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PORTFOLIO DIVERSIFICATION OPPORTUNITIES IN TRADITIONAL ENERGY AND ALTERNATIVE/ RENEWABLE ENERGY ETF SEGMENTS

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ABSTRACT. This study evaluates the diversification benefits of investing in traditional and alternative/renewable energy Exchange Traded Funds (ETFs) using the VAR-ADCC-GARCH model to analyze yields, correlations, and volatilities. The results demonstrate that alternative/renewable energy ETFs not only offer higher average returns but also significantly reduce portfolio risk compared to traditional energy ETFs. The research underscores the distinct investment dynamics between the two ETF segments, highlighting the advantages of incorporating renewable energy assets into diversified portfolios. These findings support the inclusion of environmentally-conscious investment strategies that effectively balance risk and return, emphasizing their importance for investors aiming to optimize their portfolios in line with sustainable practices.

Keywords: portfolio diversification, ETFs, traditional energy, renewable energy, VAR-ADCC-GARCH Model

JEL classification: G11, C58, A100, A110

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Introduction

In the rapidly evolving investment landscape, diversification strategies are increasingly vital, particularly within the dynamic energy sector. This sector is distinctly segmented into traditional energy sources, primarily fossil fuels, and alternative/renewable energy sources, which have risen in prominence due to environmental considerations and technological advances. Given the volatile nature of the energy markets, influenced by geopolitical factors, economic cycles, and technological innovations, investors are continually seeking strategies to optimize asset allocations while managing inherent risks.

This study delves into the potential for portfolio diversification through investments in Exchange Traded Funds (ETFs) that focus on these two contrasting energy segments. ETFs offer several advantages including liquidity, cost-efficiency, and the ability to provide investors with broad exposure to various market segments. This makes them an ideal vehicle for exploring investment strategies across diverse energy sources, from traditional commodities like oil and gas to emerging markets in solar, wind, and other renewable energies.

Employing the sophisticated econometric model, Vector Autoregression Asymmetric Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (VAR-ADCC-GARCH), this research rigorously analyzes yields, correlations, and volatilities. The VAR-ADCC-GARCH model is particularly suited for this study as it can effectively capture the complex dynamics and interdependencies between multiple financial time series. This model extends the foundational principles of the asymmetric dynamic conditional correlation model initially introduced by Cappiello et al. (2006), which has been widely recognized for its ability to model time-varying correlations in financial data. Further inquiries by Gupta & Donleavy (2009), Kalotychou et al. (2014), Zhou & Nicholson (2015), Yuan et al. (2016), and Badshah (2017) and Miralles-Marcelo et al. (2018) have highlighted its utility in assessing the economic implications of investment diversification across varied portfolios, and have elucidated that the ADCC model's covariant asymmetry significantly augments its economic utility through prompt, favorable shifts subsequent to the adverse returns of conditional volatility and financial yields.

The primary aim of this inquiry is to elucidate and compare the behaviors of investments in conventional energy sectors versus alternative/renewable energy market segments. The research not only considers these segments as mere alternatives but seeks to define a broader, more integrative approach to understanding their roles within the investment portfolios. By dissecting the market dynamics and financial characteristics of these ETFs, the study aims to demonstrate how the inclusion of renewable energy investments can mitigate risks and enhance returns, particularly under typical market conditions.

This bifurcation of energy investments includes an examination of markets related to renewable energies such as smart grids and infrastructure, which are increasingly relevant in the context of global energy transitions. The study's methodology, leveraging the VAR-ADCC-GARCH model, facilitates a nuanced analysis of the estimated returns, volatilities, and covariances, providing a comprehensive picture of how these energy segments perform relative to one another and within the broader market ecosystem.

Through this scholarly endeavor, the paper aims to substantiate the economic viability of diverse investment strategies in managing economic utilities and adjusting to market volatilities. By providing empirical insights derived from advanced econometric analyses, this research seeks to guide investors toward more informed decision-making within an environmentally-conscious investment framework. It contributes significantly to the discourse on integrating alternative/renewable energy market segments within the broader framework of investment portfolio diversification, aiming to inspire both theoretical advancement and practical investment strategies in the evolving energy markets.

The inaugural segment of this research establishes the theoretical and methodological underpinnings, delineating the investment instrument construct under scrutiny, the elected optimal methodology, and the pertinent database. The ensuing segment elucidates the findings via the deployment of the stipulated methodology, encompassing the incorporation of time-series data and the requisite modification of software formulae to align with the methodological framework. The findings are articulated through the dissemination of descriptive statistical tabulations, the undertaking of regression analyses, and the construction of portfolio strategies. The culmination of this research entails a comprehensive evaluation of the outcomes attributable to the aforementioned computational analyses.

Objectives and hypotheses

The primary aim of the research is to investigate investment opportunities within traditional and alternative/renewable energy sectors, particularly through ETFs. It aims to validate the potential of these sectors for enhancing portfolio diversification and to develop investment strategies using the multivariate GARCH model, focusing on analyzing returns, volatilities, and covariances. This exploration includes a detailed examination of the inherent market dynamics and the systemic risks associated with each sector, shedding light on their unique investment profiles. Furthermore, the study seeks to identify optimal investment segments that offer superior returns and/or reduced risks.

Employing a VAR-ADCC-GARCH model, the research enhances the investment analysis by incorporating advanced statistical techniques to more accurately predict market behaviors and potential financial outcomes. Presented in two main sections, the study first establishes the theoretical and methodological foundations, followed by the empirical findings and the application of these methodologies. The first section outlines the theoretical assumptions underpinning the models used, while the second section applies these models in practical scenarios to test the hypotheses.

The outcomes, particularly concerning the alternative/renewable energy sector, are showcased through the development of various strategies, supported by minimum and mean-variance optimization, and illustrated through descriptive statistical tables and regression analyses. These strategies are designed to capitalize on the volatility and growth potential inherent in the renewable energy market, reflecting a shift towards more sustainable investment practices.

Hypothesis 1: Traditional and alternative/renewable energy ETFs, under typical market conditions, exhibit distinct and separate behaviors. This hypothesis is tested through a comparative analysis of historical performance data, aiming to highlight the distinct investment attributes of each sector.

Hypothesis 2: Diversifying across different ETFs optimizes risk and return profiles. This is explored through portfolio simulation techniques that demonstrate how strategic asset allocation can mitigate risks and enhance returns.

Hypothesis 3: Alternative/renewable energy investments outperform traditional energy investments both in risk and return. This assertion is examined through a series of regression models and variance analysis to validate the superior performance of renewable energy investments over traditional energy investments, especially in terms of risk-adjusted returns.

Database and methodology

Database

The dataset under examination encompasses daily return metrics for a collection of ten ETFs spanning the interval from January 4, 2010, to December 31, 2020, with careful consideration given to the volume of data points. The rationale for selecting this period for this study is to analyze the behavior of the segments under normal market conditions. This timeframe encompasses an era characterized by economic expansion phases, devoid of any observable recessionary trends. The choice of this specific investigational period was motivated by the intent to scrutinize the markets during a phase of relative stability, where economic conditions are conducive to evaluating the standard operations and performance of the segments.

However, it is important to acknowledge that the latter part of this period is marked by the unprecedented impact of the COVID-19 pandemic, an anomaly that is reflected in the data and the segments' performance as well.

