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OPPORTUNITIES IN CLEAN ENERGY EQUITY MARKETS: THE COMPELLING CASE FOR NUCLEAR ENERGY INVESTMENTS

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Abstract. This study analyzes the post-pandemic dynamics and investment potential of diverse clean energy equities, including solar, wind, nuclear, and other renewable assets, highlighting nuanced differences and investment opportunities within this critical sector. The analysis reveals that nuclear energy portfolios (NLR) exhibit notable resilience, sustaining growth amidst significant market volatility. Within the mean-variance portfolio optimization (MVO) framework, this study identifies strategic investments that balance risk and return, underscoring NLR's role as a stabilizing force and return enhancer, as evidenced by its predominant allocation in both Minimum Variance and Tangency Portfolios. Employing advanced stochastic modeling and simulation techniques, the research uses a uniform distribution to generate random portfolio weights, ensuring comprehensive and unbiased exploration of the feasible solution space, thereby enhancing the robustness of the portfolio optimization process. The findings also illustrate the diversification merits of integrating clean energy equities into broader portfolios comprising traditional stocks and bonds, with nuclear-focused equity significantly enhancing the efficient frontier. Results underscore the superiority of the nuclear energy exchange-traded fund (ETF) both as a standalone investment and as a crucial component of diversified portfolios, highlighting its contribution to investment performance and risk management. This approach offers insights for investors and policymakers navigating the intersection of finance, sustainability, and economic growth post-pandemic.

Keywords: clean energy equity markets, stochastic modelling, mean-variance optimization, drawdown, Monte Carlo simulation, optimization algorithms, diversification, Sharpe ratio.

JEL Classification: C5, G11, G15, G17.

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1. Introduction

In recent decades, the global shift towards sustainable energy sources has gained momentum, driven by growing environmental concerns and the imperative to mitigate climate change (Solomon & Krishna, 2011; Gielen et al., 2019; Guliyev, 2023; Hieu & Mai, 2023; Nijsse et al., 2023; Yang et al., 2023). This shift from conventional fossil fuel-based energy systems towards renewable alternatives is a fundamental pathway to decarbonize economies and foster sustainable development (Cherp et al., 2018; Deka et al., 2023). The transition holds multifaceted significance, mitigating the adverse impacts of climate change while bolstering economic growth through new avenues for innovation, job creation, and enhanced energy security (Gökgöz & Güvercin, 2018; Le & Nguyen, 2019; Chen et al., 2020; Cergibozan, 2022). In this context, clean energy technologies have emerged as pivotal components of a sustainable future (Kittner et al., 2017; Akpan & Olanrewaju, 2023), representing promising opportunities for investors and policymakers alike. These technologies, encompassing a diverse array of renewable energy sources, energy-efficient practices, and innovative solutions, are intrinsically linked to the sphere of clean energy investments (Tolliver et al., 2020; Liu et al., 2021; Madaleno et al., 2022). As these technologies evolve and become more cost-effective, they attract significant investments (Bürer & Wüstenhagen, 2009; Husain et al., 2023), contributing to the expansion and maturation of the clean energy market (Li, 2023).

The clean energy market's emergence as a significant asset class has been further underscored by the COVID-19 pandemic, which has profoundly impacted financial markets (Li et al., 2022; Ullah, 2023), injecting substantial volatility and uncertainty into energy markets (Dutta et al., 2020c; Shaikh, 2022). This unprecedented volatility presents unique challenges and opportunities for investors in the clean energy sector (Hassan, 2022; Tudor, 2023). In this volatile environment, exchange-traded funds (ETFs) have become vital instruments, providing investors with accessible and diversified means of engaging with the rapidly evolving sector (Carbon Collective, 2024). ETFs offer an aggregated investment approach, encapsulating a variety of companies across the clean energy spectrum, including solar, wind, hydroelectric, and other renewable energy sources. This diversification mitigates company-specific risks and provides exposure to the broader clean energy movement, which is crucial given the sector's susceptibility to technological changes and regulatory shifts (Rao et al., 2023).

Against this complex backdrop, this research paper undertakes a comprehensive exploration of the risks and returns associated with diverse Clean Energy Exchange-Traded Funds (ETFs) since the onset of the COVID-19 pandemic. The primary objectives of this study are to analyze the performance dynamics of clean energy ETFs through advanced statistical methods, optimize clean energy portfolios utilizing mean-variance (MV) analysis combined with Monte Carlo simulations to identify optimal asset allocation strategies, and investigate the diversification benefits of incorporating clean energy ETFs into broader investment portfolios that include traditional equities and fixed-income securities. This involves leveraging high-dimensional covariance matrices, exploring the efficient frontier, and employing stochastic processes to enhance the robustness and precision of portfolio optimization.

Consequently, the study introduces several innovative contributions to the field of financial optimization. It leverages Monte Carlo simulations underpinned by a uniform distribution for generating asset weights, which marks a departure from traditional deterministic or heuristic optimization techniques. This methodological innovation ensures an unbiased and comprehensive exploration of the feasible weight space, mitigating biases inherent in other sampling methods. The use of a uniform distribution guarantees that the Monte Carlo simulations uniformly explore the entire solution space, which is crucial for identifying optimal portfolios offering superior risk-return trade-offs that traditional optimization methods might overlook. Moreover, this research integrates advanced stochastic modeling and simulation, effectively capturing the inherent uncertainty and variability of clean energy financial markets. This integration results in optimized portfolios that are not only theoretically sound but also practically resilient to market fluctuations. Thus, by advancing the traditional framework of Modern Portfolio Theory through the application of uniform distribution-driven Monte Carlo simulations, this study provides a more resilient and theoretically robust approach to portfolio selection. The findings offer novel evidence on the clean energy efficient frontier and its drivers, emphasizing the significant growth potential and inherent volatility associated with the sector.

The literature frequently underscores the volatility of clean energy investments, which arises from technological innovation, policy changes, and shifting investor sentiment. Henriques and Sadorsky (2008) highlighted that clean energy stocks are approximately 40% riskier than the broad-based market, attributing this to the nascent stage of technology and dependence on government policies. Zhang et al. (2021) further explained that the volatility of clean energy investments is influenced by past movements in oil prices, stock prices of high-tech firms, and interest rates. Despite these risks, the sector's alignment with long-term sustainability goals suggests strong growth potential, with many studies advocating for the inclusion of clean energy assets in diversified portfolios to capitalize on this upward trajectory (Broadstock et al., 2021).

In this context, given the growing traction of sustainable investments in financial markets, this research explores the diversification benefits of incorporating clean energy equity within stocks and bonds portfolios. Previous studies have shown mixed results regarding the diversification benefits of clean energy ETFs (La Monaca et al., 2018; Kuang, 2021a). This study aims to provide new evidence on the diversification potential of clean energy investment vehicles. By conducting a comprehensive analysis using MVO, the research assesses whether including clean energy ETFs within a diversified portfolio of stocks and bonds improves risk-return profiles and identifies which specific clean energy ETFs offer the most promising diversification advantages.

