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ORIGINAL RESEARCH

The Dynamic Linkages Among Artificial Intelligence, Sustainable Energies, Commodities, and Islamic Investments: Evidence from a Multivariate GARCH Model

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Abstract
This study aims to contribute to optimal portfolio theory by examining the dynamic correlations between Artificial Intelligence (AI) and other alternative investments. Optimal portfolio theory focuses on maximizing returns while minimizing risk through efficient asset allocation methods. Drawing on the First Trust Nasdaq Artificial Intelligence and Robotics ETF as a representative proxy, the research investigates to what degree AI-related assets behave in an interdependent manner with other types of alternative investments. To analyze these dynamic correlations, the study employs the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model. The study uses time-series data from March 1, 2019, to January 27, 2025. This econometric model allows the estimation of evolving correlations and volatilities across AI assets and other investments. Our findings indicate that crude oil provides diversification benefits to all asset classes under study, and all types of investors can obtain diversification benefits from Islamic investments, except for investors in Artificial Intelligence ETFs. Furthermore, the Artificial Intelligence ETF can provide diversification benefits to all types of investors under study, except for Islamic investment-based investors. This study incorporates the Artificial Intelligence ETF into a research framework encompassing sustainable energy, commodities, and Islamic investment—a combination rarely explored in prior research—and provides guidance on portfolio diversification strategies for interested parties.

Keywords Machine learning · Sustainable energies · Commodities · Islamic investments · Intelligent system

Introduction

Optimal portfolio theory is one of the most significant financial concepts, aiming to maximize returns while minimizing risk through an effective asset al.location strategy. Harry Markowitz developed the theory during the 1950s, and it is universally accepted as a cornerstone of modern investment management and financial research. Optimal portfolio theory encompasses key principles, including diversification, the risk-return trade-off, and the efficient frontier. The first—diversification—is in favor of diversifying investments across multiple asset classes to reduce overall risk. The second—risk-return trade-off—equates the expected returns with the acceptable level of risk for the investors. The third one—efficient frontier—provides the set of optimal portfolios that achieve the highest expected return for the given level of risk [61].

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Consequently, Sharpe [78] introduced the Capital Asset Pricing Model (CAPM) and proposed to include systematic and unsystematic risks in the work of Markowitz. Fama [34] developed the concept of the Efficient Market Hypothesis (EMH) and elaborated the implications for portfolio management. Subsequently, Black and Litterman [17] proposed another new model, the Black-Litterman model, that examined practical issues in implementing Markowitz's theory. Furthermore, Fama and French [35] developed the three-factor model and expanded the CAPM by incorporating size and value factors.

More recently, Jagannathan and Ma [46] studied the impact of constraints on portfolio optimization and revealed that certain "wrong" constraints can improve out-of-sample performance. In contrast, DeMiguel et al. [28] questioned the effectiveness of traditional optimization methods and proposed the simple 1/N equal-weighted portfolio strategy. Bessler et al. [14] evaluated the different portfolio optimization approaches and examined out-of-sample performance in a multi-asset context. Similarly, Kolm et al. [50] reviewed the portfolio optimization in depth and highlighted practical challenges and emerging trends.

In essence, highly integrated investments offer no diversification benefits because they are highly correlated with one another. The finance literature highlights the benefits of holding diversified assets, with significant effort devoted to quantifying the reduction in risk. Therefore, investors are encouraged to diversify their investments across different assets and industries [62]. However, as integration across asset classes rises, investors are increasingly seeking alternative investments, such as Artificial Intelligence (AI), sustainable energy, commodities, Islamic investments, and others, to achieve strategic asset al.location and diversification.

The AI revolution since 2010 has profoundly transformed global economies, societies, and strategic landscapes. Economically, AI is projected to contribute between 2.6 trillion and 15.7 trillion to global GDP by 2030, driven by productivity gains, automation, and the creation of new industries [5, 20]. Societally, AI has enabled breakthroughs in healthcare, such as disease prediction and drug discovery, and revolutionized education through personalized learning [42, 85]. On a global scale, AI has become a crucial element of national security and economic competitiveness, prompting nations to develop strategic frameworks and prioritize responsible AI practices to mitigate risks and ensure the ethical deployment of AI [21, 43].

