Energy Economics 124 (2023) 106831

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Does green improve portfolio optimisation?

Md Akhtaruzzaman [a,*], Ameet Kumar Banerjee [b], Sabri Boubaker [c,d,e], Faten Moussa [f]

[a] Peter Faber Business School, Australian Catholic University, Australia
[b] XLRI-Xavier School of Management, India
[c] EM Normandie Business School, Métis Lab, France
[d] International School, Vietnam National University, Hanoi, Viet Nam
[e] Swansea University, Swansea, United Kingdom
[f] Mediterranean School of Business, South Mediterranean University, Tunis, Tunisia

A R T I C L E I N F O

JEL classification:
G11
G12
G17
G19
G32

Keywords:
Green finance
Greenness
Social development goals (SDGs)
Green asset
CVaR
VaR
Portfolio optimisation

A B S T R A C T

Our study uses the GARCH-EVT-copula model to develop out-of-sample forecasts for diverse asset classes, including a green asset. To construct optimal portfolios, we apply four different portfolio allocation techniques: equal weighting, minimum variance, global minimum variance (GMV), and certainty equivalence tangency (CET) criteria. The results demonstrate that the GMV portfolio outperforms other portfolios in risk measures. Further, backtesting evidence shows that the portfolio containing a green asset performs better than the benchmark for short horizons. The results have implications for fund managers and policymakers since green asset provides valuable diversification benefits and further the cause of sustainable development.

1. Introduction

Energy plays nowadays a pivotal and strategic role in shaping the future of humanity and safeguarding the health of the ecosystem (Tan et al., 2021). Population growth and increased energy consumption have presented an enormous challenge for the environment and the development of new pathways for the expansion of the energy grid while addressing global climate change and energy consumption demands. Energy and ecological balance are complex issues that warrant worldwide concern, as they encompass the combined challenges of meeting global energy demands while mitigating health risks caused by the massive use of fossil fuels for industrial and nonindustrial reasons (Tiba and Omri, 2017).

Renewable energy has the potential to become a valuable and indispensable resource, greatly benefiting human life and well-being in this critical transitional phase (Brosemer et al., 2020). Green energy can substantially impact biodiversity, particularly the hyper diversity of the tropics, with their fast-rising human population and economies, even though >176 countries aspire to transition to clean energy sources (Edelman et al., 2014; REN21, 2017). Environmentally friendly technologies, such as green energy, urgently require the strategic intervention of scientific research and financial support. Based on this nexus, generating resources for green finance to improve the environment should be considered a fundamental requirement for sustainable development.

Green finance is a crucial source of funding for renewable energy projects aimed at reducing the adverse impact of carbon emissions on both humans and the environment. It reflects the goal of sustainability in financial decision-making with a focus on environmental and sustainability considerations, including the implementation of the United Nations Social Development Goals (SDGs) (Madaleno et al., 2022). Considering the critical importance of green finance, the literature examines the transmission of risk between green assets and traditional financial assets, portfolio diversification through the inclusion of green assets, the role of green assets as risk-mitigating instruments, and the potential of green assets as safe-haven assets (Akhtaruzzaman et al.,

* Corresponding author at: 532.06.15, Tenison Woods House, 8-20 Napier Street, Peter Faber Business School, Australia.
E-mail address: Md.Akhtaruzzaman@acu.edu.au (M. Akhtaruzzaman).

https://doi.org/10.1016/j.eneco.2023.106831
Received 19 April 2022; Received in revised form 16 April 2023; Accepted 20 June 2023
Available online 4 July 2023

2022a; Del Gaudio et al., 2022; El Ghoul et al., 2023; Le et al., 2021; Kuang, 2021; Martiradonna et al., 2023; Naqvi et al., 2022; Reboredo, 2018; Reboredo et al., 2020; Reboredo and Ugolini, 2018; Yousaf et al., 2022). However, despite the growing literature on green assets as portfolio diversifiers and risk-mitigating instruments, few studies have focused on the out-of-sample forecasting of green asset portfolio allocation. Our study fills the void in the literature by introducing a GARCH-EVT-copula model to conduct out-of-sample forecasting for portfolios containing green and traditional assets. In the GARCH-EVT-copula model, we have taken care of investors' concern about downside risks than about upside gains by applying Value at Risk and Conditional Value at Risk,[1] and extreme movements in asset prices by incorporating extreme value theory (EVT)[2] and a copula method to address extreme value dependence in a multivariate framework (Wang et al., 2010).

Our research contributes to the literature in several ways. First, we look into the diversification benefits of using a clean energy equity index (i.e., a proxy for a green asset) in a well-diversified portfolio. We have applied four different portfolio allocation techniques: an equally weighted portfolio, a certainty equivalence tangency (CET) portfolio, and minimum-variance and global minimum variance (GMV) portfolios. Our portfolio allocation techniques are based on Markowitz's (1952, 1999) theory that considers expected mean return and risk for portfolio diversification. The four distinct portfolio allocation techniques provide the novelty in our results. Following Wang et al. (2010) and Sahamkhadam et al. (2018), we use the GARCH-EVT-copula model to forecast returns and volatilities. Unlike previous works, we employ simulated returns for the equally weighted, minimum-variance, CET, and GMV portfolios. Our study is a novel attempt to incorporate a clean energy index in portfolio formation to understand how its inclusion may offer diversification benefits and reduce portfolio risk. Adding the clean energy index to the portfolio reduces risk significantly in almost all models. The results have practical implications for the fund management industry, providing insights into how adding clean or green assets into the portfolio substantially reduces risk. The efficient frontier constructed from the GMV-CVaR model dominates traditional mean-variance models. Further, we argue that the CVaR is a robust measure to capture the tail risk in the portfolio. Therefore, combined with copulas, risk management based on CVaR yields better insights about the risk embedded in a portfolio, thus extending the literature in a new field of study.

Our paper uses the GARCH-EVT-copula model to develop out-of-sample forecasting allocation for the green asset and diverse asset classes such as gold, crude oil, the US dollar, and three-month Treasury bill. We have some interesting results. First, the results provide evidence that the GMV portfolio outperforms equal-weighted, minimum-variance and CET portfolios in risk measures. Second, backtesting evidence shows that the clean energy fund portfolio performs better than the benchmark for short horizons. Finally, our results are robust to alternative specifications, sub-sample analysis, and inclusion of additional traditional financial assets. The results have implications for fund managers and policymakers and help in better implementing the Social Development Goals (SDGs).

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the methodology. Section 4 provides a detailed description of the data. Section 5 presents the results of the analysis. Section 6 discusses the robustness of the findings. Section 7 concludes.