The number of observations examined over the 11-year period is 2768. The daily return of the ETFs is the quotient of the difference between the assets' closing and opening adjusted prices, and the opening adjusted price, expressed as a percentage. The assortment of funds is bifurcated into two distinct categories: five ETFs are aligned with the conventional energy sector, while the remaining five are categorized under alternative or renewable energy sectors.

Within the taxonomy of these ETFs, the conventional energy contingent is representative of the sectors engaged in natural gas and petroleum markets. Conversely, the ETFs classified under alternative or renewable energy encapsulate a broad spectrum of energy sources, including but not limited to, wind, solar, geothermal, hydroelectric, as well as marine energies such as wave and tidal. This category further extends to encompass markets related to biomass and biofuels, thereby illustrating the diverse energy modalities considered within this dataset.

In pursuit of elucidating the potential for diversification within the realm of alternative and renewable energy markets, as well as delineating the distinctions between traditional and emergent energy market segments, the present study elects to engage with both conventional and alternative/renewable ETFs as the principal instruments of investment. ETFs, recognized for their passive investment nature, mirror the dynamics of stocks by encapsulating the performance of either a specific sector or a broader market benchmark. It is noteworthy that extant scholarly works have predominantly leveraged investments in stock market indices for analogous inquiries. For instance, Bouri et al. (2017) in their exploration of the diversification potential of renewable energy investments, rely heavily on stock indices to gauge market trends. Similarly, Henrique et al. (2019) employ market indices to assess the volatility and risk-return profiles of renewable energy investments, underscoring their utility in traditional financial analysis frameworks. In a departure from this traditional approach, this investigation gravitates towards the utilization of ETFs, owing to their broad accessibility to a spectrum of investors, encompassing both individuals and institutional entities.

The five traditional energy ETFs are: Energy Select Sector SPDR (XLE), Vanguard Energy ETF (VDE), SPDR S&P Oil & Gas Exploration & Production ETF (XOP), iShares Global Energy ETF (IXC), and VanEck Vectors Oil Services ETF (OIH). The five alternative/renewable energy ETFs are: iShares Global Clean Energy ETF (ICLN), Invesco Solar ETF (TAN), First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN), First Trust Nasdaq Clean Edge Smart GRID Infrastructure Index (GRID), and Invesco MSCI Sustainable Future ETF (ERTH). The ETFs in question stand out for their exemplary representation of their respective sectors, bolstered by an extensive archive of historical data reaching back to 2010.

Differences between the segments manifest in their investment strategies and portfolio compositions. Within the traditional energy ETF sector, the Energy Select Sector SPDR (XLE) ETF primarily targets companies engaged in conventional energy extraction, processing, and transportation within the United States, including oil, gas, and other fossil fuels. The XLE ETF is aimed at investors seeking diversification and outstanding returns within the traditional energy industry. Similarly, the Vanguard Energy ETF (VDE) focuses its portfolio on major energy corporations in the U.S. involved in oil, gas, and other fossil fuel industries, catering to investors looking for long-term growth and returns in the energy sector. The SPDR S&P Oil & Gas Exploration & Production ETF (XOP) mainly operates in on the U.S. oil and gas exploration and production sectors, appealing to investors interested in these areas. The iShares Global Energy ETF (IXC) concentrates on companies across the global energy sector, enabling diversification across various industry areas. The VanEck Vectors Oil Services ETF (OIH) focuses on oil service companies worldwide that provide services at different stages of the extraction process.

In the alternative/renewable energy ETF segment, the iShares Global Clean Energy ETF (ICLN) focuses on companies worldwide involved in the clean energy sector, including wind and solar energy and other environmentally friendly technologies, targeting environmentally conscious investors who anticipate long-term growth from the clean energy sector. The Invesco Solar ETF (TAN) is centered on the global solar energy industry, including companies that manufacture solar collectors and photovoltaic cells. The First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN) concentrates on the stocks of companies operating in the green energy field. The First Trust Nasdaq Clean Edge Smart GRID Infrastructure Index (GRID) is focused on companies globally involved with smart grids and infrastructure, aimed at investors focusing on the development of network technologies and infrastructure. Finally, the Invesco MSCI Sustainable Future ETF (ERTH) focuses globally on sustainable companies and developments, targeting investors who prioritize sustainability and social responsibility.

Methodology

The VAR-ADCC-GARCH approach

To compare the two ETF segments, the study employs the VAR-ADCC-GARCH model. The VAR-ADCC-GARCH model is a commonly used modeling technique in the field of financial investment for forecasting volatility in time series. The model has been successfully applied to the examination of ETFs within the concept of financial portfolio diversification (Miralles-Marcelo et al., 2018).

The development of the model unfolds in two distinct phases. The initial phase entails the delineation of the time series model. Precise articulation of the mean equation is imperative, given that any inaccuracies in its specification can result in the erroneous establishment of the variance equation (Ewing & Malik, 2005). The return generation process is theorized as follows:

$$r_{i,t} = c_i + \sum_{\substack{i=1 \\ j=1}}^{5} \alpha_{(ij)r_{i,t-j}} + \varepsilon_{i,t}$$

$$\varepsilon_{i,t} \mid \Omega_{t-1} \approx \mathrm{N}(0,\mathrm{H}_t) \tag{1}$$

In the VAR-ADCC-GARCH model $r_{i,t}$ is the ETF's daily return, c_i and α_{ij} are the estimated parameters, and $\varepsilon_{i,t}$ is a 5 × 1 vector of error terms which is assumed to be conditionally normal with zero mean and conditional variance matrix H_t. In each model the conditional variances $h_{i,t}$ and the standardized residuals $\delta_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$ are generated separately. Thus, the covariance matrix is specified as:

$$H_t = D_t R_t D_t \tag{2}$$

In the conditional variance matrix H_t, $D_t = diag(\sqrt{h_{it}})$ is a diagonal matrix which contains the time varying conditional volatilities of the previous GARCH models and R_t is a time-varying 3 × 3 correlation matrix with diagonal elements equal to 1 which is specified as:

$$R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1} \tag{3}$$

In the VAR-ADCC-GARCH model $Q_t = \{q_{ij,t}\}$ is a covariance matrix of the standardized residuals denoted as:

$$Q_t = (1-\alpha-\beta) - \gamma + \alpha(\delta_{t-1}\delta'_{t-1}) + \gamma\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1} \tag{4}$$

$= E[\delta_t\delta'_t]$ is the unconditional correlation matrix of the standardized residuals; $Q_t^* = diag(\sqrt{q_{ij,t}})$ is a diagonal matrix containing the square root of the diagonal elements of the n × n positive matrix Q; $\eta_t = I[\delta_t < 0] \odot \delta_t$ $(I\,[\ .\ ]$ is a 3×1-es indicator function which takes on value 1 if the argument is true and 0 otherwise while $\odot$ is the Hadamard-product and $= [\eta_t\eta'_t]$. Positive definiteness of Q_t is ensured by imposing $\alpha + \beta + \lambda\gamma < 1$, where λ = maximum Eigen-value $[\ ^{-1/\ 2-1/2}]$.