Clean energy sources, such as wind and solar, have emerged as promising investment opportunities due to their environmental benefits, economic advantages, government incentives, and social impacts [58]. Clean energy equities, notably nuclear energy, have displayed resilience and sustainable growth through market volatility [86]. Due to the increased focus on sustainability and decarbonization, it is expected that significant capital will be allocated towards clean energy sectors, hence the need to identify the suitability of these investments for diversification.

Commodities, too, have become an attractive option for investors seeking portfolio diversification, mainly because of their perceived low correlation with traditional assets like stocks and bonds [13, 90]. This characteristic made commodities an investment choice for hedging against market volatility and inflation, hence enhancing portfolio resilience [6]. Investors have a plethora of investment options in commodities, such as direct investments, commodity stocks, and commodity derivatives, to enhance their strategic asset al.location [70]. However, over the recent years, the increased financialization of commodity markets has led to increased connectedness with equity and currency markets, hence reducing diversification potential [60, 79].

Due to the ethical foundations of Islamic investments, the advocates of Islamic finance argue that Islamic investments provide diversification benefits compared to other investments [74, 80]. In contrast, some argue that Islamic investments would underperform in the long run as Islamic investment portfolios are subsets of the market and have limited potential diversification benefits [11].

This study will, therefore, examine the dynamic connections between AI and various alternative investments, including clean energy, wind energy, solar energy, natural gas, crude oil, and Islamic investments, using the First Trust Nasdaq Artificial Intelligence and Robotics ETF as a proxy. The analysis focuses on the period following the recovery from the COVID-19 pandemic. Although existing studies have examined the relationship between AI and other innovative assets [8, 12, 25, 47, 77, 92], they primarily focused on unconditional correlations or volatilities among the selected assets. However, they did not address the conditional correlations and volatilities of these assets, nor how they evolved. Furthermore, while the existing literature primarily examines conventional assets, we will also incorporate Islamic investments in our study.

We contribute to the existing literature as follows: (1) To the best of our knowledge, this is the first study that investigates the conditional correlation and volatilities of AI and other alternative investments. (2) Due to the ethical foundations of Islamic investments, we investigate whether Islamic investment provides diversification benefits to investors. (3) In the case of methodology, we employ the Dynamic Conditional Correlation - Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to investigate the correlation and volatility of the selected assets, as it imposes stronger assumptions about the correlation structure. Other methods, such as the Baba–Engle–Kraft–Kroner

(BEKK) model, is guaranteed to produce positive-definite covariance matrices but have many parameters. Vector Error Correction (VEC) is the most general, but it suffers from parameter explosion. As such, the findings of this study will provide insights for financial analysts, investors, and government policymakers on maximizing portfolio returns, reducing risk, and shaping government policies to support the AI industry.

The remaining sections of the paper are organized as follows: Sect. " Literature Review" reviews the related literature on portfolio diversification and empirical studies on the analysis of stock indices. Section "Methodology" describes the research data and methodologies. Section "Data and Research Results" presents the study's main findings. Finally, the concluding remarks and recommendations are presented in Sect. "Conclusion".

Literature Review

The AI revolution since 2010 has fundamentally transformed multiple sectors through its rapid evolution and far-reaching practical implications. These transformative implications are evident on three fronts: economic impact and innovation, societal benefits, and global strategic importance. Economically, AI has emerged as a strong driver of growth, enabling significant labor productivity gains, automation, and the creation of new industries [20]. Businesses in sectors like manufacturing, finance, and transportation are embracing AI to improve operational effectiveness and enhance decision-making, coupled with novel product designs, thereby establishing a competitive advantage in the global marketplace [5, 20].

The social contribution of AI is exponential, particularly through its implications for health and its potential to enhance education, conservation, and scientific breakthroughs. In health, for instance, AI helps enhance disease prediction, prevention, and control, as well as accelerate clinical trials and drug discovery [85]. In education, AI enables personalized learning experiences at scale, helping workforce development by meeting diverse student needs [42]. AI also facilitates environmental sustainability through the optimization of resources and climate pattern prediction, and scientific research by facilitating analysis of data at scale and pattern recognition.