2. Literature review

VaR and CVaR have frequently been used to measure downside risk (Gencay and Selçuk, 2004), mainly to estimate the potential loss at a specified confidence level. Further, GARCH models are used when financial asset returns exhibit a fat-tailed distribution (De Bondt and Thaler, 1985; Müller et al., 1997; Müller et al., 1998; Harmantzis et al., 2006; Crato and Ruiz, 2012). The Extreme Value Theory (EVT) is better suited for extreme value forecasting when combined with GARCH models (Bali, 2003; Gençay and Selçuk, 2006; Ergen, 2015). This notion has found support in the literature (e.g., McNeil and Frey, 2000; Chan and Gray, 2006; Bhattacharyya and Ritolia, 2008; Bhattacharyya et al., 2009; Deng et al., 2011; Zhao et al., 2011). Moreover, combined GARCH-EVT-copula models are better suited for measuring downside risk.

In addition, in financial markets, the prices of assets tend to affect each other (Engle and Kroner, 1995; Christoffersen et al., 2014; Banerjee, 2021), which offers flexibility in modelling the dependency structures using different frameworks to match other asset classes. As proposed by Sklar (1959), copulas have demonstrated their practicality in assessing correlations among assets. For example, Wang et al. (2010) found that the Student's *t* copula yields better estimates than Gaussian and Clayton copulas (Huang et al., 2009). Employing a combination of dynamic conditional correlation and EVT, Berger (2013) reported that the risk of a portfolio was better estimated against VaR with a static copula. Koliai (2016) used a semiparametric GARCH-EVT-copula model to stress-test portfolios and found that using an array of models affected the results of the stress scenarios. Using Kakouris and Rustem's (2014) framework, Han et al. (2017) reported that the worst-case CVaR model performs better for out-of-sample tests. Deng et al. (2011) used the copula-GARCH-EVT-CVaR model to optimise Chinese stock portfolios. They reported that the Student's *t* copula enhanced portfolio performance more than other copulas. Further, Alexander and Baptista (2004) compared the performance of risk measures using VaR and CVaR in portfolio optimisation and found that CVaR is more efficient than VaR as a risk management tool.

In contrast, Alexander et al. (2006) analysed the CVaR minimisation problem regarding derivative portfolios. Yu et al. (2009) studied three Chinese stock indices as part of a portfolio by introducing a variance gamma copula. They demonstrated that a standard Gaussian copula could not capture asset returns' excess skewness and kurtosis and that the variance gamma is a viable alternative.

Several competing copula models have been introduced and tested to forecast VaR and CVaR, including a regular vine, a canonical vine, and a drawable vine copula. Zhang et al. (2014) reported that a drawable vine copula is a better alternative to other vine copulas for forecasting CVaR. Bhatti and Nguyen (2012) applied conditional EVT and time-varying copulas to model tail dependency. They showed that the EVT–copula combination is critical to analyse tail dependence, which is vital to portfolio allocation.

[1] Generally, investors show greater concern about downside risks than about upside gains. To accommodate such asymmetry in risk, different risk measures were developed, such as lower semi variance, value at risk (VaR), and conditional VaR (CVaR). Among these risk measures, the most common is CVaR (see Rockafellar and Uryasev, 2000). CVaR provides a measure of the potential losses beyond a given threshold at a given instant in time, particularly when applied to non-normal asymmetric data, thereby emphasising the assessment of downside risk CVaR is advantageous for risk diagnosis because it is a coherent measure that considers the size and probability of loss, compared to VaR (Chen et al., 2012). CVaR has become the popular choice for portfolio risk assessment and optimisation (Akhtaruzzaman et al., 2022a,b; Kolm et al., 2014; Thampanya et al., 2020).

[2] The characteristics of VaR and CVaR capture rare events in the tails of distributions with low probabilities. At the same time, EVT directly addresses tails and is superior in estimating and forecasting risk. However, care must be exercised since the assumption of a Gaussian distribution for the returns series does not fit the EVT framework. We applied the generalised autoregressive conditional heteroscedasticity (GARCH) process to measure volatility following Huynh et al. (2022), McNeil and Frey (2000), and Frey and McNeil (2002). We use EVT for the innovation terms instead of the return series from the GARCH model. GARCH-EVT models marginal distributions, while extreme value copulas capture the multivariate dependence appropriate for non-Gaussian and nonlinear distributions (Jondeau et al., 2007; Patton, 2009).

The GARCH-EVT-copula model is primarily used for forecasting or analysing downside risk, although several studies have also explored its application in risk modelling, portfolio allocation, and backtesting. Low et al. (2013) used a Clayton canonical vine copula to test portfolio performance conditional upon minimising the CVaR. They reported that the models are efficient and appropriate for coping with higher numbers of assets in a portfolio. Cui et al. (2023) reinforced similar results by studying the cryptocurrency market and showed that CVaR outperforms the traditional portfolio-constructing techniques. The literature review reveals a void in the literature examining the impact of an alternative asset like green assets and its diversification benefits using copula-based VaR and CVaR models, even though past studies looked into the diversification benefits in other asset classes (Fonseca and Rustem, 2012; Karmakar and Paul, 2019; Topaloglou et al., 2020). In this paper, we extend the literature by examining the diversification benefits of a clean energy fund using copula-based VaR and CVaR models.

3. Methodology

This section discusses the GARCH-EVT-copula approach and introduces some copula models. It also presents the maximum likelihood estimation (MLE) and portfolio risk analysis techniques.

3.1. Tail behaviour

The tail behaviour of asset returns is modelled using EVT since EVT can be adapted to capturing extreme events. We use the peak over the threshold to compute extreme values since it was found suitable for financial time series when it is combined with standard GARCH (1,1) models. The error terms of the returns ($X = (x_1 \ldots\ldots x_n)$) are *iid*. The excess distribution $\mathscr{F}(x)$, representing the probability that the vector of errors exceeds a given level, say, u, is fitted by a generalised Pareto distribution (GPD) to adapt the *maximum likelihood* approach for the tail estimates. The distribution is represented as

$$\mathscr{F}(z) = \begin{cases} \frac{N_{u^L}}{N}\left\{1+\xi^L\frac{u^L-z}{\beta^L}\right\}^{-1/\xi^L} z<u^L \\ \varnothing(z), u^L<z<u^R \\ 1-\frac{N_{u^R}}{N}\left\{1+\xi^R\frac{u^R-z}{\beta^R}\right\}^{-\frac{1}{\xi^R}} z>u^R \end{cases} \tag{1}$$

where ξ, β, u^L, and u^R are the scale, shape, and lower and upper thresholds, respectively (Coles et al., 2001; De Haan et al., 2006; Embrechts et al., 2013a, 2013b). Further, a GARCH (1,1) framework is utilised, and then extreme value theory (EVT) is applied to the vector X (McNeil and Frey, 2000; McNeil et al., 2015).