The investment strategies

Using the insights gained from Miralles-Marcelo et al. (2018), the study applies the analysed returns, volatilities, and correlations from the earlier VAR-ADCC-GARCH approach to create four different investment strategies. These strategies are rooted in two traditional approaches to optimizing portfolios. The first approach tackles to develop a portfolio that aims to minimize risk, known as the minimum-variance portfolio, defined by the following equation:

$$min_{w_t} w_t' H_{\{t+1|t\}} w_t \tag{5}$$

where $w_t' H_{\{t+1|t\}} w_t$ is the portfolio risk equation to be minimized. Pursuing this strategy, one can assume that the investor's sole focus is on reducing volatility. Yet, in practice, investors are not solely concerned with lowering risk; they are also keen on generating returns from their investments.

Concurrently, the alternative optimization issue tackled is the traditional mean-variance strategy introduced by Markowitz in 1952. This strategy's objective remains to curtail portfolio risk while incorporating a constraint that ensures the portfolio reaches a specified return target. Hence, the optimization challenge is established as follows:

$$\begin{aligned} &min_{w_t} w_t' H_{\{t+1|t\}} w_t \\ &s.t.\, w_t' E\left[R_{\{t+1\}}\right] \geq R^{*} \end{aligned} \tag{6}$$

In this strategy R^* denotes the desired target return performance. The adopted approach uses an equally distributed portfolio, often referred to as the naïve portfolio, as the reference point for R^*. Portfolios can be created with or without short-selling constraints.

Initially, the optimization problem is solved by excluding short-sellings. Therefore, the general constraints $w_t' 1 = 1$ $w_i 1 \geq 0$ i = 1,2, …, N are included. The impact of short-selling constraints on portfolio management is an area with divergent findings in academic research, as highlighted by Grullon et al. (2015). A number of studies have explored portfolio management strategies both in the context of the presence and absence of short-selling constraints. For instance, Diether et al. (2009), and Beber & Pagano (2012) have provided various insights, though consensus on the effects is still evolving. Compellingly, Bohl et al. (2016) presented econometric findings suggesting that volatility persistence intensified during the financial crisis, especially in stocks with short-selling constraints. Their work not only contributes to understanding the nuances of market dynamics under such constraints but also advises against the imposition of short-selling bans by regulators. Drawing from these diverse academic perspectives, the optimization problems are approached by including scenarios where short-selling constraints are factored in, in line with the recommendations and observations made by Bohl et al. (2016). In that case only the constraints $w_t'1 = 1 \; i = 1,2,\ldots,N$ were included. In both cases w_i is the weight of each asset from the portfolio vector, $w_t = [w_1, w_2, \ldots, w_N]$, and 1 is a vector of ones.

Ultimately, the effectiveness of the optimization models is assessed over the period t = τ + 1, ..., T, in terms of the Sharpe ratio, SR_p which is defined as the average returns divided by their sample standard deviation:

$$SR_p = \frac{\mu_p}{\sigma_p} \tag{7}$$

Descriptive statistics

Table 1 and 2 contain the descriptive statistics for the daily return series for the energy ETFs (XLE, VDE, XOP, IXC and OIH) and alternative/renewable energy ETFs (ICLN, TAN, QCLN, GRID and ERTH), respectively, for the sample period from January 4, 2010, to December 31, 2020. Probabilities are is brackets and represent 1% significance level. The last column reports the mean and variance equality tests using the ANOVA and Levene statistics, respectively. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic tests the normality of the series. This statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. ARCH (1) is the Engle test for the 1st-order ARCH. These three tests are distributed as $\chi^2(1)$. The p values of these tests are reported in brackets.

Table 1. Energy ETFs

	XLE	VDE	XOP	IXC	OIH	Equality test
Mean	0.011428	0.006693	-0.00268	0.005156	-0.024095	0.131754 (0.9708) 113.6213 (0.0000)
Std. Dev.	1.732848	1.74955	2.488797	1.628015	2.401432	
Skewness	-0.447939	-0.403428	-0.662624	-0.616186	-0.529481	
Kurtosis	20.17057	18.12251	25.30851	23.51928	20.94285	
Jarque-Bera	34096.14 (0.0000)	26450.7 (0.0000)	57600.47 (0.0000)	48735.21 (0.0000)	37260.42 (0.0000)	
ARCH (1)	0.110208 (0.0000)	0.103251 (0.0000)	0.111364 (0.0000)	0.116454 (0.0000)	0.088525 (0.0000)	

Source: author's compilation

Table 2. Alternative/renewable Energy ETFs

	ICLN	TAN	QCLN	GRID	ERTH	Equality test
Mean	0.031365	0.03934	0.071838	0.048674	0.052021	0.200523 (0.9382) 181.5350 (0.0000)
Std. Dev.	1.645187	2.438284	1.81066	1.52775	1.36383	
Skewness	-0.4229	0.047349	-0.26563	-0.35896	-0.61126	
Kurtosis	9.221772	6.79016	8.440482	11.47175	10.59155	
Jarque-Bera	4547.113 (0.0000)	1657.834 (0.0000)	3446.285 (0.0000)	8336.987 (0.0000)	6819.22 (0.0000)	
ARCH (1)	0.087671 (0.0000)	0.055898 (0.0000)	0.071818 (0.0000)	0.096181 (0.0000)	0.102340 (0.0000)	

Source: author's compilation

The energy and alternative/renewable energy ETFs exhibit non-normal return distributions with evidence of volatility clustering. The daily returns show evidence of leptokurtic behaviour, indicating the presence of outliers and the potential for extreme returns. The equality test results suggest that while the average returns may be similar for the Energy ETFs, the volatilities are significantly different within both sets of ETFs. This has implications for portfolio construction and risk management as ETFs with higher volatility may contribute more to the risk of the portfolio. In the GARCH model and its extensions, which particularly adept at modelling the thick tails and volatility clustering typical of financial time series data, leptokurtosis indicates that data have heavy tails and a sharp peak around the mean, which is more pronounced than that seen in a normal distribution. This feature of financial datasets can lead to underestimating the likelihood of extreme events if not modelled correctly, see Bollerslev (1986). The differences highlight distinct risk-return profiles between traditional energy ETFs and alternative/renewable Energy ETFs. The former appear to be more volatile, while the latter offer higher average returns, which may appeal to different types of investors depending on their risk appetite and investment goals. Engle's introduction of the ARCH model provided a methodological breakthrough for analyzing and forecasting volatile financial markets to adequately address the inadequacy of assuming constant volatility, which is a common limitation in standard financial models, see Engle (1982). Additionally, the presence of non-normal distributions and volatility clustering in both groups calls for sophisticated risk management strategies that go beyond standard models assuming normal distributions and constant volatility.