On the global level, AI has emerged as a pillar of strategic rivalry, shaping national security, economic strength, and technological sovereignty. Numerous countries have developed national AI strategies to ensure economic prosperity and global competitiveness [43]. The formulation of responsible AI practices, such as safety measures, bias prevention, and transparency measures, is becoming ever more vital to reducing the risks of AI implementation and inherent biases [21]. These practices ensure that AI technologies are developed and implemented in a manner consistent with societal values and moral principles, thereby advancing trust and reducing potential harm.

Nonetheless, considering AI's impact extending over more than a handful of fields, scientific work pertaining to the effect of AI on financial markets, and specifically investment diversification is very limited. Though recent studies have explored the link and co-movements of cryptocurrencies, decentralized finance, and legacy assets [8, 12, 25, 47, 77, 92], comprehensive research concerning AI-based augmenting financial diversification remains at its nascent stages.

Recent studies have attempted to bridge this research gap. Huynh et al. [44] utilized copulas and Generalized Forecast Error Variance Decomposition to consider the diversification advantage of green bonds and robotics and AI stocks. The research established that heavy-tailed dependence led to substantial joint-loss risks. Asl et al. [9], however, determined quite low associations between AI technologies and the renewable energy sector. Meanwhile, Su and Zhao [82] used quantile time-frequency connectedness analysis to investigate Fourth Industrial Revolution assets and found that though short-term diversification from AI and technology stocks remains limited, these stocks provide improved long-term benefits to traditional investment portfolios.

Yousaf et al. [93] investigated AI tokens and exchange-traded funds (ETFs) using quantile value-at-risk (VaR) analysis and identified potential diversification benefits of traditional assets. Thanh Ha [84] investigated the relationship between AI and green cryptocurrencies and found that the variables under study show only weak correlations. Kuang et al. [54] investigated the asymmetric relationship between industrial artificial intelligence and green finance, and their findings indicate that industrial artificial intelligence enhances green finance in specific segments of the data distribution across various economies. When analyzing market turbulence, Naeem et al. [65] found that AI serves as a major risk transmitter, producing strong contagion effects across innovative assets. Moreover, Gubareva et al. [38] employed a generalized quantile-on-quantile connectedness approach to investigate the relationships between AI, clean technology, oil, and conventional markets and found that AI and clean technology markets are major contributors to risk spillovers.

Other recent researchers have investigated the use of clean energy assets for portfolio diversification and risk management. Kuang [52, 53] shows that clean energy stocks, together with green bonds, benefit investors in "dirty" energy stocks through risk diversification, yet the effects differ depending on the degree of international equity index integration. Clean energy stocks underperform the broader equity market but outperform traditional "dirty" energy stocks. As such, the risk-adjusted returns from adding clean energy stocks to investment portfolios depend on the clean energy sector selected by investors, as the renewable energy project developer index has the highest performance.

The intricate and dynamic interaction between clean energy assets and conventional energy markets is difficult to model. The study attempted by Dutta et al. [30] showed that elevated implied volatility in the energy sector generates detrimental effects on clean energy ETF returns, mainly when volatility levels remain strong. Stock investments in clean energy were found to perform better as hedge instruments than green bonds, especially in the crude oil markets [72]. Nasreen et al. [67] also discovered a weak relationship between clean energy stock returns and oil prices, with technology stock returns prevailing over both. Surprisingly, Ur Rehman et al. [88] discovered no meaningful differences between ESG indices (which frequently contain clean energy stocks) and traditional indices in Asian markets, indicating that socially responsible investing can be practiced by investors without affecting portfolio performance significantly. These results collectively emphasize the importance of prudent choice and active portfolio management in identifying clean energy investments.

Portfolio managers have historically chosen commodities as valuable assets because they demonstrate a low correlation with conventional asset classes, such as stocks and bonds. It has been proven through research that commodities can be used as a hedge for inflation as well as macroeconomic uncertainty [33, 49]. In addition, commodity returns are influenced by supply and demand forces, unlike those that influence stock and bond markets, providing true diversification benefits [37].