The assumption that the conditional variance following a GARCH (1,1) model is based on past literature (see Kim and Jung, 2016; Pircalabu et al., 2017; Sahamkhadam et al., 2018; Banerjee et al., 2020; Zhi et al., 2021). The return and GARCH (1,1) can be modelled as

$$r_t = \mu_t + \varepsilon_t \tag{2}$$

where $\varepsilon_t = z_t\sqrt{h_t}$, while $z_t \approx$ (i.i.d.); basically, z_t is the standardised residuals and h_t is the conditional variance of ε_t. Further h_t is presented as

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{3}$$

where $\omega > 0$, and the volatility parameters are imposed with the following restrictions ($\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$).

3.2. The copula function and models

According to Sklar (1959), for an n-dimensional distribution with continuous margins $\mathscr{F}_1, \mathscr{F}_2 \ldots\ldots\ldots\ldots \mathscr{F}_n$ a n-dimensional copula exists as

$$\mathscr{F}(x_1 \ldots . x_n) = C(\mathscr{F}_1(x_1), \ldots .. \mathscr{F}_n(x_n)) \tag{4}$$

where C is the copula that is distinctively established in $[0,1]^n$ for $\mathscr{F}$ by

$$C(\varepsilon_1, \varepsilon_2, \ldots\ldots\ldots \varepsilon_n) = \mathscr{F}\left(\mathscr{F}^{-1}(\varepsilon_1), \mathscr{F}^{-1}(\varepsilon_2) \ldots\ldots., \mathscr{F}^{-1}(\varepsilon_n)\right) \tag{5}$$

for all $\varepsilon_i \in [0,1], i = 1,2,\ldots,n$, and $\mathscr{F}^{-1}$ is the inverse cumulative distribution (*icd*) of a standard Gaussian.Further, the density functions of $\mathscr{F}$ and C are

$$f(x_1, \ldots\ldots\ldots. x_n) = c(\mathscr{F}_1(x_1) \ldots\ldots\ldots. \mathscr{F}_n(x_n)) \prod_{i=1}^{n} f_i(x_i) \tag{6}$$

$$c(u_1, \ldots\ldots\ldots, u_n) = \frac{f\left(\mathscr{F}_1^{-1}(u_1), \ldots\ldots\ldots., \mathscr{F}_n^{-1}(u_n)\right)}{\prod_{i=1}^{n} f_i\left(\mathscr{F}_i^{-1}(u_i)\right)} \tag{7}$$

where f_i and $\mathscr{F}_i^{-1}$ are the marginal densities and the functional quantile margins- While the density of the Gaussian copula is presented as

$$c(u;R) = \frac{1}{|R|^{1/2}} e^{-\frac{u'(R^{-}-I)u}{2}} \tag{8}$$

where the correlation matrix (R) inferred by, $u_i = \mathscr{F}(x_i)$, and identity matrix (I). The corresponding density of the Student's t copula with shape parameter τ is

$$c(u;R,\tau) = \frac{\Gamma\left(\frac{\tau+n}{2}\right)\left(\Gamma\left(\frac{\tau}{2}\right)\right)^n\left(1+\tau^{-1}u'R'u\right)^{-\left(\frac{\tau+n}{2}\right)}}{|R|^{1/2}\left(\Gamma\left(\frac{\tau+n}{2}\right)\right)^n\Gamma\left(\frac{\tau}{2}\right)\prod_{i=1}^{n}\left(1+\frac{u_t^2}{\tau}\right)^{-\left(\frac{\tau+1}{2}\right)}} \tag{9}$$

where $u_i = t_\tau^{-1}(\mathscr{F}(x_i;\tau))$ and $t_\tau^{-1}$is the quantile function in the density function (Ghalanos, 2015; Kim and Jung, 2016).

We further show the estimation procedure for each copula. Let the standardised multivariate normal version be given as $\phi_{\sum}$, with $\sum t$ (correlation matrix). The Gaussian copula can be written as

$$C^{Gaussian}(\varepsilon_1, \varepsilon_2, \ldots\ldots\ldots \varepsilon_n) = \phi_{\sum}\left(\phi^{-1}(\varepsilon_1), \phi^{-1}(\varepsilon_2) \ldots\ldots\ldots, \phi^{-1}(\varepsilon_n)\right) \tag{10}$$

where ϕ^{-1} is the *icd* function. From Eq. (1), we know that the marginal distribution is $\mathscr{F}(z)$. Based on the historical values of $(\varepsilon_1 \ldots\ldots\ldots\ldots \varepsilon_1)$, we obtain

$$u_t = (u_1, u_2 \ldots\ldots\ldots\ldots\ldots u_n) = (\mathscr{F}_1(z_1) \ldots\ldots\ldots. \mathscr{F}_n(z_n)) \tag{11}$$

where $\xi_t = \phi^{-1}(u_1)$ and $\phi^{-1}(u_2) \ldots\ldots\ldots$, $\phi^{-1}(u_n)$. Thus, we obtain $C^{Gaussian}(u_t) = \phi_{\sum}(\xi_t)$, and, using MLE, we estimate $\sum$.

We introduce the Student's t copula to capture the fat tail property since it is better adapted to capturing extreme events than the Gaussian copula. Let $t_{\upsilon,\sum}$ be the standardised multivariate version with $\sum$as the correlation matrix and υ the number of degrees of freedom. Then the t copula can be expressed as

$$C^t(\varepsilon_1, \varepsilon_2, \ldots\ldots\ldots \varepsilon_n) = t_{\upsilon,\sum}\left(t_\upsilon^{-1}(\varepsilon_1), t_\upsilon^{-1}(\varepsilon_2) \ldots\ldots\ldots, t_\upsilon^{-1}(\varepsilon_n)\right) \tag{12}$$

where t_υ^{-1} is the i Student's t *icd* function. From Eq. (1), we know that the marginal distribution is $\mathscr{F}(z)$. Based on the historical values of $(\varepsilon_1 \ldots\ldots\ldots\ldots \varepsilon_n)$, we obtain $u_t = (u_1, u_2 \ldots\ldots\ldots\ldots\ldots u_n) = (\mathscr{F}_1(z_1) \ldots\ldots\ldots. \mathscr{F}_n(z_n))$. We then have $\varsigma_t = t_\upsilon^{-1}(u_1), t_\upsilon^{-1}(u_2) \ldots\ldots\ldots$, $t_\upsilon^{-1}(u_{n.})$

Thus, we obtain $C^t(u_t) = t_{\upsilon,\sum}(\varsigma_t)$, and, using MLE, we estimate the matrix $\sum$.