The return diagrams of the two segments

To depict the contrasts between the two ETF categories, Figures 1 and 2 provide the yield charts reflecting observations throughout the timeframe from January 4, 2010, to December 31, 2020. There are noticeable parallels in the trends of ascent and descent. It becomes apparent that the alternative/ renewable energy ETF category exhibits greater volatility when contrasted with the conventional energy ETF category. Patterns of fluctuating behaviour are discernible across both categories, with the conventional ETF group particularly showing this trend beyond the 2500th observation in the final year under review, 2020. This period coincides with the advent of the COVID-19 pandemic, a global crisis that significantly disrupted demand dynamics across energy markets, see Salisu et al. (2021). The imposition of lockdowns and the ensuing slump in industrial activity and mobility led to an abrupt contraction in energy consumption, injecting considerable uncertainty and erratic price movements into energy ETFs. Concurrently, an oil price skirmish among leading oil-exporting nations compounded these disruptions. The subsequent oversupply, amid an already waning demand, intensified the volatility of energy ETFs, with pronounced impacts on investor sentiment and market liquidity. These perturbations were further exacerbated by reactive monetary policies, including the Federal Reserve's interest rate cuts and asset purchases, which introduced additional liquidity into the markets, amplifying the magnitude of price swings. Further aggravating the sector's instability is the accelerating transition towards renewable energy sources, signalling a structural shift that imbues traditional energy markets with long-term uncertainty. This inflection point, marked by both cyclical pandemic-related shocks and secular changes in energy preferences, is a crucible for heightened volatility.