Nevertheless, commodity portfolio performance is not without challenges. Commodity returns exhibit high market volatility due to political events, compounded by natural climate factors and other significant economic shifts worldwide. In addition, the diversification advantages of commodities are sector- and time-sensitive. For example, Jensen et al.'s [49] test showed that the benefits of diversification through commodity inclusion in a portfolio depend on the chosen commodities and the observation period. Thus, effective commodity portfolio management is best described as comprehensive decision-making and proactive actions aimed at maintaining risk control and high-quality investment.

Research on Islamic investments involving *Shari'ah*-compliant equities yields conflicting evidence on their ability to enhance portfolio diversity during prevailing market conditions and financial crises. Dewandaru et al. [29, 48] demonstrated that Islamic index performance was more resilient to economic shocks, particularly during the global financial crisis (GFC), than that of conventional indices. Such strength was due to the index being less vulnerable to highly leveraged and speculative companies, which tend to contract. In the same vein, Rizvi and Arshad [71] observed a lower correlation between Islamic-conventional indices during the GFC, which supports the decoupling hypothesis and suggests hedging properties. These results suggest that Islamic shares can offer diversification benefits, particularly during periods of economic uncertainty.

But the Covid-19 pandemic revealed a grimmer reality. While there were some studies, Alexakis et al. [7, 24], reporting that Islamic indices performed better and recovered more quickly than conventional markets at the time of the pandemic, others, e.g., Hasan et al. [40], confirmed a robust co-movement between Islamic and conventional index movements, refuting the decoupling hypothesis. Abdullahi [3] further highlighted that Islamic indices were vulnerable to financial contagion and volatility transmission during the crisis, suggesting limited safe-haven benefits. Despite this, Mirza et al. [64, 80, 81] noted that Islamic indices, utilizing strict *Shari'ah* screening, maintained their status as risk-adjusted outperformers yet exhibited elevated systematic risk. Moreover, Yarovaya et al. [91] noted the resilience of sukuk, which served as safe-haven assets during the pandemic crisis.

In short, Islamic investments retain their value as a portfolio diversification option due to their regulatory screening requirements, combined with limited exposure to volatile market sectors. Their performance during crises, such as the GFC and COVID-19, highlights their capacity for risk mitigation and ethical investment, particularly for investors who seek both resilience and *Shari'ah* compliance. However, their effectiveness as a diversification instrument will depend on market conditions and the degree of integration with traditional markets.

Methodology

To account for dynamic interactions between AI and other investments, we use Engle's (2002) DCC-GARCH model. The sophisticated econometric model is highly capable of capturing both time-varying correlations and volatility with high accuracy, providing detailed insights into the direction (positive/negative) and magnitude of the interactions. The model's ability to track in real time both volatility processes and correlation dynamics simultaneously makes it particularly relevant to investment professionals concerned with the optimal means to manage portfolio risk. DCC-GARCH also has several advantages over traditional approaches, such as the Constant Correlation (CCC) model or standard multivariate GARCH models [51]. The superior accuracy of DCC-GARCH in modeling time-varying correlations provides investors and portfolio managers with a better understanding of whether asset return volatilities are complementary or substitutable risk categories [66, 74]. This deeper insight is also crucial for developing more effective diversification strategies and adaptive portfolio adjustment mechanisms.

The multivariate DCC-GARCH model offers several robust advantages, positioning it favorably for this study. The model can effectively estimate potential contagion effects during financial crises [16, 26, 89] while allowing for the simultaneous estimation of dynamic conditional volatilities and correlations [57]. It simplifies the estimation of dynamic correlation matrices to a canonical form [32] and eliminates volatility-related bias by updating correlation coefficients dynamically to adapt to evolving volatility [23].

Moreover, the model addresses heteroskedasticity directly through correlation coefficients' estimation based on standardized residuals [22]. Like avoiding the complexity of traditional multivariate GARCH techniques while maintaining the robustness of univariate GARCH models, it avoids the complexity of standard multivariate GARCH techniques while allowing for correlation estimation across a set of asset returns [22, 57]. Another benefit lies in its ability to forecast future correlation levels among research variables [56].