3.3. MLE

The copula consists of multiple integrals in $u_j \in [0,1], \forall j$ (Eq. (4)):

$$C(u_1, u_2, \dots, u_n) = \int_0^{u_j} \dots \int_0^{u_n} \frac{\partial^n C(z_1, \dots, z_n)}{\partial z_1, \dots, \partial z_n} dz_1, \dots, dz_n = \int_0^{u_j} \dots \int_0^{u_n} c(z_1, \dots, z_n) dz_1, \dots, dz_n \quad (13)$$

The copula density in the interior $(u_1, \dots, u_n)^T \in]\,0, 1[^n$ is defined as

$$c(u_1, \dots, u_n) = \frac{\partial^n C(u_1, \dots, u_n)}{\partial u_1, \dots \dots \partial u_n} \quad (14)$$

The parameter of copula, which is a generic vector Ω represented as Eq. (4) in the multivariate form as:

$$\forall_z \in R^n : \mathscr{F}(z_1, z_2, \dots, z_n) = (C(\mathscr{F}_1(z_1), \mathscr{F}_2(z_2), \dots, \mathscr{F}_n(z_n) \,|\Omega) = C(u_1, u_2, \dots, u_n|\Omega) \quad (15)$$

By differentiating the copula, we obtain the density function:

$$C\left((u_1, u_2, \dots, u_n|\Omega) = \frac{\partial^n C(u_1, \dots, u_n)}{\partial u_1, \dots \dots \partial u_n}\right) \quad (16)$$

Eq. (15) on differentiation and using Eq. (16) obtains the density functions:

$$\forall_z \in R^n : \frac{\partial^n \mathscr{F}(z_1 z_2 \dots \dots \dots z_n)}{\partial z_1, \dots \partial z_n} = f(z_1, \dots, z_n) = \frac{\partial^n C(\mathscr{F}_1(z_1), \mathscr{F}_2(z_2), \dots, \mathscr{F}_n(z_n)\Omega}{\partial z_1, \dots, \partial z_n} = C(\mathscr{F}_1(z_1), \mathscr{F}_2(z_2), \dots, \mathscr{F}_n(z_n)\Omega) \prod_{j=1}^{n} f_1 z_j \quad (17)$$

where f_j denotes the derivative of $\mathscr{F}_j$ with respect to z_j; f_j is the jth density function. Further, following Sklar (1959), the log-likelihood is yielded by Eq. (17) as:

$$l(z_1, z_2, \dots, z_n) = \sum_{i=1}^{n} log(c(\mathscr{F}_1(z_{i1}), \mathscr{F}_1(z_{i2}), \dots, \mathscr{F}_d(z_{in})\Omega)) \prod_{j=1}^{n} f_i z_{ij} = \sum_{i=1}^{n} \left[log(c(\mathscr{F}_1(z_{i1}), \mathscr{F}_2(z_{i2}), \dots, \mathscr{F}_d(z_{id})\Omega)) + log(f_1 z_{ij}) \right] \quad (18)$$

3.4. Portfolio analysis

Markowitz's (1952, 1999) theory considers the expected mean return and risk important for portfolio diversification. However, based on the classical framework, the literature has explored improving the portfolio allocation, starting from the naïve allocation–based equi-proportional allotment (DeMiguel et al., 2009) to the models suggested by Sharpe (1963, 1994) and Merton (1980). This paper uses different portfolio allocations to understand portfolio risk metrics, where a clean energy fund is a portfolio's core component. We use four different allocation techniques, and the details of each of them are provided in the following.

First, for an n-dimensional portfolio with asset returns $r_t = (r_{1,\dots\dots}, r_n)$ and with asset weights as returns $w_t = (w_{1,\dots\dots}, w_n)$ and $\sum$ the covariance matrix, the portfolio return and risk are measured by $w_t^T r_t$ and $w_t^T \sum w_t$, respectively. For the case of the equal-weighted portfolio, we impose $w_t = (\frac{1}{n}, \dots, \frac{1}{n})$, that is, equal weights to all the assets under consideration. Second, the certainty equivalence tangency (CET) with the imposition of maximisation of the Sharpe (1963) ratio could be written as

$$Maximise_{w_t} \frac{w_t^T r_t}{\sqrt{w_t^T \sum w_t}}$$

subject to

$$\{w_t^T 1 = 1 \text{ for all } (1, 2, \dots, n) \quad (19)$$

$w_t \geq 0$ only for long positions}

Third, we use the optimisation technique proposed by Merton (1980). The global minimum variance (GMV) minimises the variance instead of maximising the expected return. The GMV model can be expressed as

$$Minimise_{w_t} \frac{w_t^T r_t}{\sqrt{w_t^T \sum w_t}}$$

subject to

$$\{w_t^T 1 = 1 \text{ for all } (1, 2, \dots, n) \quad (20)$$

where $w_t \geq 0$ only for long positions}

Finally, prior literature has used downside risk as a yardstick for optimality in portfolio allocation. For example, the risk measure (VaR) is combined with Markowitz's portfolio, to get optimality in mean–VaR portfolio (Consigli, 2002). However, the modification to VaR to minimise losses beyond the VaR led to the development of the CVaR (Xu et al., 2016). The integration form of CVaR (see Rockafellar and Uryasev, 2000) is as follows:

$$Minimise_{w_{t,\alpha}} f(w_t, \beta) = \alpha + \frac{1}{q(1-\beta)} \times \sum_{k=1}^{q} \left[-w_t^T r_t - \alpha \right]^+$$

subject to

$$\{w_t^T 1 = 1 \text{ for all } (1, 2 \dots . n) \quad (21)$$

$w_t \geq 0$ only for long positions

$\mu(w_t) \leq -R\}$

3.5. Algorithm

We define the parameters in this section: L is the window length, t_0 is the initiation of iterations, T is the interval length, and K is the number of samples for each iteration $[t_0 + 1, T]$. Using a rolling window view, steps 1 through 8, as explained below, are replicated for each time point $[t_0 + 1, T]$ during the iteration. Initial observations are required for one-step-ahead out-of-sample forecasting at $t_0 + 1$, which is $[t_0 - L + 1, t_0]$, and followed by $[t_0 - L + 2, t_0 + 1]$. Initially, t_1 is equal to t_0. The entire algorithm can be explained as follows:

