbon allowance are represented in the study, thus making the empirical analysis more comprehensive and robust.

Since the emergence of the EU-ETS in 2005, the body of knowledge on clean energy and the carbon market has shown rapid growth. Considering EUAs as a production factor, Kara et al. (2008) found that 1 euro/ton CO_2 change might result in 0.74 euro/MWH rise in power prices. Based on the argument that carbon prices impact the energy sector because of their significant exposure to overall EU CO_2 emissions. Therefore, replacing fuel oil, coal, and natural gas influences the price of carbon allowances due to the disparity in carbon emissions through these fossil fuels. Exploring the topic holds immense importance for diversification in portfolio management (Luo & Wu, 2016). Carbon assets can control risk in the portfolio management of energy stocks (Reboredo, 2015). Dutta et al. (2018), Reboredo (2013), Reboredo (2014), and Luo & Wu (2016) suggested that carbon assets have likely diversification benefits due to their relative independence from financial markets. Wen et al. (2017) confirmed the results by creating portfolios that included EUAs.

In contrast, Leitao et al. (2021) argue that green assets such as green bonds significantly influence CO_2 prices. The portfolio risk of the portfolios having CO_2 futures was lower than that of energy stocks without CO_2 futures. Moreover, Andersson et al. (2016) concluded that investors can hedge their risk through carbon allowances as the financial returns are not sacrificed, and the risk is significantly reduced while the tracking error is minimized. These results can be informative for passive investors. Assessing the values of energy commodity futures with the carbons assets, Wen et al. (2017) found that dynamic portfolio diversification is better than the hedged portfolios in reducing carbon risk. Adding to this, Zhang et al. (2017) checked the diversification benefits of including carbon assets in financial portfolios. They first studied the correlation between the carbon market and other financial markets and found a highly significant relationship in the short term, which diminishes in the long run. Consequently, their results revealed that carbon assets help lessen the volatility of an optimal portfolio, but the overall return seems to fall.

Several studies have used copula models to model market dependency. For example, Reboredo et al. (2019) and Reboredo (2013) test the dependency between EUA and crude oil prices. Bai et al. (2019) used a robust portfolio approach to examine the portfolio performance of renewable energy. However, due to its convenience and effectiveness, multivariate GARCH remains the most popular model for analyzing dependency between markets. Various studies have used GARCH models to capture the linkage between carbon variables and other financial markets. Koch et al. (2014) checked the dependency between the allowance market and the energy market with the same approach. Zhang et al. (2017) and Zhang and Sun (2016) analyzed volatility spillovers between carbon and other financial markets through DCC GARCH models. Luo and Wu (2016) applied the GARCH model to investigate the correlation among EUAs, crude oil, and the stock market; however, Mean-Variance and CoVaR methods were used to examine portfolio performance. Moreover, Dutta (2019), Lin and Chen (2019); Lin and Jia (2020) are the recent studies to use multivariate GARCH models.

In the present study, the GO-GARCH model is employed for testing the time-varying dependency between clean energy stock and carbon assets. Furthermore, risk reduction effectiveness and value-at-risk reduction strategies are used for evaluating portfolio performance. Multivariate GARCH models have been frequently used to study the volatility and co-volatility between several markets (Papantonis, 2016). Commonly, there are numerous risk factors in stock indices that need to be modeled through covariance matrix dynamics, making the process of estimating portfolio risk cumbersome. In comparison to other models which possess the above difficulty, GO-GARCH is computationally uncomplicated and yet efficient. By taking few principal components, GARCH can be extended to generalized O-GARCH, which applies calculations to a few main factors, capturing the orthogonal deviations in the root data (Ding, 1994; Lam et al., 2009). Thus, it possesses the simplicity of the univariate model and the efficiency of the multivariate model. Moreover, this approach is superior to multivariate models as it results in no noise in the data, has no dimensionality constraints, and can be applied to even unreliable and scant data (Alexander, 2000). According to Engle (2002), GO-GARCH is preferred to all other alternatives of estimating dynamic covariance matrices.

Introduction in section 1 of the paper covers the background of the study, objectives, significance, and related literature. The remainder of the paper is organized as follows. Section 2 deals with the data and the overview of the methodology. The next section describes the results, followed by the discussion part in section 4. Finally, section 5 consists of the conclusion, implications, and limitations of the study.