Engle's (2002) DCC-GARCH model of multivariate form is an extension of Bollerslev's (1990) [18] CCC estimator by a two-stage estimation process. The first one is the estimation of conditional variances for each equity index via a univariate GARCH (X, Y) model applied to k asset returns, as in (1).

$$h_{it} = \omega_{i} + \sum_{x=1}^{X_i} \alpha_{ix} r^2_{it-x} + \sum_{y=1}^{Y_i} \beta_{iy} h_{it-y}, \text{for } i = 1,2,\ldots,\text{k} \tag{1}$$

where the non-negative parameters are ω_{i}, α_{ix} and β_{iy} and the totalling of $\sum_{x=1}^{X_i} \alpha_{ix} + \sum_{y=1}^{Y_i} \beta_{iy}$ is less than one. The conditional variance of each asset is denoted by h_{it}, more importantly, the short-term persistence of shocks to return X (the ARCH effects) and the contribution of shocks to return Y to long-term persistence (the GARCH effects) are denoted by and α_{ix} and β_{iy}

The DCC estimator uses standardized residuals from the first step as input to estimate dynamic conditional correlations across asset classes over time.

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

where H_t is the matrix of multivariate conditional covariance, the diagonal matrix D_t contains the time-varying standardized residuals (ε_t) that were produced from the univariate GARCH estimation with $\sqrt{h_{ii,t}}$ on the i^{th} diagonal, I = 1,2,….k, whereas, the matrix R_t represents the dynamic correlation coefficients over time, consisting of off-diagonal elements. More specifically, the Dynamic Conditional Correlation specifications of Engle [31] can be presented as (3 and 4):

$$D_t = \operatorname{diag}\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots, \sqrt{h_{kk,t}}\right) \tag{3}$$

$$R_t = Q_t^{*-1} \cdot Q_t \cdot Q_t^{*-1} \tag{4}$$

where the symmetric positive definitive matrix is k x k and $Q_t = (q_{ij,t})$ is obtained from (5):

$$Q_t = (1 - \phi - \gamma)\ \bar{Q} + \gamma\ Q_{t-1} + \phi\sigma_{i,t-1}\sigma_{j,t-1} \tag{5}$$

where Q_t represents a k-dimensional square matrix that depicts the time-varying covariance patterns of standardized residuals $\left(\sigma_{it} = \frac{\epsilon_{it}}{\sqrt{h_{it}}}\right)$ whereas ? represents the unconditional correlations of $\sigma_{i,t}\sigma_{j,t}$. The non-negative parameters are φ and γ that satisfy $\varphi + \gamma < 1$.

Therefore, the conditional correlation of two asset returns at time t can be presented in (6):

$$\rho_{ij,t} = \frac{(1 - \varphi - \gamma)\,\bar{q}_{ij} + \varphi\,\sigma_{i,t-1}\,\sigma_{j,t-1} + \gamma\,q_{ij,t-1}}{\left[(1 - \varphi - \gamma)\,\bar{q}_{ii} + \varphi\,\sigma^2_{i,t-1} + \gamma\,q_{ii,t-1}\right]^{1/2}\left[(1 - \varphi - \gamma)\,\bar{q}_{jj} + \varphi\,\sigma^2_{j,t-1} + \gamma\,q_{jj,t-1}\right]^{1/2}} \tag{6}$$

The matrix Q_t contains elements positioned at the intersection of i^{th} line and j^{th} column. Following Bollerslev et al. [19], when assuming a Gaussian distribution, the model's conditional log likelihood function can be expressed as shown in (7):

$$L = -\frac{1}{2}\sum {}_{t=1}^{T}\left[\left(k\log(2\pi) + \log|D_t|^2 + \epsilon'_t D_t^{-1} D_t^{-1}\epsilon_t\right) + \left(\log|R_t| + \sigma'_t R_t^{-1}\sigma_t - \sigma'_t\sigma_t\right)\right] \quad (7)$$

The model operates with k equations across T observations. In the first step, only the volatility component (D_t) is maximized, effectively reducing the log-likelihood to the sum of univariate GARCH model log-likelihoods. The second step maximizes the correlation component (R_t), conditional on the previously estimated parameters, using standardized residuals from the first step.