i. Eqs. (2) and (3) are used to estimate the GARCH (1,1) parameters with MLE, and the standardised residuals are then obtained: $\widehat{x}_j = (\widehat{x_1}, \widehat{x_2}, \dots, \widehat{x_n})$ for $\widehat{x}_j \approx i.i.d. \forall j\ (1, 2, \dots, n)$, where

$$t \in [t_0 - L + 1, t_0] \quad (22)$$

ii. The standardised residuals estimated from step (i) comprise a vector $\widehat{x}_t$, which is further used to calculate the upper and lower tails and centre of the Gaussian kernel distribution as the GPD in Eq. (1):

$$\widehat{v_j} = \widehat{\mathscr{F}_k(\widehat{x}_j)}, t \in [t_0 - L + 1, t_0], j \in [1, n], \text{where } v_t \sim \widehat{U(0, 1)} \quad (23)$$

iii. Sklar's theorem is applied as in Eq. (4), and estimated uniforms $\widehat{v}_j$ are inserted, following step (ii). The parameter Ω is approximate using the MLE provided in Eq. (18) for the Gaussian (Eq. (11)) and Student's t (Eq. (12)), with $\Omega = \Sigma$:

$$\widehat{\mathscr{F}}(\widehat{v_1}, \widehat{v_2}, \ldots, \widehat{v_n}) = \widehat{C}\left(\widehat{\mathscr{F}_1}(\widehat{v_1}), \widehat{\mathscr{F}_2}(\widehat{v_2}), \ldots, \widehat{\mathscr{F}_n}(\widehat{v_2}) \,|\widehat{\Omega}\right) \tag{24}$$

iv. We generate K uniform random numbers $(w_1, w_2, \ldots, w_i), \forall i = 1, \ldots, K$, for individual series $j = 1, \ldots, n$, which we use to estimate the multivariate copula distribution in step (iii) to get K uniforms with a dependency structure:

$$\widehat{u_j} = (\widehat{u_1}, \widehat{u_2}, \ldots, \widehat{u_n}) = C(\widehat{\mathscr{F}_1}(w_1), \widehat{\mathscr{F}_2}(\widehat{w_2}), \ldots, \widehat{\mathscr{F}_n}(w_n) \,|\widehat{\Omega}), \widehat{u_j} \sim U(01) \tag{25}$$

v. To recalculate the new standardised residuals portfolio optimisation, the simulated uniform random numbers of step (iv) are fed into the inverse to derive the marginal distribution functions of step (iii):

$$\widehat{Z} = [\widehat{z_i}] = (\widehat{z_1}, \widehat{z_2}, \ldots, \widehat{z_n}) = \left(\widehat{\mathscr{F}_1^{-1}}(\widehat{u_1}), \widehat{\mathscr{F}_2^{-1}}(\widehat{u_2}), \ldots, \widehat{\mathscr{F}_n^{-1}}(\widehat{u_n})\right) \tag{26}$$

vi. The residual vectors $\widehat{Z}$ from step (v) are replaced in the GARCH framework to generate the forecasting model. We estimate K one-step forecasts for time instant $t = t_0 + 1$:

$$\widehat{r_t^i} = \left(\widehat{r_{t,1}^1}, \widehat{r_{t,2}^2}, \ldots, \widehat{r_{t,n}^k}\right) \tag{27}$$

vii. The forecasted returns from step (vi) are used for optimisation is described in Section 3.4 to obtain the optimal weights (w_t) for the CET, min-variance, GMV and equally weighted portfolios.

The optimal weights and real asset returns are used for calculating the portfolio return $R_t = w_t^T r_t$.

4. Data description

The sample used in our study for portfolio formation consists of the daily prices of the First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN),[3] gold, crude oil, the US dollar, and a three-month Treasury bill. Following the literature, we use QCLN as a proxy for a green asset (Rizvi et al., 2021). We also use the daily prices of the S&P 500 index against which to test the portfolio's performance. The data are collected from Refinitiv Datastream. The sample starts on 1 December 2006, coinciding with the introduction of the clean energy index, and ends on 8 March 2022. Following Sahamkhadam et al. (2018) and Karmakar and Paul (2019), we use a rolling window for the prediction.

Table 1 presents descriptive statistics. Crude oil appears to have the highest mean return, while the T-bill has the lowest mean return during the sample period. Since T-bill is a risk-free asset, the T-bill has the lowest risk as measured by standard deviation. Skewness deviates from zero, implying a skewed distribution of returns. The skewed distribution in the return of financial assets is widespread in the literature (see Akhtaruzzaman et al., 2021a; Akhtaruzzaman et al., 2021b; Akhtaruzzaman et al., 2022b; Akhtaruzzaman et al., 2022c; Banerjee et al., 2022; Siddique et al., 2021). The kurtosis value is more than three in all the series, implying that return series have fat tails and deviate from the normal distribution. Jarque–Bera's test confirms the non-normality for all the series.

Table 1
Descriptive statistics.

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Green asset	0.00031	0.02129	−0.47040	5.84230	5811***
T-bill	0.00003	0.00006	3.74778	18.65866	67102***
Gold	0.00029	0.01098	−0.47222	6.28564	6705***
Crude oil	0.00035	0.02758	0.59681	20.44847	69630***
US Dollar	0.00004	0.00468	−0.06434	2.79459	1299***

*** Denotes the statistical significance at the 1% level.

5. Empirical results

In the first step, we calibrate the volatility model parameters over the in-sample period. We estimate the model for each combination of different assets (i.e., the Clean Edge Green Energy Index Fund, gold, crude oil, the US dollar, and three-month Treasury bill) in the portfolios. Table 2 reports GARCH (1,1) parameters that are significant at appropriate levels, indicating that innovation terms follow Student's *t*-distribution. We extract the filtered residuals individually using the GARCH (1,1) model to construct the marginals and utilise the cumulative density function for the interior and the GPD to fit the upper and lower tails, as shown in Eq. (1). The benefit of this methodology is that the *iid* notion for EVT is least likely to be violated. We then use a GARCH-EVT model to define the marginal distribution for the innovations under the assumption that the conditional distribution of the residuals of the GARCH (1,1) model follows the Student's *t* distribution.