2. Methods

2.1. Data

We consider the daily prices of carbon assets (EUA) and the clean energy index (ERIX). The EUA in EU-ETS represents the leading carbon trading allowance market in the world, and the ERIX index is the most representative renewable energy market index of Europe. It consists of the top ten largest and most liquid companies in the wind, solar, hydro, and biomass energy sectors.

The data is obtained from Datastream, a glog bal database of Thomson Reuters. The sample period starts from the trading date of the ERIX index from October 13, 2005, to October 13, 2020, covering almost all three phases of EUA (Phase-III ended in December 2020).

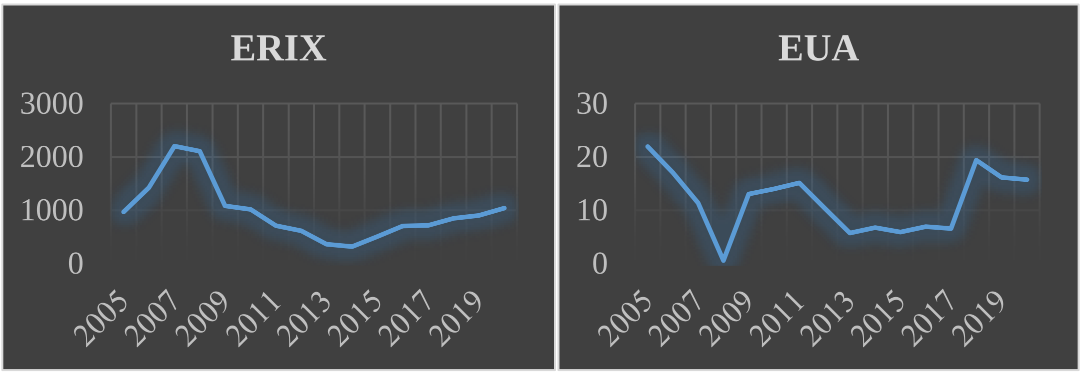

Figure 1. Price movements of ERIX and EUA.

Figure 1 is showing the price trends of the EUA and ERIX index, where allowance prices depict greater volatility than the clean energy stocks. In 2008, a sharp decline in the prices can be seen; the possible reason being the global financial crises that severely affected the Eurozone, driving energy demand downwards; thus, reducing the demand for carbon allowances. This decline can again be witnessed in mid-2011 and 2020 due to the economic slowdown in Eurozone and Covid-19 pandemic causing global economic downturns.

Table 1. Descriptive statistics.

	EUA	ERIX
Min	−0.4321	−0.1297
Max	0.2382	0.0795
Mean	0.0067	0.0033
Std. Dev.	0.0316	0.0164
Skewness	−0.8162	−0.3595
Kurtosis	17.7436	6.2519

Table 1 presents the summary statistics of the return series of both indices. The volatility and range between maximum and minimum values are higher for EUA than ERIX, whereas the mean of both return series is positive and exhibits excess kurtosis.

Table 2. Correlation matrix.

	ERIX	EUA
ERIX	1	
EUA	−0.40*	1

Notes: *Represents significance at 10% level.

Table 2 presents the Pearson Correlation results of the variable ERIX and EUA. Both the markets are negatively correlated to each other with 10% significance. The correlation value is −0.40 which is negative, implying that adding carbon assets to the clean energy stock portfolio might yield higher value as the markets move in the opposite direction.

Table 3. Unit Root diagnostics test.

	PP	ADF	KPSS
EUA	−54.6872***	−20.0822***	0.0477
ERIX	−53.9489***	−25.1472***	0.0838

Notes: PP, ADF, and KPSS are unit root tests. *** represents the rejection of the null hypothesis of unit root and non-stationarity at 1% significance level.

Table 3 shows the unit root diagnostic tests of both markets. The results confirm the stationarity with significant PP (Phillips and Perron) and ADF (Augmented Dickey-Fuller), and insignificant KPSS (Kwiatkowski–Phillips–Schmidt–Shin).