However, the Gaussian assumption underlying the model has been criticized for inadequately capturing daily returns, potentially leading to an underestimation of portfolio risk. While the two-step likelihood estimation method is consistent [32], it may lack efficiency under Gaussian conditions [69]. Therefore, to determine the most appropriate distributional assumption for our analysis, we compare Maximum Likelihood (ML) tests using both normal and Student's t-distributions across the selected asset classes.

Data and Research Results

The main objective of this study is to examine the dynamic correlations and volatilities of AI and other alternative investments. To achieve our objective, we employ daily closing price data from the First Trust Nasdaq Artificial Intelligence and Robotics ETF (ROBT), S&P Global Clean Energy (SPCLEN), First Trust Global Wind Energy ETF (FAN), Invesco Solar ETF (TAN), natural gas (NGF), crude oil (OVX), and DJ Islamic Market US Titans 50 Index (DJIUS50). The sample period covers March 1, 2019, to January 27, 2025. The data are transformed into compounded asset returns by calculating the natural logarithm of the differences between the selected asset prices.

The mean returns of selected asset classes in Table 1 show that Natural Gas (0.0001848) and Artificial Intelligence and Robotics ETF (0.0001204) have relatively higher daily average returns. In comparison, S&P Global Clean Energy (0.0000410) and DJ Islamic Market US Titans 50 Index (0.0000844) have relatively lower daily average returns compared to other assets. Meanwhile, crude oil has the

Table 1 Descriptive statistics of selected assets

	Mean	Std. deviation	Skewness	Kurtosis
ROBT	0.0001204	0.004554	−0.796	10.717
OVX	0.0000668	0.017441	2.039	21.038
SPCLEAN	0.0000410	0.002584	−0.482	8.107
TAN	0.0001124	0.006888	−0.373	5.742
FAN	0.0000924	0.005336	−0.613	13.406
NGF	0.0001848	0.012356	-1.350	36.385
DJIUS50	0.0000844	0.001565	−0.563	11.910

Table 2 Unconditional correlations of selected assets

		Correlation	Lower C.I.	Upper C.I.
DJIUS50	ROBT	0.865	0.851	0.877
	OVX	-0.214	-0.262	-0.166
	SPCLEAN	-0.036	-0.086	0.015
	TAN	0.01	-0.04	0.06
	FAN	-0.01	-0.06	0.04
	NGF	-0.001	-0.051	0.049
FAN	ROBT	0.022	-0.028	0.072
	OVX	-0.021	-0.071	0.03
	SPCLEAN	0.055	0.005	0.105
	TAN	0.01	-0.04	0.06
	DJIUS50	-0.01	-0.06	0.04
	NGF	0.416	0.373	0.456
NGF	ROBT	0.034	-0.017	0.084
	OVX	-0.006	-0.056	0.045
	SPCLEAN	0.092	0.042	0.142
	TAN	0.003	-0.047	0.054
	FAN	0.416	0.373	0.456
	DJIUS50	-0.001	-0.051	0.049
OVX	ROBT	-0.211	-0.258	-0.162
	SPCLEAN	0.007	-0.043	0.058
	TAN	-0.001	-0.051	0.049
	FAN	-0.021	-0.071	0.03
	DJIUS50	-0.214	-0.262	-0.166
	NGF	-0.006	-0.056	0.045
ROBT	OVX	-0.211	-0.258	-0.162
	SPCLEAN	-0.02	-0.07	0.03
	TAN	-0.001	-0.051	0.049
	FAN	0.022	-0.028	0.072
	DJIUS50	0.865	0.851	0.877
	NGF	0.034	-0.017	0.084
SPCLEAN	ROBT	-0.02	-0.07	0.03
	OVX	0.007	-0.043	0.058
	TAN	0.034	-0.016	0.084
	FAN	0.055	0.005	0.105
	DJIUS50	-0.036	-0.086	0.015
	NGF	0.092	0.042	0.142
TAN	ROBT	-0.001	-0.051	0.049
	OVX	-0.001	-0.051	0.049
	SPCLEAN	0.034	-0.016	0.084
	FAN	0.01	-0.04	0.06
	DJIUS50	0.01	-0.04	0.06
	NGF	0.003	-0.047	0.054