In summary, this study makes significant contributions to the existing literature by offering a comprehensive analysis of Clean Energy Exchange-Traded Funds (ETFs) in the context of global sustainability imperatives. By analyzing the risks and returns associated with various niche sectors within the clean energy equity markets and leveraging advanced optimization techniques, the study develops and evaluates optimized clean energy portfolios. Additionally, it assesses the diversification benefits these portfolios offer when integrated into stock and bond portfolios. This multifaceted approach provides invaluable insights for investors seeking sustainable investment avenues and policymakers aiming to shape resilient and environmentally conscious energy systems in the post-pandemic era. Consequently, the findings contribute nuanced understandings to the evolving domain of clean energy finance, offering practical guidance to stakeholders navigating the complex intersection of finance, sustainability, and economic growth. In particular, current findings highlight the unique position of nuclear energy equities within the clean energy spectrum. Nuclear equities demonstrate resilience and sustained growth, attributed to their stable production unaffected by external factors, which in turn enhances investor confidence and underscores their potential as a stabilizing component in clean energy portfolios.

The rest of the paper is structured as follows: Section 2 outlines the methodology, including the optimization approach and data used; Section 3 presents the main findings, which are further discussed in Section 4; and Section 5 concludes.

2. Materials and methods

2.1. Data

This research encompasses the period from January 2020 to December 2023, focusing on five clean energy exchange-traded funds (ETFs): NLR, FAN, ICLN, QCLN, and TAN. These selected ETFs represent a comprehensive spectrum of clean energy equities, each with distinct holdings that emphasize various segments within the clean energy domain. NLR (VanEck Vectors Uranium+Nuclear Energy ETF) primarily invests in companies involved in uranium mining, production of nuclear components, and nuclear energy generation, offering targeted exposure to the nuclear energy sub-sector. FAN (First Trust Global Wind Energy ETF) focuses on companies that are primarily involved in the wind energy industry, including manufacturers of wind turbines, providers of maintenance services, and wind farm operators. TAN (Invesco Solar ETF) targets the solar energy sector, investing in companies that produce solar panels, develop solar projects, and provide solar power-related services. ICLN (iShares Global Clean Energy ETF) offers broad exposure to the global clean energy sector, holding stocks of companies involved in a variety of clean energy activities, including renewable electricity generation, energy storage, and energy efficiency. QCLN (First Trust NASDAQ Clean Edge Green Energy Index Fund) includes companies across multiple clean energy sub-sectors, such as solar, wind, biofuels, and advanced batteries, providing diversified exposure to the clean energy market.

The selection of these ETFs facilitates an in-depth comparative analysis of various sub-sectors within clean energy equities, enabling the identification of relative strengths and weaknesses across different domains. Notably, this particular sample of ETFs has not been extensively assessed in prior research, providing a fresh perspective on the clean energy equity landscape. The analysis period, which spans both the COVID-19 pandemic and the subsequent recovery phase, offers a unique opportunity to evaluate shifts in market dynamics and investor sentiment. Assessing the performance of these ETFs during this time frame allows for a critical examination of the resilience and challenges faced by clean energy equities in response to the pandemic.

For a robust comparative analysis and to assess diversification benefits, daily price data for two relevant diversified portfolios, one equity (EFA) and one bond (PGHY), are also included for the same period. Historical pricing data for all seven ETFs (denoted as Pt) were sourced from the Yahoo Finance platform, ensuring accuracy and consistency. The daily price series, adjusted for dividends and other corporate actions, were transformed into logarithmic returns to facilitate robust statistical analysis.

This comprehensive dataset enables a thorough investigation of the performance dynamics and risk-return profiles of clean energy ETFs, thereby contributing valuable insights into the evolving landscape of clean energy equity investments.

2.2. Method

The analytical framework is executed within the R programming environment, capitalizing on its advanced libraries for financial modeling and portfolio optimization.

2.2.1. Comparative performance visualization

To elucidate the performance trajectories of the selected ETFs, cumulative return charts were generated. These charts are crucial for understanding the compounded growth dynamics of the ETFs over the analysis period. In constructing these visualizations, the cumprod() function in R was employed to compute the cumulative product of sequential returns for each ETF. This method ensures an accurate depiction of the compounded periodic returns, articulated as follows:

$$R_j = \prod_{t=1}^{n} (1 + R_{tj}) - 1, \quad (1)$$

where $R_{t,j}$ represents the return for each individual period t for a specific ETF j, and n denotes the total number of compounding periods.

These cumulative return charts are integral to the research objectives, providing a visual representation of the ETFs' growth patterns. By plotting these cumulative returns over time, analysts can conduct a comparative analysis of the performance of different ETFs within the portfolio. This visualization enables the identification of nuanced trends and performance anomalies, facilitating a comprehensive assessment of the relative strengths and weaknesses across various clean energy equity sub-sectors.

Linking these visualizations to the research objectives, the charts aid in evaluating the resilience and performance of clean energy ETFs during the COVID-19 pandemic and subsequent recovery period. They offer insights into the effectiveness of diversification strategies and the overall risk-return profiles of the ETFs. By highlighting periods of growth, decline, and stability, these visual tools support informed investment decisions and strategic evaluations based on historical performance patterns and trends.

2.2.2. Maximum drawdown evaluation

The maximum drawdown (MDD) quantifies the largest peak-to-trough decline experienced by an asset over a specified period, providing crucial insights into potential downside risk and the magnitude of loss during adverse market conditions (Pospisil & Vecer, 2008, 2010; Bacon, 2023). In this study, MDD is essential for evaluating the resilience and risk profiles of clean energy ETFs during the COVID-19 pandemic and subsequent recovery, directly linking to the research objectives.

To compute MDD, let $P(t)$ represent the price of the asset at time t, where t = 1, 2, ...,T. Define $M(t)$ as the maximum value of $P(t)$ up to time t:

$$M(t) = \max_{\tau \in [1,t]} P(\tau). \tag{2}$$

Estimate the drawdown at each time point t as the relative decrease from the running maximum:

$$D(t) = \frac{M(t) - P(t)}{P(t)}. \tag{3}$$

Identify the Maximum Drawdown over the entire period as the maximum of individual drawdowns:

$$MDD = \max_{t \in [1,T]} D(t). \tag{4}$$

For this research, MDD is computed for each clean energy ETF (NLR, FAN, ICLN, QCLN, TAN) from January 2020 to December 2023. This analysis is pivotal in assessing the potential magnitude of losses investors might face. Visualizations of these drawdowns were created using the chart.Drawdown() function in R's {PerformanceAnalytics} package (Peterson et al., 2020), illustrating each ETF's susceptibility to significant declines and aiding in comparative performance analysis.

2.2.3. Portfolio construction and optimization

This study employs an innovative application of uniform distribution-driven Monte Carlo simulations to conduct portfolio construction and mean-variance optimization within the clean energy equity market. A total of 10,000 random portfolios (Pi) are generated to encompass a broad spectrum of potential asset compositions within this investment universe.

Asset allocation within these portfolios is determined through a uniform distribution of weights (w_{pj}), ensuring an exhaustive and unbiased exploration of various asset combinations. The uniform distribution, denoted as $U(a,b)$, where a and b are the lower and upper bounds, respectively, offers an equal probability for any value within this interval, with the probability density function (PDF) given by:

$$f(x) = \frac{1}{(b-a)}, \text{ for } a \le x \le b. \tag{5}$$

In this research, the weights (w_{pj}) are uniformly distributed as:

$$W_{pj} \sim U(0,1), \text{ for } p = 1,2,\ldots,10{,}000 \text{ and } j = 1, 2, \ldots, 5, \tag{6}$$

where p denotes the portfolio index and j denotes the ETF index.