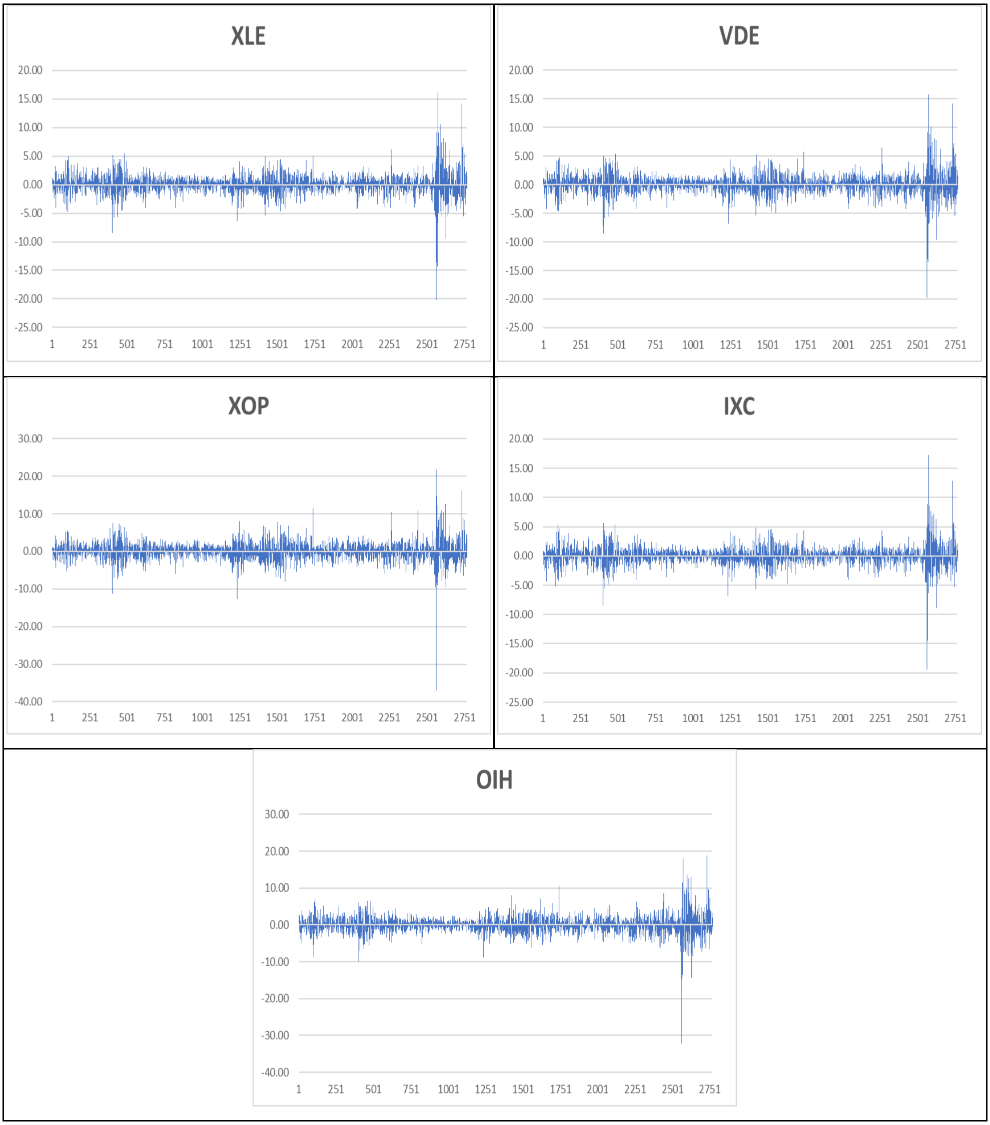

Figure 1. The return diagrams of the energy ETFs
Source: author's compilation

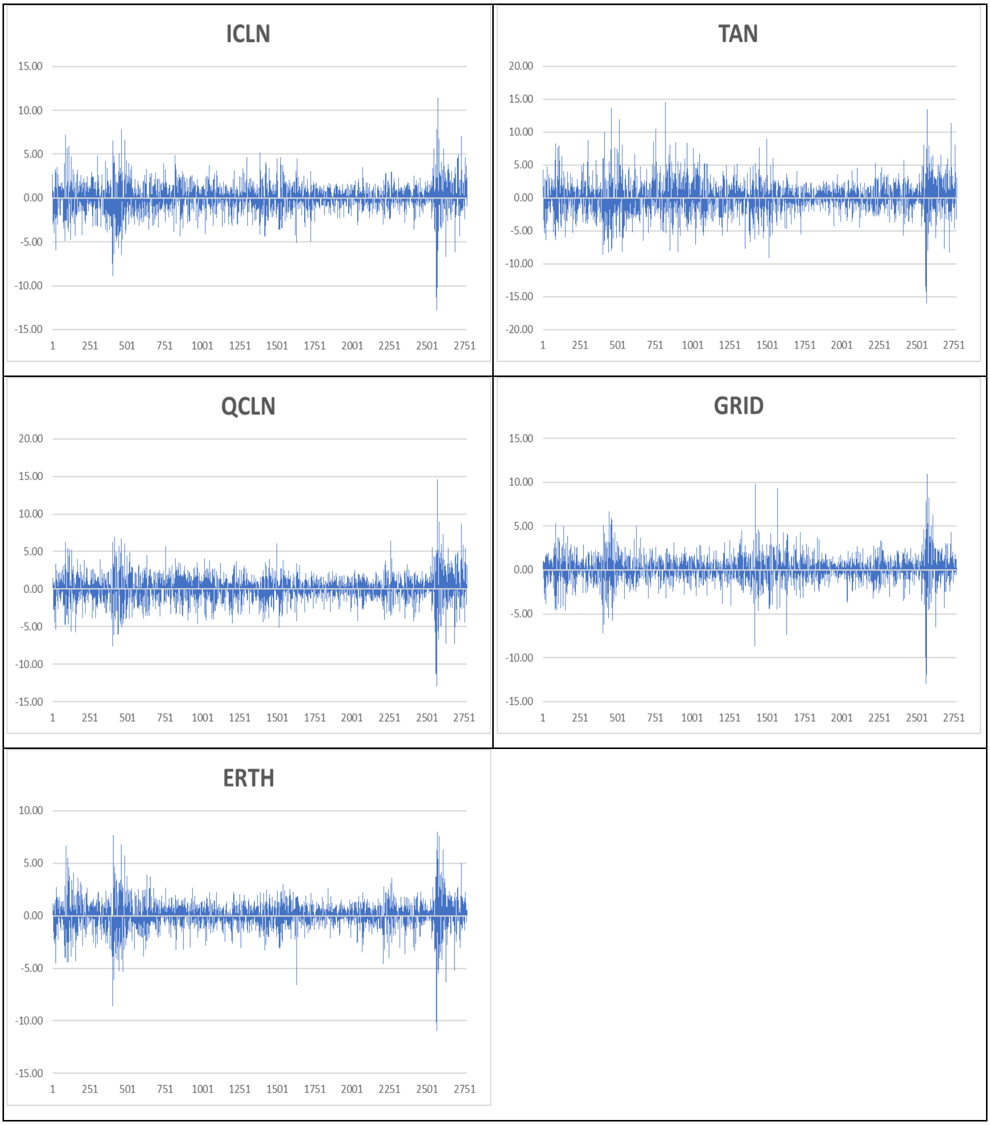

Figure 2. The return diagrams of the alternative/renewable energy ETFs
Source: author's compilation

Results and discussion

GARCH parameters

Table 3 and 4 detail the GARCH parameters (C, ω, α and β) and their probabilities in brackets for energy and alternative/renewable energy ETFs from January 4, 2010, to December 31, 2020. *** represents the 1% significance level, ** represents the 5% significance level, * represents the 10% significance level, - represents not significant. In this research GARCH models are employed to understand the volatility dynamics of financial assets. Through modelling the variance of the current error term as a function of the previous periods' error terms and variances. The importance of the statistical significance of these parameters in his paper helps to affirm that the model's outputs are robust and not due to random variations, see Bollerslev (1986). The Constant (C) term represents the long-term mean of the dataset. ω is the baseline variance, or the long-run average volatility when previous periods' shocks are not considered. It is the intercept of the variance equation and reflects the part of the current variance that is unexplained by the lagged terms. α is a parameter (associated with (RESID(-1)^2), which measures the response of the variance to shocks in the previous period. A higher value indicates that recent shocks have a greater impact on current volatility, a phenomenon often referred to as volatility clustering. The β parameter (associated with GARCH(-1)) indicates the persistence of volatility shocks to future periods. A high β suggests that volatility tends to be persistent through time, (Bollerslev, 1986). The probability values associated with each parameter signifies the statistical significance. Low probability values (typically less than 0.05) indicate that the parameter is statistically significant and not likely the result of random variation.

Table 3. Energy ETFs

ETF	Constant (C)	ω	α (RESID(-1)^2)	β (GARCH(-1))
XLE	0.049762 (0.0224)**	0.032596 (0.0020)***	0.110230 (0.0000)***	0.881210 (0.0000)***
VDE	0.046133 (0.0413)**	0.032646 (0.0024)***	0.103309 (0.0000)***	0.888169 (0.0000)***
XOP	0.067069 (0.0538)*	0.065611 (0.0049)***	0.111506 (0.0002)***	0.883950 (0.0000)***
IXC	0.045537 (0.0215)**	0.027961 (0.0008)***	0.115383 (0.0000)***	0.878901 (0.0000)***
OIH	0.030812 (0.3231)-	0.036321 (0.0043)***	0.089336 (0.0001)***	0.908370 (0.0000)***

Source: author's compilation

Table 4. Alternative/renewable energy ETFs

ETF	Constant (C)	ω	α (RESID(-1)^2)	β (GARCH(-1))
ICLN	0.045249 (0.0646)*	0.044073 (0.0015)***	0.089155 (0.0000)***	0.894564 (0.0000)***
TAN	0.045939 (0.2187)-	0.032528 (0.0096)***	0.056151 (0.0000)***	0.940136 (0.0000)***
QCLN	0.073212 (0.0072)***	0.042165 (0.0024)***	0.071358 (0.0000)***	0.915175 (0.0000)***
GRID	0.075973 (0.0013)***	0.054969 (0.0002)***	0.096392 (0.0000)***	0.878326 (0.0000)***
ERTH	0.075050 (0.0001)***	0.035039 (0.0001)***	0.103609 (0.0000)***	0.875798 (0.0000)***

Source: author's compilation

It can be observed that for energy ETFs, the constants (C) across different ETFs vary slightly, suggesting differences in their long-term average returns. The α and β parameters are highly significant (p-values close to 0), which indicates strong support for the GARCH modelling approach in describing the volatility of these ETFs. The magnitude of the α coefficients is relatively small but significant, indicating that while past shocks have an impact, it is not overwhelmingly large. The β coefficients are close to 1, suggesting a high degree of volatility persistence. This means that when the volatility level changes, these changes are likely to persist into the future. For alternative/renewable energy ETFs the constants (C) are similar in magnitude to those of the Energy ETFs, but the interpretation might differ due to the nature of the assets. The α coefficients again are significant and similar in magnitude to the Energy ETFs, indicating a consistent impact of past shocks across different types of ETFs. The β values are very high (also close to 1), suggesting that volatility is highly persistent, which is a common characteristic in financial time series data.

While the structure of the GARCH model is consistent across both types of ETFs, the interpretation may differ based on the sector. For instance, alternative/ renewable energy ETFs might be subject to different market dynamics compared to traditional energy ETFs, including different reactions to market-wide events or news about technological developments and regulatory changes. The degree of persistence in volatility (β) might suggest that the market's view of risk in these sectors remains consistent over time. It is important to consider that these GARCH parameters alone do not provide the complete picture. Overall, the GARCH parameters show the existence of some significant dynamic relationships between the ETFs. In practice, analysts would further investigate the causes behind the volatility patterns. This is why the VAR-ADCC-GARCH approach is applied in the next section.

VAR-ADCC-GARCH parameters

Table 5 exhibits the VAR-ADCC-GARCH parameters on the energy and alternative/renewable energy ETFs for the sample period from January 4, 2010, to December 31, 2020. $***$ represents the 1% significance level, $**$ represents the 5% significance level, $*$ represents the 10% significance level, - represents not significant. To analyze ETFs from two different segments, a cross-segment comparison is created by evaluating them in pairs. With 25 distinct pairs, the relationship between each pair can be individually examined. This approach allowed to understand the interconnectivity and correlation within each pair across different market segments.

Table 5 contributes to the understanding of the persistence of volatility and correlation shocks in financial time series data. Theta (1) shows the direct correlation, and indicates the immediate impact of a new shock to the correlation between the two time-series. A significant theta (1) with a low probability value suggests a strong response in the direct correlation to new information or market events. Theta (2) shows the indirect correlation via latent variable, and captures the impact of shocks to the indirect correlation. The latent variable could represent unobserved market factors or risk drivers that affect both time series. A significant and persistent theta (2) suggests that the latent variable plays an important role in the correlation dynamics between the ETFs over time. Theta (3) is the latent variable correlation which reflects the persistence of shocks to the latent variable itself. It shows how changes in the latent variable's volatility affect the correlation with the time series. A non-significant theta (3), indicated by a high p-value, suggests that the latent variable's own shocks do not persistently influence the correlation between the ETFs. If the sum of theta (1) and theta (2) is below 1, the stability condition is met, which means the ADCC-GARCH model is stable. If this condition is not met, it suggests that shocks to the correlation have a unit root, implying non-mean reverting behavior which could indicate instability in the correlation over time. Impact of market volatility on the returns highlights the importance of the DCC and ADCC-GARCH models in capturing the time-varying correlations and the asymmetric effects of volatilety transmission between prices and industry returns, see Ullah (2021).