Table 3 Unconditional volatilities of selected assets

1	First trust nasdaq artificial intelligence and robotics ETF (ROBT)	0.0045695
2	S&P global clean energy (SPCLEN)	0.0026075
3	First trust global wind energy ETF (FAN)	0.0053795
4	Invesco solar ETF (TAN)	0.0069218
5	Natural gas (NGF)	0.012466
6	Crude oil (OVX)	0.017564
7	DJ Islamic Market US Titans 50 Index (DJIUS50)	0.0015729

highest standard deviation (0.017441), while the Islamic index has the lowest standard deviation (0.001565).

The Unconditional correlations of selected assets in Table 2 indicate that the Islamic index and Artificial Intelligence and Robotics ETF have negative or lower correlations with almost all assets except the correlations between them (0.865). Global Wind Energy ETF and Natural gas have lower or negative correlations with the selected assets, with the exception of the relatively higher correlation between them (0.416). Crude oil returns exhibit a negative, lower correlation with other assets. Similarly, S&P Global Clean Energy and the Invesco Solar ETF have negative or lower correlations with other assets.

From the unconditional volatilities of selected assets (Table 3), it can be seen that crude oil (0.017564) and Natural gas (0.012466) have the highest. In contrast, the Islamic Index (0.0015729) and S&P Global Clean Energy (0.0026075) exhibit the lowest volatilities among other assets.

However, the above tests cannot tell us how correlations and volatilities between selected assets change over time, including the direction (positive/negative) and strength of these relationships. Therefore, to explore the dynamic linkages of the selected assets, we proceed with a DCC-GARCH analysis.

Table 4 ML estimation of the t-distribution model on selected asset returns

Parameter	Estimate	Standard error	T-Ratio[Prob]
lambda1_ROBT	0.91355	0.012267	74.4734[0.000]
lambda1_OVX	0.84196	0.033927	24.8168[0.000]
lambda1_SPCLEAN	0.80684	0.040320	20.0111[0.000]
lambda1_FAN	0.87233	0.025683	33.9658[0.000]
lambda1_TAN	0.87658	0.043079	20.3481[0.000]
lambda1_NGF	0.94127	0.014806	63.5730[0.000]
lambda1_DJIUS50	0.89224	0.018286	48.7931[0.000]
lambda2_ROBT	0.058671	0.0076970	7.6225[0.000]
lambda2_OVX	0.12160	0.023310	5.2166[0.000]
lambda2_SPCLEAN	0.11614	0.021574	5.3832[0.000]
lambda2_FAN	0.085281	0.014969	5.6972[0.000]
lambda2_TAN	0.071443	0.018999	3.7603[0.000]
lambda2_NGF	0.056460	0.013857	4.0746[0.000]
lambda2_DJIUS50	0.075897	0.011579	6.5544[0.000]
delta1	0.97989	0.0030283	323.5730[0.000]
delta2	0.010693	0.0011700	9.1390[0.000]
df	8.8867	0.57007	15.5887[0.000]

Maximized Log-Likelihood = 42339.0

df is the degrees of freedom of the multivariate t distribution

Empirical Results

To determine the most appropriate distributional assumption for our analysis, we compared Maximum Likelihood (ML) tests using both normal and Student's *t*-distributions across the selected asset classes. The results strongly favour the *t*-distribution model, which yielded a substantially higher Maximized Log-Likelihood value of 42339.0 compared to 39358.6 for the normal distribution. Furthermore, the estimated degrees of freedom for the *t*-distribution were 8.89, well below the threshold of 30. This low degree of freedom value, combined with the higher likelihood score, indicates that the *t*-distribution provides a superior fit for modelling the heavy-tailed characteristics commonly observed in asset return distributions.

As shown in Table 4, the t-DCC analysis reveals statistically significant volatility parameters across asset classes, indicating a gradual volatility decay. This pattern suggests that the impact of market shocks on return volatility diminishes progressively over time, rather than persisting indefinitely.