This methodological innovation in using uniform distribution for weight allocation mitigates biases inherent in other sampling methods and ensures comprehensive coverage of the feasible solution space (Bardakci & Lagoa, 2019). Each of the 10,000 randomly generated portfolios undergoes evaluation for their risk and return characteristics. The returns of each portfolio (R_i) are computed as the weighted sum of individual asset returns:

$$R_p = \sum_{j=1}^{5} w_{pj} R_j, \tag{7}$$

where R_j denotes the returns of the individual ETFs and w_{pj} represents the weights of the ETFs in portfolio p.

The Sharpe ratio (SRi) (Sharpe, 1998) for each portfolio is calculated to measure the risk-adjusted return:

$$SR_p = \frac{R_p - r_f}{\sigma_p}, \tag{8}$$

where r_f is the risk-free rate (set to 0% in all estimations performed in this study), and σ_p is the standard deviation of portfolio returns, with $p = 1,2,\ldots,10{,}000$.

This approach facilitates the construction of the efficient frontier, plotting risk against return for all generated portfolios, thus offering a comprehensive view of the risk-return landscape within the clean energy equity market. The efficient frontier elucidates the trade-offs between risk and return, aiding in informed investment decisions. Two paramount portfolios identified through this analysis are the Minimum Variance Portfolio (MVP) and the Tangency Portfolio (TP), pivotal in the context of mean-variance portfolio optimization (Markowitz, 1952; Sharpe, 1963, 1966).

The MVP, representing the portfolio with the lowest possible volatility, is derived by solving the optimization problem:

$\min_{\mathbf{w}} \mathbf{w}^T \Sigma \mathbf{w}$ subject to $\mathbf{1}^T \mathbf{w} = 1$ to ensure a fully invested portfolio, where $\mathbf{w}$ is the vector of asset weights in the portfolio, Σ is the covariance matrix of asset returns, and $\mathbf{1}$ is a vector of ones.

The TP, which maximizes the Sharpe ratio, is determined through the formulation:

$$\max_w \frac{w^T (\mu - r_f)}{\sqrt{w^T \Sigma w}}, \tag{9}$$

subject to $\mathbf{1}^T \mathbf{w} = 1$, with μ representing the vector of expected returns for each ETF, and r_f the risk-free rate.

Moreover, the study investigates the diversification benefits of incorporating individual clean energy ETFs within portfolios predominantly composed of diversified equities (EFA) and bonds (PGHY). Utilizing the mean-variance optimization framework, the research constructs and analyzes 10,000 random portfolios for each distinct scenario. These scenarios involve combinations of EFA, PGHY, and individual clean energy ETFs (NLR, FAN, ICLN, QCLN, TAN). This exhaustive exploration aims to thoroughly examine the risk-return dynamics and identify optimal allocations that maximize returns while effectively managing risk within mixed portfolios.

Identifying the MVP and TP within these contexts provides crucial benchmarks for constructing portfolios that prioritize either risk minimization or optimal risk-adjusted returns, thus aiding investors' strategic decision-making processes by offering insights into the most efficient asset allocations (Pospisil & Vecer, 2008; Bacon, 2023; Bardakci & Lagoa, 2019).

The proposed application of uniform distribution-driven Monte Carlo simulations advances the traditional framework of Modern Portfolio Theory, providing a resilient and theoretically robust approach to portfolio selection, particularly within the clean energy equity domain.

3. Results

3.1. Performance and risk of clean energy investments in the post-pandemic period

Figure 1 depicts the cumulative monthly returns of five clean energy ETFs – NLR, FAN, ICLN, QCLN, and TAN – coupled with EFA and PGHY from January 2020 to December 2023 and showcases intriguing trends in their market performance, reflecting varying trajectories amid the complex financial landscape.

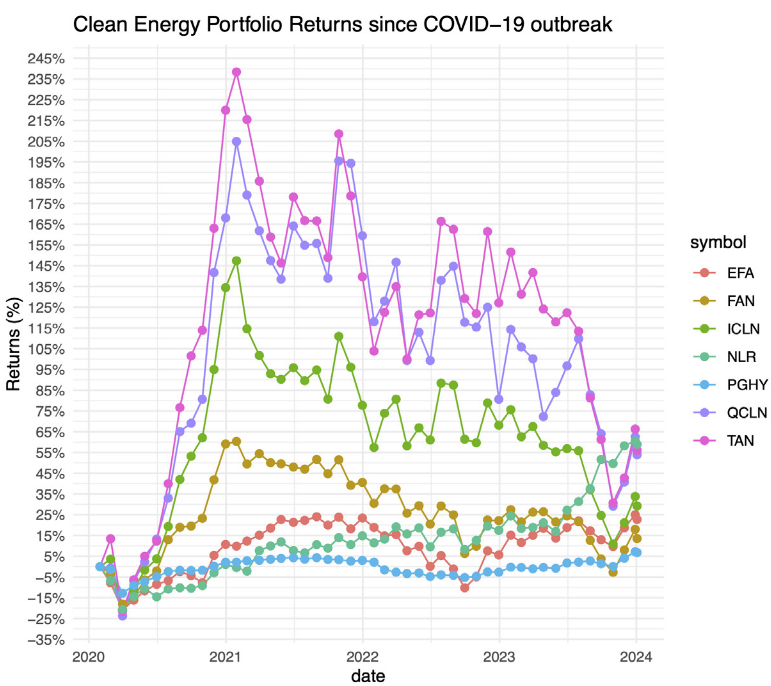

Figure 1. Cumulative returns of clean energy, equity, and fixed-income ETFs (1.01.2020 – 31.12.2023)

Initially, all ETFs experienced a sharp decline until March 2020, reflecting the broader market turmoil induced by the onset of the COVID-19 pandemic. Following this downturn, there was a notable recovery for most ETFs until the year's conclusion, albeit with differing magnitudes of ascent. Particularly, TAN, QCLN, and ICLN exhibited more substantial recoveries compared to their counterparts, signifying a robust resurgence in these clean energy ETFs' market valuations. Conversely, NLR exhibited a more restrained recovery during this phase.

Subsequent to this recovery period, a divergence in price movements among the clean energy ETFs became evident. While TAN, QCLN, and ICLN, alongside FAN, experienced downturns post-recovery, NLR showcased a unique trend by continuing its upward trajectory, depicting an opposite performance pattern compared to other clean energy ETFs. This distinctive behavior positions NLR as an outlier within the clean energy sector, demonstrating resilience and sustained growth amid the clean energy market's overall downward trend in the latter part of the observed period.

Notably, during the latter half of 2023, a notable deviation was observed, wherein NLR emerged as the sole ETF, demonstrating a significant upward movement among the seven ETFs under scrutiny. This period witnessed a distinct contrast, with the other ETFs, including FAN, ICLN, QCLN, and TAN, exhibiting declines in prices. EFA displayed a slight increase, albeit with considerable volatility, which stands in stark contrast to the steady and substantial rise displayed by NLR.