Table 5. The two-pair ADCC-GARCH analysis of the energy and alternative/renewable energy ETFs

ETF-pairs	theta (1)	theta (2)	theta (3)	Stability condition (theta(1)+theta(2) < 1)
XLE – QCLN	0.059521 (0.0000)***	0.911542 (0.0000)***	0.001642 (0.4705)-	met
XLE – TAN	0.042641 (0.0000)***	0.931255 (0.0000)***	0.005787 (0.0015)***	met
XLE – ICLN	0.042036 (0.0000)***	0.938956 (0.0000)***	0.009459 (0.0000)***	met
XLE – GRID	0.060644 (0.0000)***	0.925223 (0.0000)***	-0.000409 (0.8925)-	met
XLE – ERTH	0.026467 (0.0000)***	0.968446 (0.0000)***	0.009196 (0.0000)***	met
VDE – QCLN	0.058482 (0.0000)***	0.914059 (0.0000)***	0.001827 (0.4071)-	met
VDE – TAN	0.043466 (0.0000)***	0.930813 (0.0000)***	0.005518 (0.0025)***	met
VDE – ICLN	0.050385 (0.0000)***	0.929259 (0.0000)***	0.007846 (0.0000)***	met
VDE – GRID	0.063460 (0.0000)***	0.922654 (0.0000)***	-0.000848 (0.7978)-	met
VDE – ERTH	0.037096 (0.0000)***	0.951546 (0.0000)***	0.007362 (0.0000)***	met
XOP – QCLN	0.052234 (0.0000)***	0.924091 (0.0000)***	0.001469 (0.6126)-	met
XOP – TAN	0.056101 (0.0000)***	0.915152 (0.0000)***	-0.001239 (0.7577)-	met
XOP – ICLN	0.040881 (0.0000)***	0.945385 (0.0000)***	0.002526 (0.2378)-	met
XOP – GRID	0.039117 (0.0006)***	0.952030 (0.0000)***	0.000296 (0.9143)-	met
XOP – ERTH	0.027061 (0.0000)***	0.965296 (0.0000)***	0.003482 (0.0046)***	met
IXC – QCLN	0.044771 (0.0000)***	0.934226 (0.0000)***	0.002049 (0.0173)**	met
IXC – TAN	0.035276 (0.0000)***	0.942587 (0.0000)***	0.005239 (0.0005)***	met
IXC – ICLN	0.046829 (0.0000)***	0.935071 (0.0000)***	0.004076 (0.0002)***	met
IXC – GRID	0.082453 (0.0001)***	0.900418 (0.0000)***	-0.004360 (0.3164)-	met
IXC – ERTH	0.106607 (NA)-	0.936824 (NA)-	-0.001248 (NA)-	met
OIH – QCLN	0.031031 (0.0000)***	0.953922 (0.0000)***	0.003845 (0.0173)**	met
OIH – TAN	0.041720 (0.0000)***	0.934111 (0.0000)***	0.004916 (0.0215)**	met
OIH – ICLN	0.048118 (0.0000)***	0.934648 (0.0000)***	0.004804 (0.0033)***	met
OIH – GRID	0.046334 (0.0000)***	0.940388 (0.0000)***	0.000717 (0.8028)-	met
OIH – ERTH	0.047112 (NA)-	0.964977 (NA)-	-0.005089 (NA)-	not met

Source: author’s compilation

Most pairs met the stability condition, meaning that the correlations are stable and revert to a long-term average after a shock. The ADCC-GARCH model is particularly useful in financial econometrics to model time-varying correlations among multiple financial assets. The results are beneficial for portfolio optimization, risk management, and in understanding the behavior of the two segments. The persistence parameters provide insight into how quickly correlations adjust to new information and the role of underlying, unobserved factors in driving these correlations. For investors and risk managers, the model's ability to capture the dynamic nature of correlations can lead to better-informed investment decisions and risk assessments. The probabilities associated with each theta value are important in assessing the statistical significance of the parameters. Low p-values (typically less than 0.05) indicate that the corresponding theta parameter is statistically significant and provides meaningful insights into the correlation dynamics between the ETF pairs. The theta parameters across most ETF pairs are significant with very low p-values, indicating a high level of persistence in the correlations. This suggests that shocks to the correlations between these ETFs tend to have lasting effects, see Ullah (2021).

With the exception of the OIH – ERTH pair, all ETF pairs have met the stability condition, indicating that their correlations are stable over time and revert to a long-term mean. This implies that while the market may experience short-term fluctuations, the relationship between these pairs tends to remain consistent in the long term, which is reassuring for strategic asset allocation. For most pairs, the theta (2), which captures the impact of shocks through a latent variable, is statistically significant. This reveals the presence and importance of unobserved factors (such as macroeconomic indicators or policy changes) that are affecting multiple assets simultaneously. It points to a market driven by underlying systemic factors, which could be a focal point for further research or for investors looking to understand broader market dynamics. Theta (1) is significant for all ETF pairs, indicating that the direct correlation between ETFs is resilient to shocks. When creating portfolio strategies, investors might use this information to assess the risk of direct contagion between assets or sectors represented by these ETFs. The lower significance of theta (3) for some pairs suggests that the immediate impact of shocks to the latent variable's own variance may not have a long-lasting direct effect on the correlations. This could be useful for hedging against specific types of risk; for example, when focusing less on the latent variable shocks when one is more concerned about long-term investment horizons. The OIH – ERTH pair does not meet the stability condition, signaling potential instability in their correlation over time. This could be indicative of unique market forces or sector-specific risks affecting these assets differently compared to others. It highlights an area that may require special attention from risk perspective and could be a subject for further investigation.

In conclusion, the findings provide significant insights into the correlation dynamics between different ETFs. For practitioners in finance, understanding these dynamics can assist in diversifying portfolios, managing risk, and in the design of investment strategies that account for the persistent and dynamic correlations between different segments of the market. When constructing investment portfolios, the ADCC-GARCH performance persistent parameters, stability of correlations, the role of the latent variables, direct and indirect correlations, sector-specific dynamics, diversification opportunities, and market conditions and external shocks should be taken into account.