2.2. *Methodology*

2.2.1. Generalized Orthogonal GARCH

We chose the generalized OGARCH model to examine the carbon asset association with other markets, such as the clean energy market. The GO-GARCH model of Van der Weide (2002) is linked with a set of independent univariate and conditionally uncorrelated GARCH processes, which uses marginal density parameters and relate them to the observed data (Ghalanos, 2014) that can offer more flexibility in the estimation, compared to other MGARCH models.

In the GO-GARCH model, the market return is denoted by (r_t), the conditional mean (m_t) which is a function of (r_t) contains error term (ε_t) and an AR(1) term.

$$Q_t = r_t + \varepsilon_t \tag{1}$$

The model draws $Q_t - r_t$ on a set of unobservable independent factorsf_t.

$$\varepsilon_t = Af_t \tag{2}$$

where the mixing matrix A is divided into a rotational matrix U and an unconditional covariance matrix. The covariance matrix of r_t will then be computed as:

$$og_t = var(r_t) = w_t var(Q_t) w_t^T = w_t z_t w_t^T \tag{3}$$

where Z_t = diag matrix, with the dependent column variance in Qt represented by its elements modeled by GARCH (1, 1).

$$Q_{i,j} = v_i + \varepsilon_{i,j}$$

$$\sigma_{i,j}^2 = \alpha_0 + \alpha_1\, \varepsilon_{i,j-1^2} + \alpha_2\, \sigma_{i,j-1}^2 \tag{4}$$

where $Q_{i,j}$ is the i-th principle component on j time, v_i is a constant, $\sigma_{i,j}^2$ is the conditional variance of $\varepsilon_{i,j}$, $\varepsilon_i = \sigma_{i,j}\, \mu_{i,j}$ with $\mu_{i,j} \sim N(0,1)$ for j=1, … , T.

Solving for og_t, conditional coefficient between security i and e is given as:

$$Q_{i,e} = \frac{\mathbf{og}_{tie}}{\sqrt{(\mathbf{og}_{tii}\mathbf{og}_{tie})}} \tag{5}$$

2.2.2. Portfolio strategies

The optimal weights are achieved according to the weights designed by (Jammazi and Reboredo, 2016; Chkili et al., 2016), which uses correlations provided by the bivariate models of DCC, ADCC, and GO-GARCH. The output of the portfolios (II, III, and IV) is contrasted to that of the Portfolio benchmark (I), which consists solely of renewable energy. Portfolio II is designed according to Kroner and Ng (1998), and its construction is as under:

$$w_t^F = \frac{h_t^S - h_t^{FS}}{h_t^C - 2h_t^{FS} + h_t^S} \tag{6}$$

where the conditional variance and covariance on the spot (clean energy) and future (clean energy and carbon market) returns are denoted by $h_{F,t}$ and $h_{SF,t}$. By construction, the weight of the clean energy stock in the portfolio is equal to $(1 - w_t^F)$.

Portfolio III follows variance minimizing strategy, which means an investor has a long position in spot assets (clean energy stock market) and a short position in futures assets (mixed portfolio), which is given by

$$\beta_t = \frac{h_t^{FS}}{h_t^F} \tag{7}$$

Portfolio IV is an equally weighted portfolio that follows DeMiguel et al. (2009) with a good out-of-sample approach.

The risk reduction effectiveness (RE) measured for Portfolios II, III, and IV is determined by the percentage reduction in the variance compared to Portfolio (I). It is represented as follows

$$RE = 1 - \frac{Var(P_i)}{Var(I)} \tag{8}$$

where i= II, III, IV and the variances in the clean energy and carbon assets portfolios and the variance of the benchmark portfolio (I), respectively, are expressed by Var (P_i) and Var (P_I). Higher positive values suggest greater efficacy of risk-reduction.

A portfolio's value-at-risk can be given by considering a certain confidence level (1-p):

$$VaR(p) = \mu_t - t_v^{-1}(p)\sqrt{h_t} \tag{9}$$

where μ_t and h_t denote the portfolio's conditional mean and standard deviation, accordingly, and t_v^{-1} (p) signifies the pth quartile of the distribution of t and the degrees of freedom of v.

3. Results

The GO-GARCH model is compared with DCC and ADCC to estimate volatility and correlation forecasts. The symmetric and asymmetric DCCs are estimated with a multivariate student-t distribution to check non-normality in the distribution and estimate GO-GARCH with a multivariate affine negative inverse Gaussian (MANIG) distribution.