The chart underlines the dynamic and divergent performance trajectories of different clean energy ETFs, emphasizing the variance in their resilience and market adaptability amid changing economic and environmental conditions. NLR's consistent and sustained growth, particularly in the latter part of the observed period, underscores its distinct behavior and potentially unique market positioning within the clean energy sector, warranting deeper exploration and scrutiny. The contrasting price movements among the clean energy ETFs further accentuate the need for investors to consider the nuances of individual ETFs within the sector and underscore the importance of diversified strategies when navigating the clean energy investment landscape.

Table 1 presents the descriptive statistics of daily returns for seven exchange-traded funds (ETFs), covering the period from January 2020 to December 2023. These statistics offer an insightful portrayal of the distributional characteristics, variability, and shape of the daily returns for each ETF during this period, providing crucial information for investors and financial analysts.

Table 1. Descriptive statistics

	EFA	FAN	ICLN	NLR	PGHY	QCLN	TAN
Minimum	–0.1164	–0.1234	–0.1371	–0.1243	–0.0874	–0.1391	–0.1754
Median	0.0005	0.0000	–0.0005	0.0011	0.0000	0.0013	–0.0003
Mean	0.0002	0.0002	0.0003	0.0005	0.0001	0.0005	0.0005
Maximum	0.0813	0.0986	0.1080	0.0778	0.0524	0.1364	0.1266
Stdev	0.0135	0.0166	0.0222	0.0143	0.0062	0.0279	0.0296
Skewness	–1.1209	–0.5184	–0.3681	–1.002	–3.299	–0.1818	–0.2035
Kurtosis	13.128	7.848	4,814	11.441	62.778	2.084	3.206

The minimum daily returns across the ETFs range from –0.1754 to –0.0874, depicting the worst-performing days for each ETF within the specified timeframe. On the contrary, the maximum daily returns range from 0.0524 to 0.1364, representing the most profitable days. These observations highlight the considerable variance in performance extremes within the ETFs during the studied period. In examining the central tendency of returns, the mean and median values provide valuable insights and indicate the relative overperformance of QCLN and TAN during the considered timeframe. Furthermore, the data shows that ICLN, QCLN, and TAN have the largest standard deviations, indicating higher volatility compared to the other ETFs during the analysis period. All ETFs present a negative skewness coefficient, suggesting a longer left tail in their return distributions. Additionally, most portfolios show relatively high kurtosis values, indicating that their return distributions have more extreme values compared to a normal distribution. Overall, the descriptive statistics provided for the clean energy ETFs – FAN, ICLN, NLR, QCLN, and TAN – confirm that these assets exhibit higher returns and increased risk compared to the diversified equity ETF, EFA, during the period of January 2020 to December 2023. Of note, among the clean energy portfolios, NLR presents the lower risk, showing a daily standard deviation of 1.43%, slightly higher than the risk associated with the diversified equity portfolio EFA, whereas its return is close to three-fold higher. These findings underscore the higher return potential of clean energy ETFs but also emphasize the increased risk associated with these investments compared to the more diversified equity ETF, EFA. Investors seeking potentially higher returns through clean energy ETFs should be aware of the elevated level of volatility and risk involved in these assets compared to a diversified equity portfolio like EFA. As such, this information is crucial for investors when making informed decisions and managing their risk-return trade-off within their investment portfolios.

The analysis of the maximum drawdown chart (Figure 2) further corroborates the earlier findings regarding the higher risk associated with clean energy ETFs compared to the diversified equity ETF EFA.

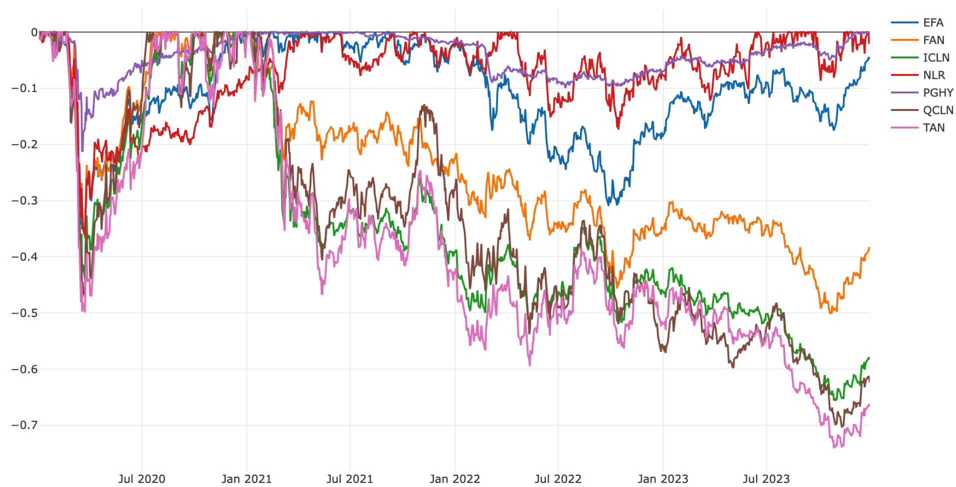

Figure 2. Maximum drawdown for clean energy, equity, and fixed-income ETFs (1.01.2020 – 31.12.2023)

Observing the maximum drawdown chart, it becomes evident that all clean energy ETFs – FAN, ICLN, QCLN, and TAN – exhibit notably higher maximum drawdowns compared to the diversified equity ETF EFA, signifying more significant and sustained losses experienced by these clean energy investments at various points during the study period. This higher magnitude of drawdown indicates the susceptibility of clean energy ETFs to periods of considerable decline or volatility, which might be concerning for risk-averse investors or those with shorter investment horizons.

Remarkably, the maximum drawdown for NLR, a clean energy ETF focused on nuclear energy, deviates from this trend by displaying a comparatively lower drawdown magnitude when compared to the other clean energy ETFs and even EFA. This distinctive behavior suggests that NLR might possess a relatively more stable or less volatile performance profile than its clean energy counterparts, showcasing comparatively lower downside risk or losses during adverse market conditions.

The identification of higher maximum drawdowns in the majority of clean energy ETFs compared to the diversified equity ETF EFA reaffirms the earlier conclusion of increased risk in the clean energy sector. Investors interested in clean energy ETFs need to acknowledge and carefully assess these higher drawdowns, as they represent potential downside risks and highlight the need for effective risk management strategies when incorporating these assets into an investment portfolio. The comparatively lower drawdown experienced by NLR could offer insights into diversification benefits or risk mitigation within the clean energy sector and warrants further investigation and consideration by investors seeking exposure to this specific energy niche.

3.2. Clean energy portfolio optimization

Next, the investigation engages in portfolio optimization among the five clean energy exchange-traded funds (ETFs) in the post-COVID-19 period by conducting a thorough exploration involving the construction and analysis of a large number of random portfolios. Particularly, the current exhaustive approach of constructing 10,000 random portfolios and analyzing their risk-return characteristics facilitates a comprehensive exploration of the clean energy ETF investment landscape, enabling the identification of portfolios that offer minimized risk and optimized risk-adjusted returns within the specified period.

The following chart (Figure 3) depicts the annual risk and returns of the 10,000 random portfolios constructed from the five clean energy exchange-traded funds (ETFs): NLR, FAN, ICLN, QCLN, and TAN. It offers a comprehensive view of the risk-return landscape resulting from the portfolio optimization process within the clean energy market.