Further fitting the GPD requires defining a threshold value (Wang et al., 2010). We set the threshold at 10% and estimate the copula parameters. We apply two different copula forms, the Gaussian and Student's *t*, following Wang et al. (2010). Once the copula function is fitted, the distribution of the residuals for any marginals or dependency structure is generated (step (iv) in the algorithm). We then simulate 10,000 uniform random numbers and feed them into the inverse function of the marginals for each series (*step (v)*). Once the returns are obtained, we estimate the optimal weight for the portfolios using four different methods: equal weighting, minimum-variance, CET, and the GMV. Following a rolling window approach, we reiterate the out-of-sample period procedure and backtest the portfolio's performance against the benchmark.

Following the procedure above, we estimate the VaR and CVaR for the simulated innovations obtained from following the Gaussian and then the Student's *t* copula forms, keeping the window fixed at the 99th percentile. The estimation procedure is rolled over to compute the next interval's VaR and CVaR. Figs. 1 and 2 present the tail probabilities and profile likelihood curves for the equally weighted and GMV portfolio estimators. The results for the four distinct weight allocations for the GARCH-EVT-Gaussian and GARCH-EVT-Student's *t* copulas are presented in Table 3. The GARCH-EVT-Student's *t* copula model performs

Table 2
Results of GARCH (1,1) Estimation.

	ω	α	β
Green asset	0.0335***	0.0916***	0.9047***
T-Bill	0.0020***	0.0954***	0.8737***
Gold	0.0063***	0.0346***	0.9623***
Crude oil	0.0725***	0.0896***	0.9013***
Dollar	0.0006***	0.0381***	0.9591***

Notes: The return and GARCH (1,1) can be modelled as

$$r_t = \mu_t + \varepsilon_t \tag{2.}$$

where $\varepsilon_t = z_t\sqrt{h_t}$, while $z_t \approx (i.i.d.)$; z_t is the standardised residuals and h_t is the conditional variance of ε_t. Further h_t is presented as

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{3a}$$

where the parameter restrictions are $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$.
*** Denotes the statistical significance at the 1% level.

[3] Several studies used QCLN as a green asset (see Miralles-Quirós and Miralles-Quirós, 2019; Naqvi et al., 2022)

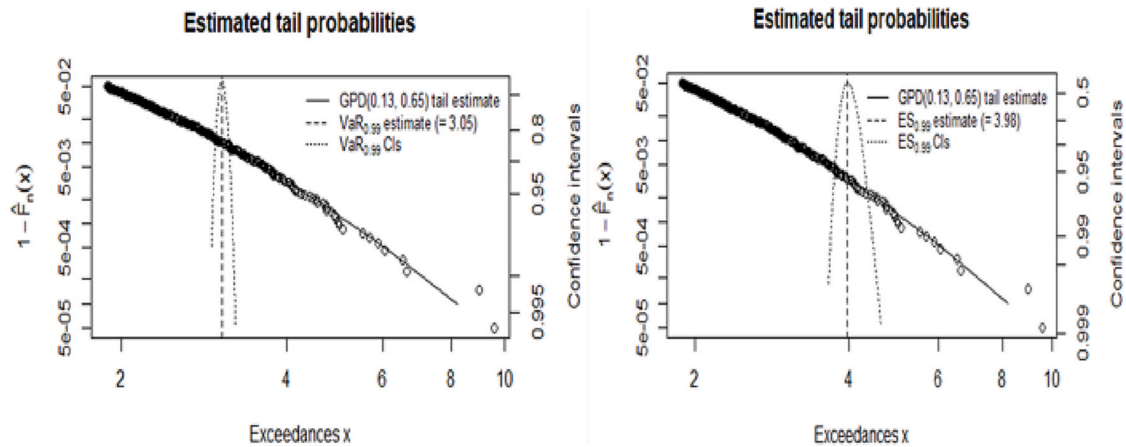

Fig. 1. The tail distribution and the profile likelihood curve for an equally weighted portfolio.
The first (second) graph presents the estimated tail probabilities of VaR (CVaR) at the 99% confidence interval. The tail distribution is for an equally weighted portfolio.

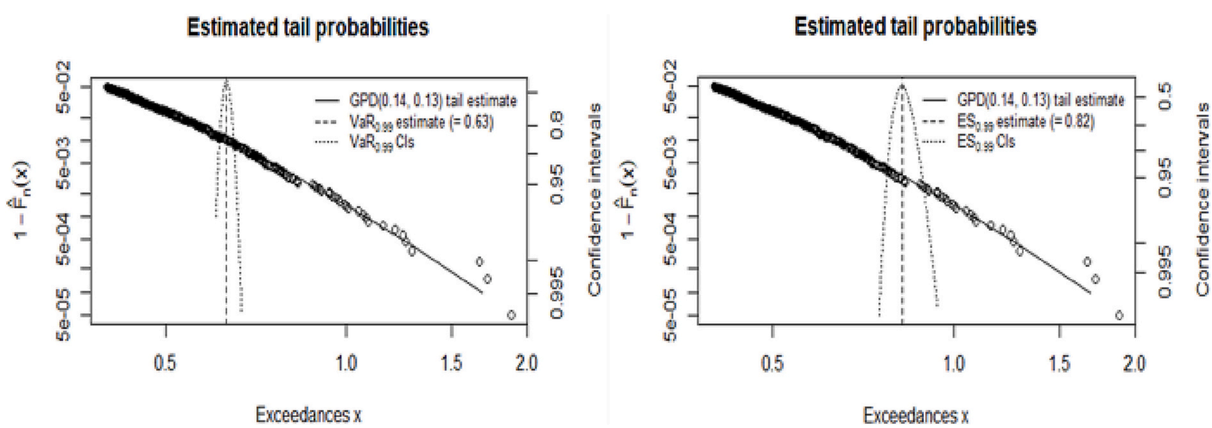

Fig. 2. The tail distribution and the profile likelihood curve for a Global Minimum Variance (GMV) portfolio.
The first (second) graph presents the estimated tail probabilities of VaR (CVaR) at the 99% confidence interval. The tail distribution is for a GMV portfolio.

Table 3
Portfolio risk calculated based on different apportionment techniques.