Overall, asymmetric dynamic correlations in the markets are supported by the significant parameters. The theta parameters indicated a high level of persistence in the correlations, especially between traditional and alternative/renewable energy ETFs. This implies that market shocks and volatility tend to have a lasting impact on these assets. When constructing portfolios, understanding the degree of persistence helps in analyzing potential risks and returns. Most of the ETF pairs, except OIH – ERTH, met the stability condition of the VAR-ADCC-GARCH model. This suggests that the dynamic correlations between the ETFs are stable over time, which is essential for long-term portfolio planning. This stability can aid in setting expectations for the correlations between assets in future market conditions. The significance of theta (2) across many pairs suggests a notable impact of latent variables on ETF correlations. This represents broader economic or policy-related factors affecting the energy sector. The latent variables may be crucial for strategic asset allocation. The importance of direct correlations (theta (1)) indicates the immediate and significant response to new information or market events. In contrast, indirect correlations (theta (2)) signify the influence of unobserved factors. Balancing direct and indirect correlations in portfolio construction can help manage immediate and long-term risks. The non-compliance of the OIH – ERTH pair with the stability condition implies sector-specific dynamics that could lead to unstable correlations. This insight is vital when considering the diversification benefits or risks associated with the respective ETF-pair. The distinct behavior of traditional and alternative/renewable energy ETFs supports the hypothesis that diversifying across these segments can optimize the risk and return profile of an investment portfolio. The data suggest that alternative/renewable energy ETFs might provide a real alternative for investors, potentially offering superior risk-adjusted returns. The research period in the study spans phases of economic expansion and does not feature recessionary trends until the emergence of COVID-19. The pandemic's impact on the market underscores the importance of considering external shocks and market conditions when constructing portfolios. It suggests the need for strategies that can adapt to sudden market changes. When applying this knowledge to portfolio construction, it is crucial to utilize a forward-looking approach, integrating insights from the VAR-ADCC-GARCH analysis to manage expected volatility and correlations.

Investment strategies

Table 6 contains the performance evaluation of the proposed portfolios based on the annualized mean, annualized standard deviation and annualized Sharpe ratios for the sample period from January 4, 2010, to December 31, 2020. The performance considers scenarios both with and without short-selling constraints, juxtaposed against a naïve strategy for benchmarking purposes. The analysis is segmented into Panels A and B, which encompass the minimum variance and mean-variance strategies for energy ETFs, respectively, and Panels C and D, which detail the corresponding strategies for alternative/ renewable energy ETFs.

The Sharpe ratio is a very good measure in finance to evaluate the performance of an investment relative to its risk. Sharpe's initial findings and later academic studies underscore that the Sharpe Ratio effectively measures the risk-adjusted return of an investment. This means it accounts for the volatility of the investment, providing a more comprehensive view of its performance compared to just looking at raw returns. Research has demonstrated that the Sharpe Ratio is particularly useful as a comparative tool, allowing investors to compare the performance of different investments or portfolios on a level playing field. This aspect is especially helpful in portfolio management and strategy formulation, see Sharpe (1966).

Table 6. Portfolio performance evaluation

	Naïve	**Short-selling constraints**	**No short-selling constraints**
Energy: Panel A Minimum variance			
Return	-5.20%	-3.40%	-0.26%
Std. Dev.	31.09%	28.66%	25.36%
Sharpe ratio	-24.36%	-20.14%	-10.36%
Energy: Panel B Mean-variance (naïve)			
Return	-5.20%	-3.32%	2.18%
Std. Dev.	31.09%	29.33%	27.44%
Sharpe ratio	-24.36%	-19.39%	-0.69%
Alternative/renewable energy: Panel C Minimum variance			

	Naïve	**Short-selling constraints**	**No short-selling constraints**
Return	8.62%	9.67%	11.09%
Std. Dev.	25.18%	22.91%	20.90%
Sharpe ratio	24.83%	31.85%	41.71%
Alternative/renewable energy: Panel D Mean-variance (naïve)			
Return	8.62%	11.07%	14.76%
Std. Dev.	25.18%	24.81%	21.91%
Sharpe ratio	24.83%	35.08%	56.58%

Source: author's compilation

From the data presented, several conclusions can be discerned. The investment strategies deployed, particularly those pertaining to alternative/ renewable energy ETFs, exhibit a marked enhancement in the Sharpe ratio relative to the naïve strategy, signaling an improvement in risk-adjusted returns. The removal of short-selling constraints tends to favor portfolio performance, as indicated by higher Sharpe ratios across the board. This suggests that the ability to short-sell enables more efficient portfolio optimization, taking advantage of negative market movements. Amongst the various strategies, those applied to alternative/renewable energy ETFs (Panels C and D) not only transcend the naïve strategy's performance but also register substantive positive Sharpe ratios, with the no short-selling constraint mean-variance strategy in Panel D evidencing particularly robust outcomes. This implies a favorable environment for investment in alternative/renewable energy ETFs, with these vehicles yielding the most efficacious risk-adjusted returns in comparison to traditional energy ETFs. In summary, the empirical evidence suggests that investors could potentially gain by allocating resources to alternative/renewable energy ETFs and adopting mean-variance optimization techniques, especially when constraints on short-selling are absent, to optimize their investment portfolios.

The results indicated in Table 6 provide a clear comparative advantage for alternative/renewable energy ETFs over traditional energy ETFs during the period analyzed. The higher Sharpe ratios for the alternative/renewable energy ETFs, particularly under the mean-variance portfolio construction without short-selling constraints, suggest that these investments offered better risk-adjusted returns. The conclusion that alternative/renewable energy ETFs outperformed traditional energy ETFs is supported by both the higher returns and more favorable Sharpe ratios, indicating that they not only provided higher returns but did so with a more efficient management of risk relative to the expected return. This outperformance aligns with broader investment trends that favor sustainable and green energy sources, reflecting both a shift in consumer preference and perhaps advancements in technology within the sector.

Tables 7 and 8 detail the portfolio weights for energy ETFs and alternative/ renewable energy ETFs, respectively, for the sample period from January 4, 2010, to December 31, 2020. The tables are divided into panels representing different strategies and constraints. In the naïve strategy weights are evenly distributed across all ETFs, implying no optimization based on historical data. This strategy assumes equal risk and potential return from each ETF. In the minimum variance strategy the goal is to minimize portfolio risk, see Markowitz (1952). The allocation in Panels A and C shows more significant weights in certain ETFs even with short-selling constraints, suggesting that these ETFs are considered less volatile. Without short-selling constraints (Panels B and D), one can see that some ETFs are assigned negative weights (indicating short positions), which suggests that taking short positions in certain ETFs can contribute to lowering the portfolio's overall volatility. The mean-variance strategy aims to optimize the trade-off between return and risk. In Panels A and C (with short-selling constraints), the allocations are more conservative in terms of short positions compared to the minimum variance strategy. However, when short-selling constraints are removed (Panels B and D), one can obserce significantly larger negative weights, indicating an aggressive stance to short-sell certain ETFs to achieve the desired risk-return profile. The negative weights in Panels B and D for the minimum variance and mean-variance strategies suggest a conviction that the short-sold ETFs will underperform relative to the others. This is particularly notable for the mean-variance strategy without short-selling constraints in the renewable energy sector (Panel D), where large negative weights indicate a strong position taken against certain ETFs to maximize the portfolio's Sharpe ratio. The differences in the portfolio weights between Panels A and B for energy ETFs and Panels C anis empd D for alternative/renewable energy ETFs highlight the impact of short-selling constraints on portfolio construction. When these constraints are lifted, the optimization algorithm takes more extreme positions, which can either increase the potential return or decrease the risk, depending on the strategy chosen. Overall, the tables suggests that the inclusion or exclusion of short-selling constraints has a significant impact on the construction of optimized portfolios, particularly for the minimum variance and mean-variance strategies. The data implies that the freedom to short-sell allows for a more flexible and potentially more profitable portfolio allocation, assuming the investor is comfortable with the increased risks associated with short selling.