Two important portfolios in Figure 3 are marked in red to delineate the Minimum Variance Portfolio (MVP) and the Tangency Portfolio (TP). The MVP exhibits an annualized risk of 23.01% coupled with a corresponding return of 11.52%. In contrast, the TP portrays a slightly higher annualized risk at 25.13% alongside a greater return of 12.75%. These plotted portfolios serve as focal points, showcasing the trade-off between risk and return inherent in portfolio optimization. Moreover, the visual representation underscores the distinctive risk-return profiles established by the optimization process, with the MVP prioritizing risk minimization and the TP aiming to attain the optimal balance between risk and return. The positioning of these portfolios within the spectrum of the 10,000 random portfolios accentuates their strategic significance, offering insights into their relative performance and illustrating the efficacy of the optimization approach in identifying portfolios that cater to varying risk appetites while seeking to maximize returns.

The bar charts (panel a and panel b in Figure 4) depicting the weights of the five clean energy Exchange-Traded Funds (ETFs) – NLR, FAN, ICLN, QCLN, and TAN – within the Minimum Variance Portfolio (MVP) and the Tangency Portfolio (TP) illustrate noteworthy insights into the optimal compositions derived from the portfolio optimization process. In both charts, NLR emerges with the most substantial weight allocation, comprising approximately 72% in the MVP and

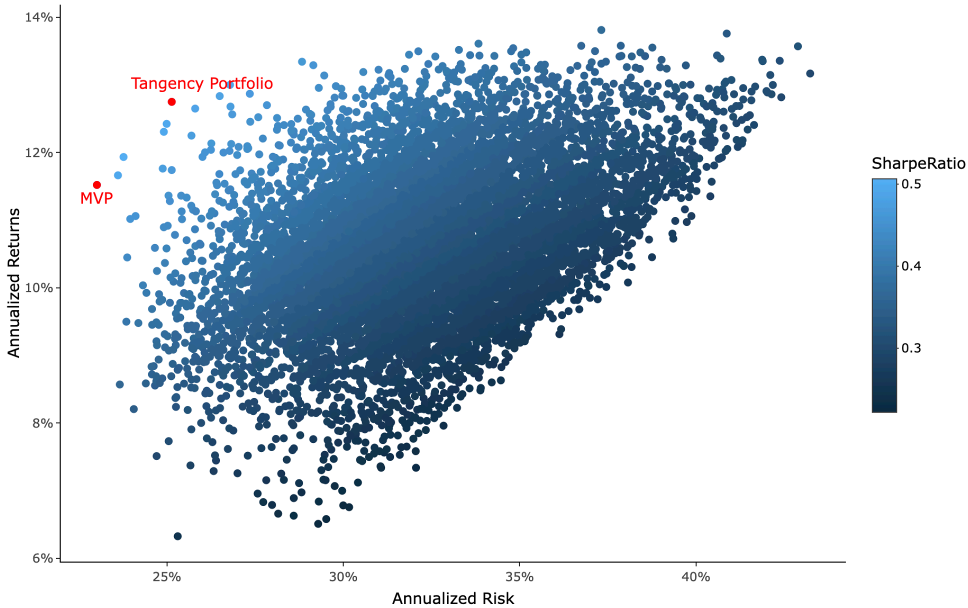

Figure 3. Optimization of clean energy investments among five clean energy Exchange-Traded Funds (ETFs) (January 2020 – December 2023)

approximately 68% in the TP, underscoring its dominant role within these optimal portfolios. Moreover, the Tangency Portfolio showcases QCLN as the second-largest constituent, with over 12% of the portfolio weight, followed by FAN with slightly over 10%. Conversely, in the Minimum Variance Portfolio, FAN secures the second-largest allocation, accounting for over 19% of the portfolio, followed by QCLN with a weight of over 6%. These bar charts serve as valuable visual representations, offering insights into the optimal weightings assigned to each ETF within the two distinct portfolio strategies. The prominence of NLR in both scenarios indicates its considerable impact on the risk-return dynamics, significantly influencing the composition of these portfolios. The varying allocations of QCLN and FAN between the MVP and TP highlight the nuanced differences in the risk-adjusted return profiles, emphasizing the trade-offs between minimizing risk and maximizing returns within the clean energy ETF domain.

Table 2 presents all the weight allocations and corresponding Sharpe ratios resulting from portfolio optimization among the five clean energy Exchange-Traded Funds (ETFs) – NLR, FAN, ICLN, QCLN, and TAN – along with individual investments allocating 100% to each clean energy ETF.

Notably, the undiversified portfolios, where 100% of the investment is allocated to a single clean energy Exchange-Traded Fund (ETF), exhibit significantly lower Sharpe ratios compared to the Tangency Portfolio (TP) and Minimum Variance Portfolio (MVP). This observation is consistent across most ETFs, indicating that concentration in a single asset generally yields inferior risk-adjusted returns. However, it's important to note that NLR stands as an exception among these undiversified portfolios, demonstrating a relatively higher Sharpe ratio compared to the other individual ETFs. This divergence suggests that NLR's risk-return profile might offer some advantages when invested solely in. The higher Sharpe ratios in the TP and MVP allocations, however, further demonstrate the value of diversification in achieving better risk-adjusted returns.