Model	Distribution	Equally weighted			Min-Variance			GMV			CET		
		P	*Q*	*ES*	*P*	*Q*	*ES*	*P*	*Q*	*ES*	*P*	*Q*	ES
GARCH-EVT-Copula VaR	Gaussian	99%	3.0152	3.5645	99%	0.9251	1.2349	99%	0.5862	0.7852	99%	2.1355	3.0694
GARCH-EVT-Copula CVaR	Gaussian	99%	3.1507	3.9728	99%	1.1051	1.5193	99%	0.7156	0.9746	99%	3.5230	4.9205
GARCH-EVT-Copula VaR	Student's *t*	99%	3.0512	3.9802	99%	1.1892	1.2436	99%	0.6313	0.8194	99%	1.8179	2.4629
GARCH-EVT-Copula CVaR	Student's *t*	99%	3.1367	4.0311	99%	1.2752	1.5792	99%	0.6376	0.8210	99%	2.8486	3.5297

The VaR and CVaR are estimated post modelling the dependence structure using GARCH-EVT-Copula model. *P*, *Q*, and *ES* denote percentile, quantile threshold potential loss, and the expected shortfall, respectively.

better than the GARCH-EVT-Gaussian copula at the 99th percentile, supporting the findings of Sahamkhadam et al. (2018) and Wang et al. (2010). The GMV model has the lowest VaR and CVaR at the 99th percentile, indicating the lowest portfolio risk among the four models. Hence, the GMV model outperforms equal-weighted, min-variance and CET portfolios in downside risk measures.

Our results are consistent with those of Stoyanov et al. (2013), who investigated the response of the CVaR to the tail's thickness, and with those of Karmakar and Paul (2019), who find that the component GARCH-EVT-Copula model predicts downside risks more accurately than other models. As the findings of Stoyanov et al. (2013), we show that CVaR is less responsive to small differences in the tail index. Further, the results corroborate the scope of improvement over the minimum-variance portfolio. The results show that there is space to improve the CVaR of the minimum-variance portfolio as the minimum-variance portfolio CVaR may not be the least, as witnessed in the GMV portfolio CVaR values. As shown by Karmakar and Paul (2019), we find that the GARCH-EVT-Student's *t* copula model performs better than other models in predicting downside risk measures.

Backtesting ensures the model's robustness when the data are heavy-tailed. When portfolio managers closely monitor prices and frequently rebalance their portfolios, non-Gaussian data becomes problematic. Hence, it requires sophisticated techniques to handle non-Gaussian data to yield an efficient portfolio. However, when the frequency of rebalancing is increased, the marginal benefits of using complex modelling diminish as asymmetry and non-normality decrease, making investments in sophisticated computations less attractive. However, the literature has challenged the traditional outlook towards risk using VaR in the current environment (Dionne et al., 2009; Dionne et al., 2015). Hence, to examine the rebalancing strategies, we modify the de Melo Mendes and Marques (2012) model to varying frequencies and target risk tolerances, with one, three, and six months and one year. We used a 12-month rolling window strategy with monthly intervals. Backtesting of the portfolio considered the performance, including the clean energy fund and its robust performance compared to the S&P 500 benchmark index. Portfolio optimisation is pursued on all the different methods. Table 4 presents the results from the GMV model. The results demonstrate that the GMV portfolio outperforms the S&P500 benchmark index for the short horizons. These results support the findings of de Melo Mendes and Marques (2012) that the marginal benefit of portfolio rebalancing is best reflected when the rebalancing is conducted once after three months but within six months period to avail better portfolio return against the benchmark.

Fig. 3 provides the weights recommendation and rebalance from the GMV model over the sample period while Fig. 4 shows the drawdown risk of the portfolio against the benchmark. The results show that the portfolio constructed from the GMV model has less drawdown risk than that of the benchmark. The results provide newer insights into the benefits of portfolio diversification using clean energy funds and risk-mitigating properties. The results may excite the fund management industry and portfolio managers. The inclusion of green assets in the portfolio creates opportunities for better performance and potential gains for the large financial institution with risk mitigation, hence demanding the exploration of a newer asset class for eventual gains as measured by the CVaR model.

6. Robustness

To check the robustness of our results, we applied alternative specifications, a sub-sample analysis, and inclusion of additional diverse assets in the portfolio. First, we tested all the models using the dynamic quantile (*DQ*) test of Engle and Manganelli (2004), following Chen et al. (2012), against the conditional coverage (CC) of Christoffersen (1998) and unconditional coverage (UC) of Kupiec (1995). We performed Engle and Manganelli's (2004) *DQ* test with four lags ($q = 4$) for this paper. However, we ran the test for $q = 1$, 2, and 3 and found minimal sensitivity to the selection of q. The test results support our earlier results at a 1% significance level (*DQ* test statistics = 39.9676, p-value = 0.0000), providing additional validity to our backtesting results. Second, we divided the sample into pre-COVID–19 (1 December 2006–30 December 2019) and COVID–19 (1 January–31 March 2020) periods to check whether the results differ in tranquil and turmoil periods.[4] The results for the sub-sample analysis remained qualitatively similar, and the portfolio containing a green asset during the COVID–19 period aided in better performance (See Appendix Table A1). Third, we have extended the portfolio by adding a real estate index and Dow Jones Industrial Average (DJIA) index to check the robustness. The addition of the newer assets into the portfolio has not changed the dynamics of the results (see Appendix Table A2 for the details).

Table 4
Net performance of the portfolio against the benchmark index.

	1-month	3-month	6-month	1-year
Portfolio	2.64	4.47	6.11	7.30
Benchmark	0.88	2.70	8.00	11.33

The portfolio and benchmark (S&P500 index) returns are expressed in percentages. The performance is evaluated based on the rolling window estimates for the GMV portfolio.

7. Conclusion

Our study uses four optimisation processes, namely, equally weighted, minimum-variance, GMV, and CET to optimise our portfolios. We aim to provide guidance to portfolio managers on when to implement the robust tail and dependence models. Our findings indicate that portfolios utilising the GARCH-EVT-Student's t-copula-CVaR model perform better than those using the VaR model. Thus, the results incentivise fund managers to review and rebalance portfolios over periods. Portfolio managers could be incentivised to employ a GARCH-EVT-copula-CVaR model better to understand portfolio formation and its risk–return characteristics. In addition, the robustness tests validate that the empirical findings are robust to alternative specifications, subsample analysis, and the addition of assets to the portfolio. Our findings show that the inclusion of clean energy funds in portfolios is beneficial for diversification. As a result of the low or negative correlation between the clean energy index and other asset classes, clean energy asset offers shelter against price oscillations in these markets. The results also indicate that combining the clean energy index with other asset classes can benefit active investors who actively trade in the short term instead of passive investors who typically invest for the long term. Finally, our findings should also be of interest to policymakers. Given the notable growth of sustainable finance to achieve climate change goals, clean energy funds go a long way towards achieving the goals of clean and green energy. Hence, the intervention of policymakers can aid in further accelerating the pace of development. Furthermore, the accruing diversification benefits of clean energy funds can bolster the confidence of policymakers to scale up the market for clean energy funds to achieve the dualistic goal of commitment to the environment without sacrificing financial or economic growth. Our results promote policies supporting the development of this market.