Table 4 shows the estimated parameters of DCC and ADCC. For all stock indices, the conditional mean (μ) for the DCC GARCH model is statistically significant and positive; however, the mean value is greater for ERIX. The estimated coefficients for AR(1) for both DCC and ADCC are statistically negative and insignificant in the case of ERIX, whereas significantly positive for EUA. For both DCC and ADCC models, the coefficient values (ω) of the conditional variance are slightly higher for the clean energy market (ERIX) compared to the carbon market (EUA). The estimated coefficients of the (α) terms representing the long-run volatility persistence are positive and statistically significant in both markets for DCC models; however, for ADCC models, only EUA coefficients are significant. For short-term volatility persistence, the coefficients of (β) are significantly positive in the case of ERIX and EUA for both models.

Moreover, the asymmetric coefficients (ϒ) are statistically significant and positive for the clean energy market, whereas negatively insignificant in the carbon market. These results of (ϒ) for ERIX show that the negative residuals will increase the conditional volatility for this series. The findings of this study are in line with Basher and Sadorsky (2016), which argues that different leverage effects may be seen due to different contract liquidity, arbitrage activities, or asymmetric information. The shape parameters (λ) are equivalent to degrees of freedom (d.f). As the number of d.f. reaches infinity, the shape of the t-distribution changes to normal distribution. The shape parameters for both markets are more than 8 in both models but greater in the case of the ADCC model.

Table 4. Estimates of DCC and ADCC models.

	ERIX	EUA
Parameter Estimates of DCC		
μ	0.065336***	0.013284***
	(0.01434)	(0.004765)
AR (1)	−0.014715	0.04878***
	(0.014575)	(0.014827)
ω	0.014713***	0.000944***
	(0.004167)	(0.000208)
α	0.086571***	0.036735***
	(0.010249)	(0.002429)
β	0.908122***	0.955794***
	(0.010326)	(0.000661)
λ	8.155709***	8.629631***
	(0.946984)	(1.021479)
Parameter Estimates of ADCC		
μ	0.033114**	0.01379***
	(0.014424)	(0.00482)
AR(1)	−0.009366	0.048458***
	(0.014271)	(0.014808)
ω	0.020955***	0.000868***
	(0.004707)	(0.000204)
α	0.00000	0.039941***
	(0.007577)	(0.00507)
β	0.908073***	0.957142***
	(0.011583)	(0.000532)
ϒ	0.154644***	-0.007307
	(0.020096)	(0.007914)
λ	9.74964***	8.663788***
	(1.337822)	(1.027544)

Note: ***, **, * shows significance at 1%, 5% and 10% levels. The values in parenthesis are standard errors.

Table 5. GO-GARCH parameters estimates.

	F1 (ERIX)	F2 (EUA)
Omega	0.008023	0.007469
Alpha1	0.043078	0.080302
Beta1	0.950262	0.913516
Skewness	0.062621	0.126950
Shape	0.822276	3.197485

Note: All specifications in the GO-GARCH model include a constant and an AR(1) term in the mean equation.

We use the generalized orthogonal GO-GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to estimate volatility and correlation forecasts. GO-GARCH is used to measure the dependency and the volatility of an asset. In Table 5, it appears that the short-run persistence of volatility (α) alpha is lower than the (β) beta long-term persistence of volatility, which implies that the EUA and ERIX take a long time to get out of the market shocks completely. The combined value of alpha and beta is for EUA and ERIX is near to 1, implying that volatility effects remain in the markets for a long time. The research findings of the GO-GARCH model are consistent with the research findings of the DCC and ADCC models.

Table 6. Portfolio optimization.

	Portfolio II	Portfolio III	Portfolio IV
Risk Reduction	0.9433	0.0192	0.7535
VaR Reduction	0.7641	0.0124	0.5050

Note: Table shows risk reduction effectiveness and VaR reduction results. Portfolio I is the benchmark portfolio composed of clean energy stocks; Portfolios II and III are given by Eq. (9) and (10). Portfolio IV has equal weights.