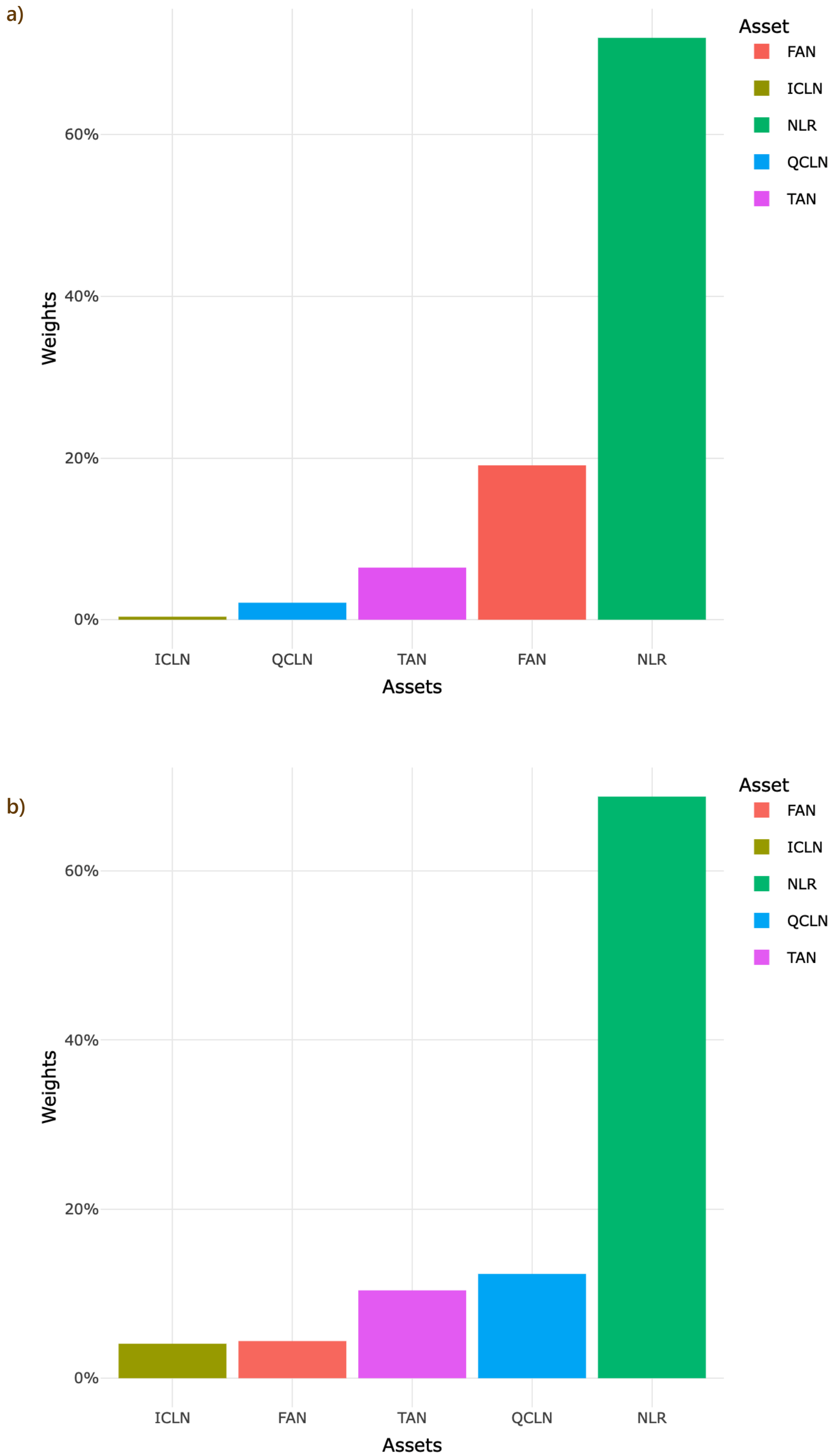

Figure 4. Clean energy Asset Weights: a – in MVP; b – in TP

Table 2. Risk adjusted performance of diversified and undiversified clean energy portfolio investments

Allocation	FAN	ICLN	NLR	QCLN	TAN	Sharpe Ratio
TP	0.044	0.0408	0.688	0.123	0.104	0.507
MVP	0.191	0.004	0.720	0.021	0.064	0.501
100% FAN	1					0.036
100% ICLN		1				0.042
100% NLR			1			0.454
100% QCLN				1		0.078
100% TAN					1	0.039

Note: * The Sharpe ratio is calculated at a confidence level of 95%, annualized, and presupposes a risk-free rate of 0%.

3.3. Diversification benefits of clean energy investments

The subsequent analysis endeavors to probe into the potential diversification advantages stemming from the inclusion of various clean energy exchange-traded funds (ETFs) within portfolios primarily constituted of diversified equities ('EFA') and bonds ('PGHY') during the observed period from January 2020 to December 2023. To this end, within a mean-variance optimization framework, 10,000 random portfolios are generated for each scenario, combining 'EFA' and 'PGHY' with individual clean energy ETFs (NLR, FAN, ICLN, QCLN, and TAN).

Figures 5–9 illustrate the optimization outcomes, highlighting the Tangency Portfolio (TP) resulting from the EFA-PGHY-NLR combination (i.e., depicted in Figure 7) as the most promising in terms of performance. These visuals underscore the superiority of the optimized portfolio with EFA, PGHY, and NLR, indicating notably enhanced risk-adjusted returns compared to other combinations.