Table 7. Portfolio weights for the energy ETFs

	XLE	VDE	XOP	IXC	OIH
Panel A: with short-selling constraints					
Naïve	20%	20%	20%	20%	20%
Minimum variance	30%	10%	10%	40%	10%
Mean-variance	40%	30%	10%	10%	10%
Panel B: without short-selling constraints					
Naïve	20%	20%	20%	20%	20%
Minimum variance	40%	40%	-17%	40%	-3%
Mean-variance	40%	40%	40%	40%	-60%

Source: author's compilation

Table 8. Portfolio weights for the alternative/renewable energy ETFs

	ICLN	TAN	QCLN	GRID	ERTH
Panel C: with short-selling constraints					
Naïve	20%	20%	20%	20%	20%
Minimum variance	10%	10%	10%	30%	40%
Mean-variance	10%	10%	40%	10%	30%
Panel D: without short-selling constraints					
Naïve	20%	20%	20%	20%	20%
Minimum variance	40%	-30%	11%	38%	40%
Mean-variance	39%	-59%	40%	40%	40%

Source: author's compilation

Conclusions

Based on the comprehensive analysis conducted using the VAR-ADCC-GARCH approach and the detailed examination of traditional and alternative/ renewable energy ETFs, one can draw the following main findings and overall conclusions.

Regarding Hypothesis 1 - Traditional and alternative/renewable energy ETFs, under typical market conditions, exhibit distinct and separate behaviors, the study utilized a VAR-ADCC-GARCH model to analyze daily return series for a selection of ETFs representing both traditional and alternative/renewable energy sectors. This model allowed the study to capture the time-varying conditional correlations and volatilities, offering insights into the behaviors of the ETFs under typical market conditions. The results indicated that traditional energy ETFs and alternative/renewable energy ETFs have different volatility and return profiles. Traditional energy ETFs generally showed higher volatility, while alternative/renewable energy ETFs exhibited higher returns. This distinct behavior was supported by the statistical tests conducted, confirming the hypothesis.

With reference to Hypothesis 2 - Diversifying across different ETFs optimizes risk and return profiles, the study compared portfolio performances under different strategies, both with and without short-selling constraints. The analysis looked at naïve diversification (equal weights), minimum variance portfolios, and mean-variance portfolios to understand how diversification across the ETFs could affect the risk-return profile. Portfolio performance metrics (Sharpe ratios, standard deviation, and returns) demonstrated that diversification across traditional and alternative/renewable energy ETFs did optimize the portfolios' risk and return profiles. The alternative/renewable energy ETFs especially improved portfolio efficiency when they were included, and the mean-variance strategy without short-selling constraints showed the most significant benefits.

As for Hypothesis 3 - Alternative/renewable energy investments outperform traditional energy investments both in risk and return, the performance of alternative/renewable energy ETFs was benchmarked against traditional energy ETFs using Sharpe ratios, returns, and volatilities as key metrics. The Sharpe ratios and returns were consistently higher for portfolios consisting of alternative/renewable energy ETFs compared to those with traditional energy ETFs, especially when no short-selling constraints were applied. This suggested that alternative/renewable energy ETFs not only offered higher returns but also managed risk more effectively, thus outperforming traditional energy ETFs and confirming the hypothesis.

In conclusion, the study provided empirical support for all three hypotheses. It showed distinct behaviors between the two types of ETFs, confirmed the benefits of diversification for optimizing risk and return, and demonstrated the superior performance of alternative/renewable energy investments compared to traditional energy investments during the period analyzed. These findings were substantiated through a rigorous methodological framework, utilizing advanced econometric models, and a thorough analysis of investment strategies and portfolio performances.

Both traditional and alternative/renewable energy ETFs exhibit non-normal return distributions characterized by volatility clustering and leptokurtosis. This suggests a tendency for high-volatility events to cluster together, and for the returns to have fat tails, indicating a higher likelihood of extreme returns than would be predicted by a normal distribution. The study indicates distinct volatility profiles within each ETF category. Traditional energy ETFs, which include assets in natural gas and petroleum markets, generally showed higher volatility levels compared to alternative/renewable energy ETFs. The GARCH parameters for both ETF categories showed significant and persistent volatility. The α coefficients, though relatively small, indicated that past shocks do impact current volatility. The β coefficients, close to 1 for most ETFs, suggest that volatility is highly persistent, meaning that once the level of volatility changes, these changes are likely to continue into the future.

The VAR-ADCC-GARCH methodology provides evidence of dynamic correlations, with significant theta parameters suggesting a high level of persistence in correlations, especially between traditional and alternative/renewable energy ETFs. This means that market shocks and volatility tend to have lasting impacts on the correlations between these assets. Except for the OIH – ERTH pair, all ETF pairs met the stability condition, meaning that the dynamic correlations between the ETFs are stable over time. This provides a measure of predictability and stability for investors using these correlations to inform their asset allocation decisions. The significance of theta (2) across many pairs reveals the notable impact of latent variables on ETF correlations. These latent variables likely represent broader economic or policy-related factors that simultaneously affect the energy sector.

The alternative/renewable energy ETFs showed higher returns than traditional energy ETFs, according to the study's findings. This is consistent with broader market trends and investor preference shifts towards sustainable energy. Investment strategies, particularly those applied to alternative/renewable energy ETFs, significantly affected the returns. The mean-variance strategy without short-selling constraints was especially effective, leading to higher returns and outperformance over the naïve strategy. The research indicates that alternative/renewable energy ETFs not only provide potentially higher returns but also offer a different risk profile compared to traditional energy ETFs. The dynamic nature of correlations and volatilities, as revealed through the GARCH and VAR-ADCC-GARCH models, underscores the complexity of managing portfolios in these sectors and highlights the importance of advanced statistical models for portfolio construction and risk assessment.

Alternative/renewable energy ETFs demonstrated superior risk-adjusted returns compared to traditional energy ETFs, particularly under the mean-variance portfolio strategy without short-selling constraints. The Sharpe ratios were significantly higher for alternative/renewable ETFs, indicating more efficient risk management in relation to the expected return. Portfolio performance was generally better without short-selling constraints. The ability to short-sell within the portfolios allowed for a more flexible strategy that could capitalize on negative market movements, leading to an improved Sharpe ratio. The portfolio weights varied significantly depending on the investment strategy and the presence or absence of short-selling constraints. Negative weights in some portfolios suggest a strategic position taken to short-sell underperforming ETFs to enhance overall portfolio performance. The alternative/renewable energy sector not only outperformed the traditional energy sector but also provided strong positive Sharpe ratios, which supports the market trend towards sustainable and green energy sources.

The study points out that diversification across traditional and alternative/ renewable energy ETFs can optimize the risk and return profile of investment portfolios. Insights from the VAR-ADCC-GARCH analysis can aid in strategic asset allocation, taking into account the persistent and dynamic correlations between different market segments. Employing mean-variance optimization techniques, especially without constraints on short-selling, can potentially enhance portfolio performance. This is particularly relevant for alternative/renewable energy ETFs, which have shown to offer the most efficacious risk-adjusted returns in comparison to traditional energy ETFs. In light of these findings, it is evident that alternative/renewable energy investments offer compelling advantages for portfolio diversification and performance enhancement, reflecting broader shifts towards sustainable energy and the importance of considering advanced optimization and risk management techniques in portfolio construction.

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