We will compare the clean energy portfolio performance containing carbon assets (Portfolio II, III, IV) with the clean energy stock portfolio not containing any carbon assets (Portfolio I) to assess any value-addition using different portfolio strategies. Thus, the results in table 6 depict risk reduction relative to the returns of the assets. Risk reduction gains and diversification benefits are greater in Portfolio II and IV. Regarding the downside risk measures (value-at-risk reduction at 95% level of confidence), Portfolio II provides the highest VaR reduction followed by Portfolio IV and III. Portfolio (II) based on risk minimization strategy and Portfolio IV with equally allocated weights outperforms the benchmark Portfolio (I) with clean energy stock only.

Thus, one can say that adding carbon assets to the clean energy stock adds significant value to the clean energy stock portfolio and the best optimization strategy is Portfolio II. The results are consistent with Zhang et al. (2017) study, which found that adding carbon assets to financial portfolios yields diversification benefits.

4. Discussion

EUA can be considered a turning point in lowering environmental damage (Benz et al., 2006). However, continuing allowance trading is insufficient to meet the emission reduction targets successfully; it is also important to establish risk control strategies for carbon risk (Balcılar et al., 2016). Since most previous studies have concentrated on general co-movements between carbon assets and clean energy stocks, they overlooked the value addition to clean energy stock portfolios by including carbon assets, which creates a gap. We add to the literature using the GO-GARCH model to examine the time-varying relationship between the markets under consideration and then build optimal portfolios to compare the values of clean energy stock portfolios with and without carbon assets. We focus on the EU-ETS and ERIX index, the biggest and most representative markets of the assets in consideration. Our results indicate that the EUA stock is independent of the ERIX index leading to value addition by adding carbon assets to the clean energy stock portfolio. This is an initial study on the impact of the addition of the carbon assets to clean energy stock portfolios while modeling the dependence of the variables through GO-GARCH and considering the risk and downside risk measures for portfolio diversification. The empirical analysis reveals that the EUA prices negatively affect clean energy prices, but this effect is significantly positive with green bonds (Leitao et al., 2021). We build portfolio strategies to assess the impact on the value against the benchmark Portfolio strategy I (clean energy stocks). However, Portfolio II, III, and IV are computed relative to risk-minimizing strategy, variance-minimizing strategy, and equally weighted portfolio. The results indicate that the inclusion of carbon assets to clean energy stocks provides the highest risk reduction for Portfolio II. In particular, carbon assets can decrease portfolio risk and increase portfolio return when added to a clean energy stock portfolio. Moreover, our findings are in line with the studies of Liu et al. (2015), which proposed that the carbon assets are weakly correlated to clean energy stock portfolios.

5. Conclusions

EUA allowances and clean energy are imperative for lowering carbon emissions on a global scale. However, the relation of carbon assets and clean energy stock remains understudied, as the risk management strategies essential for achieving the carbon emission targets have been consistently overlooked. The present paper is an effort to fill this vacuum by elucidating the impact of adding carbon assets to the clean energy stock portfolios. Upon adding carbon assets to alternate assets (clean energy stock portfolios), the risk and the downside risk both tend to fall, and diversification benefits can be achieved. Thus, establishing that simultaneous investment in carbon assets and clean energy stock portfolio is more profitable for clean investors. Therefore, the results highlight the importance of mixed portfolio construction for diversification purposes.

The study has important implications for investors, policymakers, and portfolio managers. Adequate knowledge about value addition by carbon assets can help investors to make better decisions regarding asset allocation. Thus, investors can maximize their value and protect their investment from downside risk by using the information. For policymakers, this information can assist them in designing incentive strategies to attract investors towards more green investments. As the primary goal of emission trading schemes and clean energy stock is to reduce GHG emissions, these policies can provide opportunities for shifting towards green technology. Furthermore, the results allow portfolio managers to devise diversification strategies based on mixed portfolios.

Moreover, this paper is limited to only the European carbon and clean energy market; however, it can be extended to Chinese emerging carbon markets and the clean energy sector. Global and sectoral clean energy indices can also be considered. Other than emission trading schemes, another way of pricing carbon to reduce GHG is to apply a carbon tax due to its simplicity, scope, compatibility with low-carbon transition, and cost-effectiveness (O'Mahony, 2020). Advanced methodologies such as copula and switching copula can be applied to measure the dependence patterns of these markets in different regimes.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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