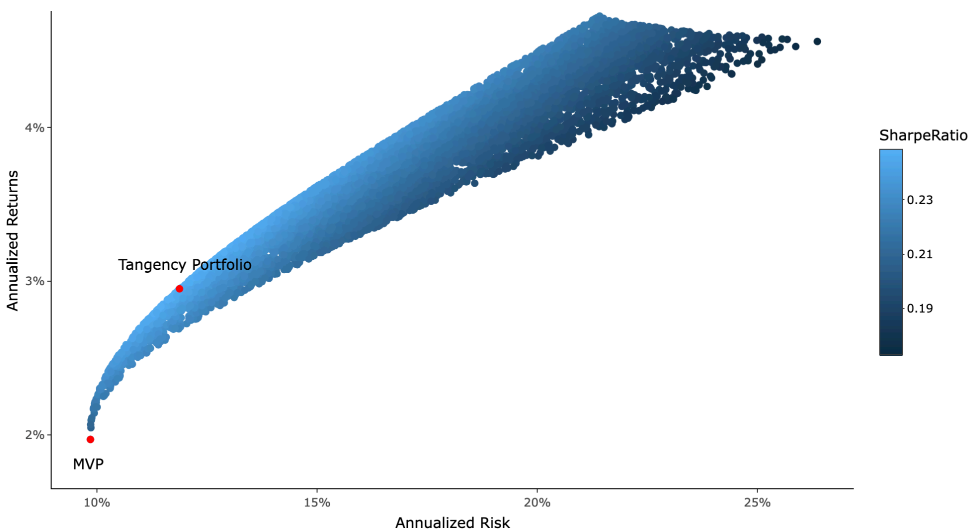

Figure 5. Optimization between EFA-PGHY-FAN

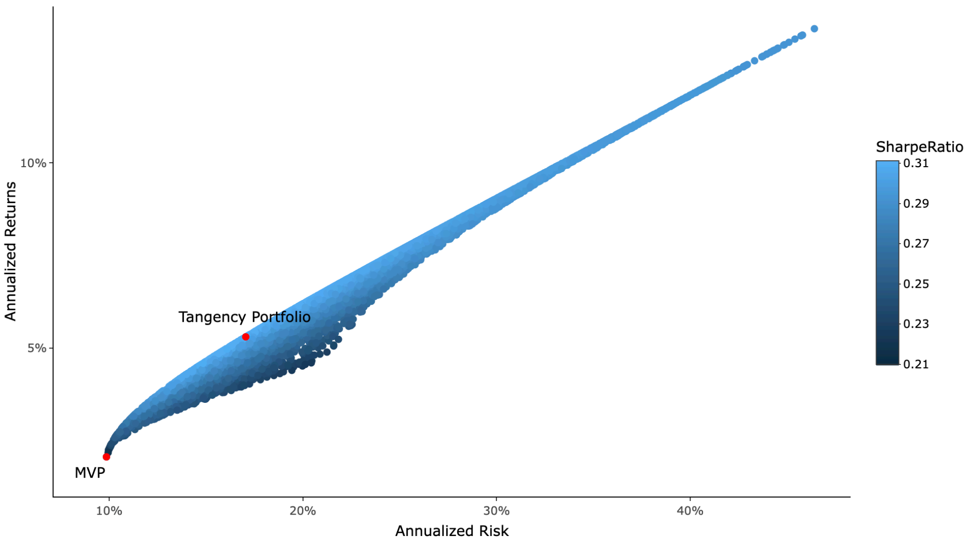

Figure 6. Optimization between EFA-PGHY-TAN

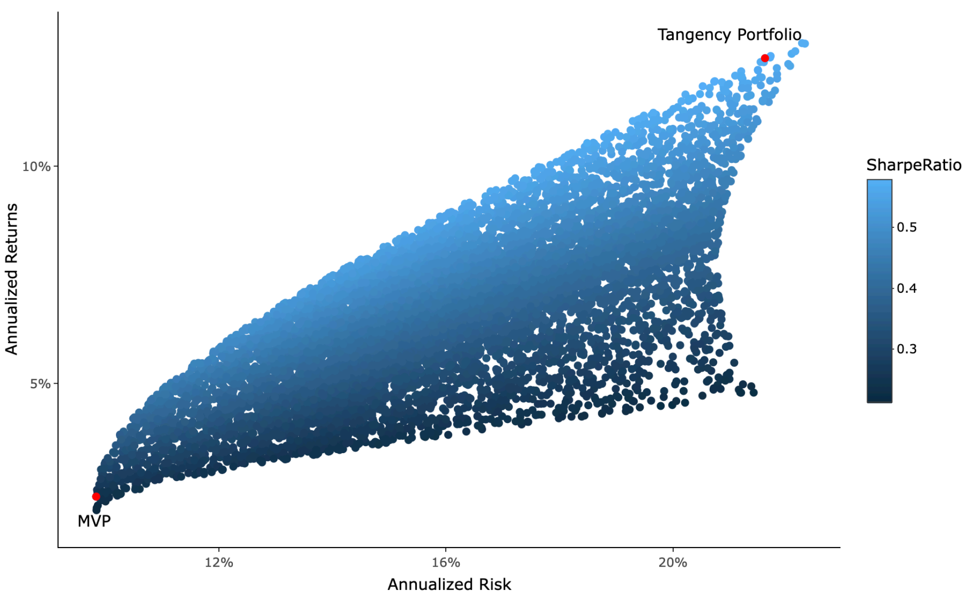

Figure 7. Optimization between EFA-PGHY-NLR

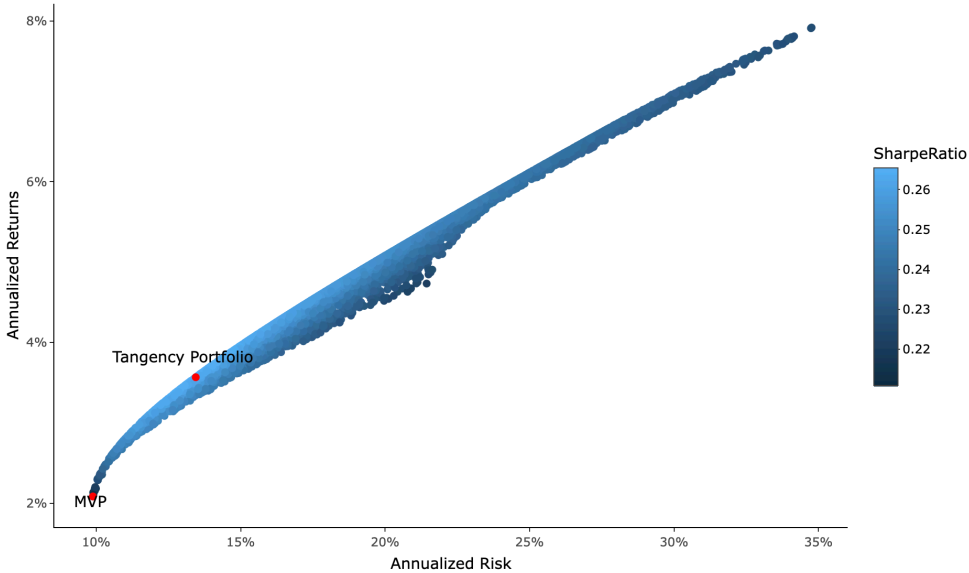

Figure 8. Optimization between EFA-PGHY-ICLN

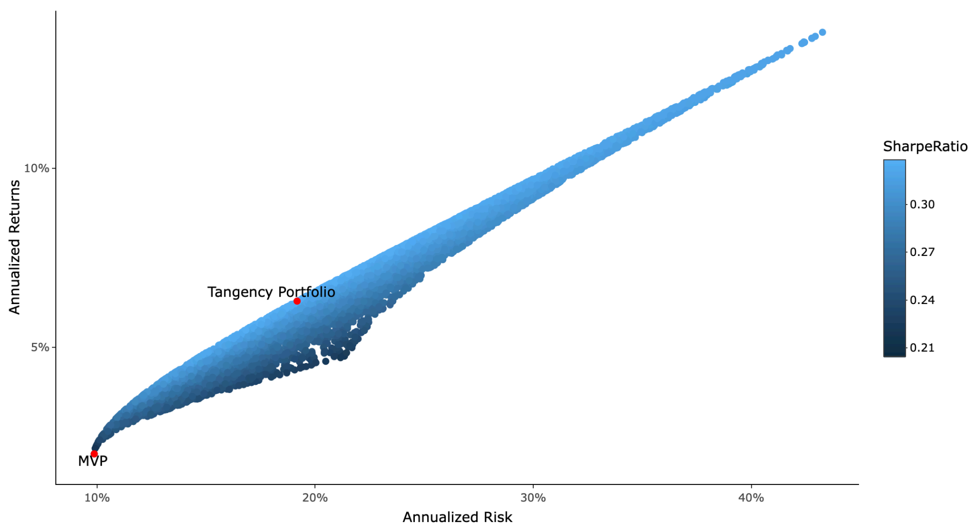

Figure 9. Optimization between EFA-PGHY-QCLN

Finally, Table 3 displays the allocations (weights), returns, risks, and Sharpe ratios for the Tangency Portfolio (TP) formed by optimizing among EFA, PGHY, and individual clean energy ETFs (NLR, FAN, ICLN, QCLN, and TAN), revealing increased Sharpe ratios for all portfolios augmented with clean energy equity. Each entry in the table represents the allocation percentages of the respective assets within the optimized portfolio, along with the corresponding return, risk (standard deviation), and Sharpe ratio. For comparative purposes, a traditional assets-only portfolio is also included.

Table 3. Allocation and performance of tangency portfolios

EFA	PGHY	FAN	Return	Risk	Sharpe Ratio*
0.358	0.641	0.000410	0.0295	0.117	0.251
EFA	PGHY	TAN	Return	Risk	Sharpe Ratio
0.0591	0.661	0.280	0.0531	0.171	0.311
EFA	PGHY	NLR	Return	Risk	Sharpe Ratio
0.000996	0.101	0.898	0.120	0.208	0.578
EFA	PGHY	ICLN	Return	Risk	Sharpe Ratio
0.183	0.631	0.186	0.0357	0.134	0.265
EFA	PGHY	QCLN	Return	Risk	Sharpe Ratio
0.00385	0.629	0.367	0.0629	0.192	0.328
EFA	PGHY		Return	Risk	Sharpe Ratio
0.371	0.629		0.0299	0.120	0.249

Note: * The Sharpe ratio is calculated at a confidence level of 95%, annualized, and presupposes a risk-free rate of 0%.

The first allocation comprising EFA, FAN, and PGHY shows PGHY with the highest allocation, resulting in a return of 2.95% and a risk of 11.9%, with a Sharpe ratio of 0.249. The second allocation involving EFA, PGHY, and TAN allocates more to PGHY, yielding a return of 5.31% with a risk of 17.1% and a Sharpe ratio of 0.311. The fourth combination of EFA, ICLN, and PGHY also favors PGHY but distributes weights more evenly across ICLN and EFA, producing a return of 3.57% with a risk of 13.4% and a Sharpe ratio of 0.265. In contrast, the last allocation with EFA, PGHY, and QCLN emphasizes PGHI (63%), followed by QCLN (36.7%), resulting in a return of 6.29%, a risk of 19.2%, and a Sharpe ratio of 0.328.