Our research reveals a wide range of risk management possibilities when addressing portfolio allocation with a variety of clean energy funds, as well as its risk measurement. This incorporates a combination of using expected shortfall (ES) as a complementary measure for VaR or a modified approach of using copulas with ES to revisit risk measurement techniques in portfolio risk management. Future research can be extended to include diverse asset classes to optimise portfolios. For example, researchers can study the use of gray energy instead of green energy in portfolios. In addition, it would be interesting to see if future research examines the net performance of portfolios using modified ES models or algorithmic techniques to broaden the area.

CRediT authorship contribution statement

Md Akhtaruzzaman: Conceptualization, Methodology, Formal analysis, Data curation, Investigation, Writing – original draft, Writing – review & editing. **Ameet Kumar Banerjee:** Conceptualization, Methodology, Formal analysis, Data curation, Investigation, Writing – original draft, Writing – review & editing. **Sabri Boubaker:** Supervision, Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Faten Moussa:** Formal analysis, Methodology, Resources, Validation, Writing – review & editing.

Appendix A. Appendices

[4] Following Albuquerque et al. (2020), we have considered the Quarter 1 of 2020 as the COVID–19 period.

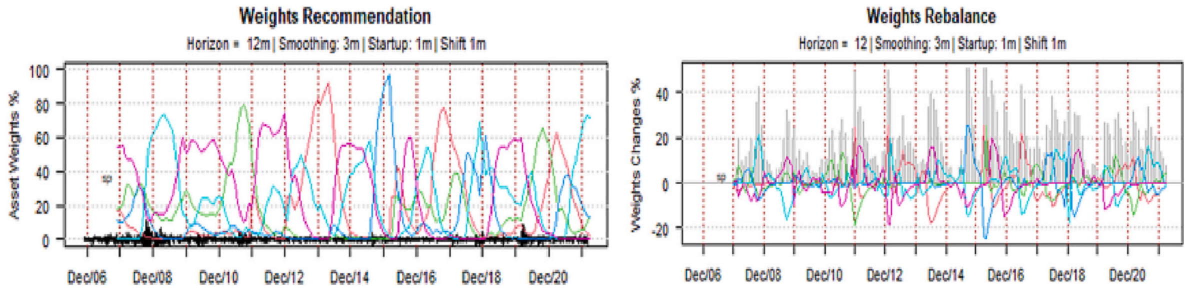

Fig. 3. Weights recommendation and rebalance for the portfolio.
Weights Recommendation graph shows the smoothed recommended weights every month for the next month's investment. The weights rebalance graph shows to which amount the weights were rebalanced using the GMV model. Red, green, pink, black and blue lines represent green assets, gold, crude oil, T-bill, and US Dollar index, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

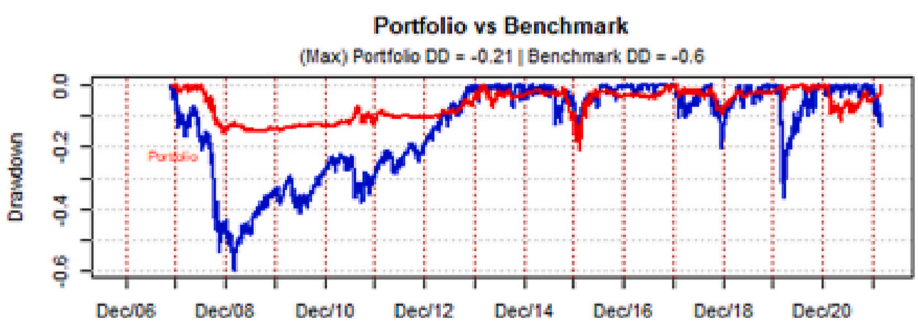

Fig. 4. The backtest plot portfolio vs benchmark.
Drawdowns graph shows the drawdowns of the optimised portfolio using the GMV model at the end of each month in comparison to the benchmark. Red and blue lines represent the optimised portfolio and S&P500 benchmark, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table A1: Net performance of the portfolio against the benchmark index during pre-COVID–19 and the COVID–19 period

	1-month	3-month	6-month	1-year
Panel A: Pre-COVID–19 period (1 December 2006–30 December 2019)				
Portfolio	2.42	4.65	6.43	7.42
Benchmark	0.77	2.28	6.61	9.27
Panel B: COVID–19 period (1 January–31 March 2020)				
Portfolio	2.78	3.86	5.71	6.56
Benchmark	−5.25%	−0.24%	4.94%	13.94%

The portfolio and benchmark (S&P500 index) returns are expressed in percentages. The performance is evaluated based on the rolling window estimates. We used a 12-month rolling window strategy with monthly intervals.

Table A2: Net performance of the portfolio against the benchmark index.

	1-month	3-month	6-month	1-year
Portfolio	2. 32	4.16	6.27	7.38
Benchmark	0.88	2.70	8.00	11.33

The portfolio and benchmark (S&P500 index) returns are expressed in percentages. The performance is evaluated based on the rolling window estimates. We used a 12-month rolling window strategy with monthly intervals. We have added a real estate index and DJIA to the portfolio.

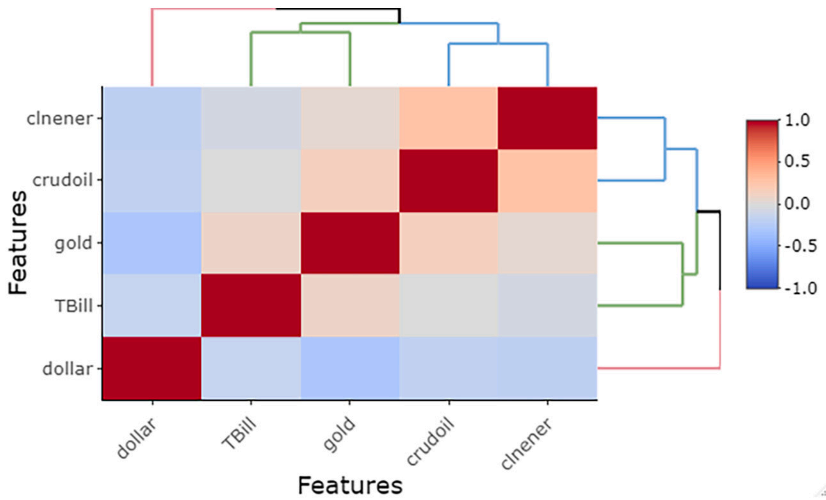

Fig. A1: Correlation heat map.
The figure represents the correlation heat map for Clean Energy, Gold, Crude Oil, T-bill and US dollar returns.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106831.

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