On the other hand, the third allocation, comprising EFA, NLR, and PGHY, significantly favors NLR, allocating about 89.8% of the portfolio to the nuclear energy ETF, with minimal allocations to EFA (0.1%) and PGHY (10.1%). This strategy yields a higher return of 12% with a risk of 20.8% and a Sharpe ratio of 0.578, indicating better risk-adjusted returns. However, such concentration on NLR entails higher risk, which may not suit all investor preferences. Therefore, while this allocation with NLR shows potential for superior risk-adjusted returns, it should be assessed alongside its higher concentration risk.

4. Discussion

The study unveils a complex array of findings regarding the performance and risk of clean energy investments in the post-pandemic period, particularly focusing on five clean energy ETFs encompassing diverse renewable energy sources.

The divergence in performance trajectories among ETFs such as TAN, QCLN, and ICLN compared to NLR post-recovery highlights the nuanced investment landscape within the clean energy sector, corroborating earlier findings (Kuang, 2021b). The resilience demonstrated by NLR, as evidenced by its consistent upward trajectory and relatively stable returns, positions it as a potentially more secure investment within this volatile sector. This observation is corroborated by broader literature, which suggests that clean energy investments, particularly those in well-established technologies with robust policy support, tend to exhibit lower volatility and higher resilience (Bumpus & Comello, 2017).

Further insights into the variability and risk profile of diverse clean energy ETFs are gleaned from the high standard deviations observed in ETFs such as ICLN, QCLN, and TAN, indicating greater risk (Ahmad et al., 2018). This increased risk can be attributed to the innovative and rapidly evolving nature of the technologies within these sectors. The negative skewness across all ETFs suggests substantial potential losses when they occur, aligning with the inherent risks of the clean energy market (Henriques & Sadorsky, 2008).

Examining maximum drawdown data corroborates the higher risk associated with clean energy ETFs, reflecting the sector's sensitivity to market fluctuations and policy changes (Dutta et al., 2020a, 2020b). Interestingly, the findings deviate from those of Hoepner et al. (2019), which indicate that ESG engagement mitigates downside risks, and from Yoo et al. (2021), who report higher returns and lower risks associated with increased ESG scores during the COVID-19 pandemic. These results also contrast with Broadstock et al. (2021), who suggest a positive correlation between ESG performance and future stock performance or risk mitigation during crisis periods.

Notably, NLR's lower drawdown suggests that a nuclear energy-focused portfolio might be a safer investment within the clean energy spectrum. This is likely due to nuclear energy's role as a base-load power source, which does not directly compete with fossil fuels like other renewable sources (Hore-Lacy, 2010; Pioro & Duffey, 2015; Verbruggen & Yurchenko, 2017; Kan et al., 2020). Nuclear energy's consistent and stable energy production further enhances its attractiveness (Yüksel & Dinçer, 2022). During periods of uncertainty, the reliability of nuclear power plants to generate electricity without interruptions or dependence on external factors, such as weather conditions, may bolster investor confidence. This stability likely contributes to the resilience of nuclear energy ETFs, attracting investors seeking a secure and steady investment option.

The mechanisms influencing these results are multifaceted. Market volatility, driven by economic conditions and geopolitical events, significantly impacts the performance of clean energy ETFs. Policy changes, such as government incentives for renewable energy or regulatory shifts, play a crucial role in shaping market dynamics. Technological advancements in clean energy technologies can lead to rapid changes in the market, affecting the competitiveness and attractiveness of different energy sources. Additionally, investor sentiment, shaped by broader economic trends and specific events within the energy sector, influences investment flows and market valuations. These factors collectively impact the risk-return profiles of clean energy ETFs.

The portfolio optimization analysis, involving the construction of 10,000 random portfolios from five clean energy ETFs, elucidates the intricate interplay between risk and return in portfolio construction. The use of a uniform distribution of weights ensures an unbiased exploration of various asset allocations, facilitating a comprehensive analysis of the investment landscape. Identifying the Minimum Variance Portfolio (MVP) and the Tangency Portfolio (TP) underscores the effectiveness of diversification in managing risk while seeking optimal returns, a principle well-established in investment literature (Wagner & Lau, 1971). Consistent with Naqvi et al. (2022), the study demonstrates that green energy ETFs can enhance the efficient frontier, providing valuable diversification benefits to sustainability-focused investors. Furthermore, in line with Rao et al. (2023), the results emphasize the importance of risk management strategies and resilient investment approaches in green energy markets. The significant allocation to NLR in both the MVP and TP further highlights its potential role as a stabilizer within a clean energy investment portfolio.

Moreover, the research explores the diversification advantages of incorporating clean energy ETFs alongside traditional equity and fixed-income investments. The superior performance of the TP, comprising EFA, PGHY, and NLR, suggests that integrating clean energy ETFs with traditional assets can improve the risk-adjusted returns of an investment portfolio. This aligns with previous studies advocating for the inclusion of renewable energy assets in diversified portfolios due to their long-term growth potential and diversification benefits (Broadstock et al., 2021).

Finally, the risk-adjusted performance analysis indicates that undiversified clean energy ETF investments generally yield lower Sharpe ratios compared to diversified portfolios. However, NLR's relatively higher Sharpe ratio, even as an undiversified investment, suggests unique attributes that contribute to a more favorable risk-return profile. This finding underscores the importance of a nuanced approach to investing in the clean energy sector, considering individual ETF characteristics and the broader market context (Wüstenhagen & Menichetti, 2012).

In light of these findings, it is crucial to consider the specific characteristics of individual clean energy ETFs and the broader context in which they operate. As the clean energy investment landscape continues to evolve, especially in the post-pandemic period, the sector's potential for delivering sustainable returns amidst volatility remains compelling for investment professionals and a fertile ground for academic research. This is especially relevant in understanding the relationship between human well-being and climate change mitigation, as emphasized by Lamb and Steinberger (2017), who highlight the importance of balancing energy efficiency with sustainable development goals to inform investment decisions in the clean energy sector.

5. Conclusions

The global landscape underscores the significance of renewable energy in achieving sustainability goals and fostering economic growth. Despite the increasing interest in clean energy investments, a comprehensive understanding of the associated risks and returns remains underexplored. This study addresses this gap by examining the risk-return profiles of clean energy-focused equities, optimizing clean energy portfolios, and evaluating their diversification benefits for stock and bond portfolios.

The research employs advanced stochastic modeling and portfolio optimization techniques to provide insights into the performance of clean energy-focused equities. The empirical framework involves constructing 10,000 random portfolios across multiple scenario using a uniform distribution of weights to explore various asset allocations comprehensively. Major findings reveal that clean energy-focused equities exhibit higher volatility compared to traditional investments but also offer potential for enhanced returns through strategic diversification. Nuclear energy equities, in particular, show resilience and sustained growth, attributed to their stable production unaffected by external factors like weather conditions, thereby boosting investor confidence.

However, the study has limitations, including its reliance on historical data, which may not fully predict future market behavior or account for unforeseen events. The concentration risk associated with certain assets also necessitates a cautious approach. Future research should focus on real-time data analysis and explore more diversified and adaptive strategies to mitigate risks and align with evolving market conditions and individual risk tolerance levels.

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