A key finding is that across all asset classes, the sum of lambda1 and lambda2 coefficients remains below unity (e.g., lambda1_ROBT + lambda2_ROBT = 0.9258). This mathematical property indicates that the return volatilities do not follow an Integrated Generalized Auto Regressive Conditional Heteroskedasticity (IGARCH) process, meaning shocks to volatility are transitory rather than permanent.

These characteristics create a market environment that presents both opportunities and risks for different types of investors [76]. While short-term traders and speculators may find favourable conditions for profit-taking, long-term investors and portfolio managers face increased risk exposure despite potential short-term gains. This market structure suggests the importance of carefully timed entry and exit strategies to optimize investment outcomes.

Conditional Volatilities of Selected Asset Classes

Figure 1 presents the conditional volatilities of the selected asset classes. From the figure, it is observed that the conditional volatilities of the asset returns move closely together over time. The crude oil returns have the highest conditional volatilities, while the DJ Islamic Market US Titans 50 Index returns have the lowest conditional volatilities among other assets. Our findings are consistent with those of Liu et al. [10, 59]. Liu et al. [59] found that crude oil price volatility negatively affects share returns. Bahloul and Khemakhem

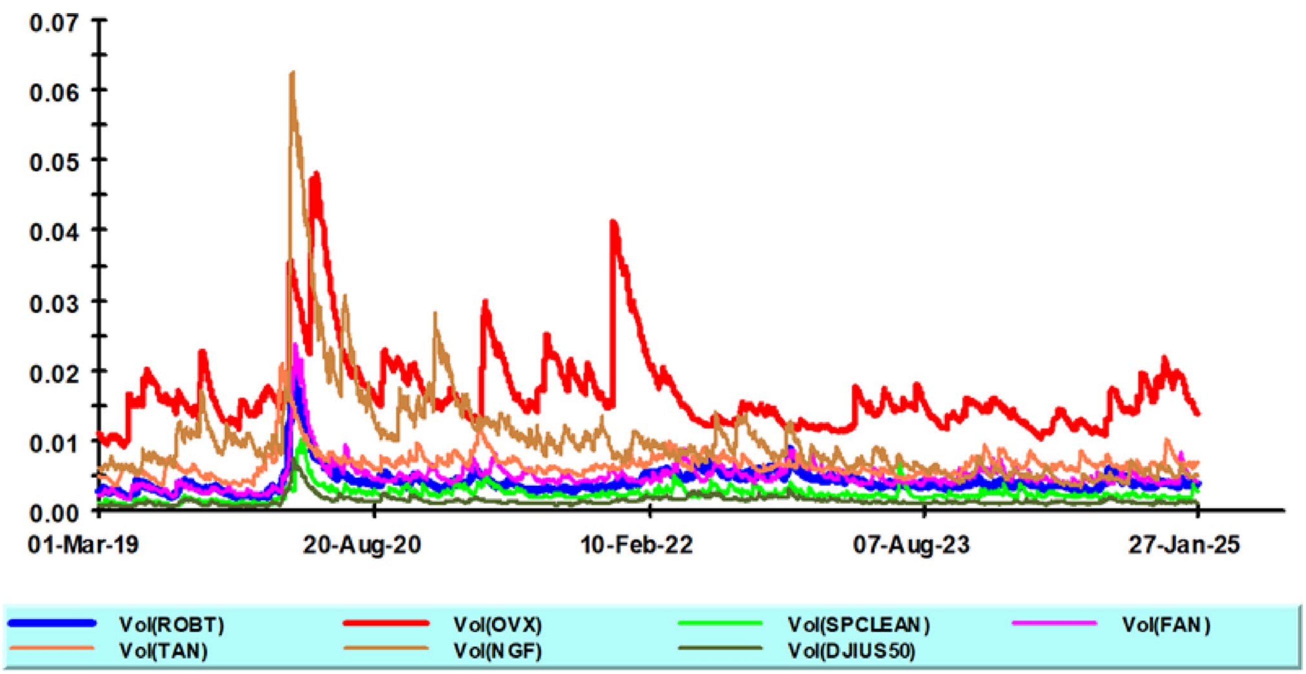


Fig. 1 The conditional volatilities of selected asset classes

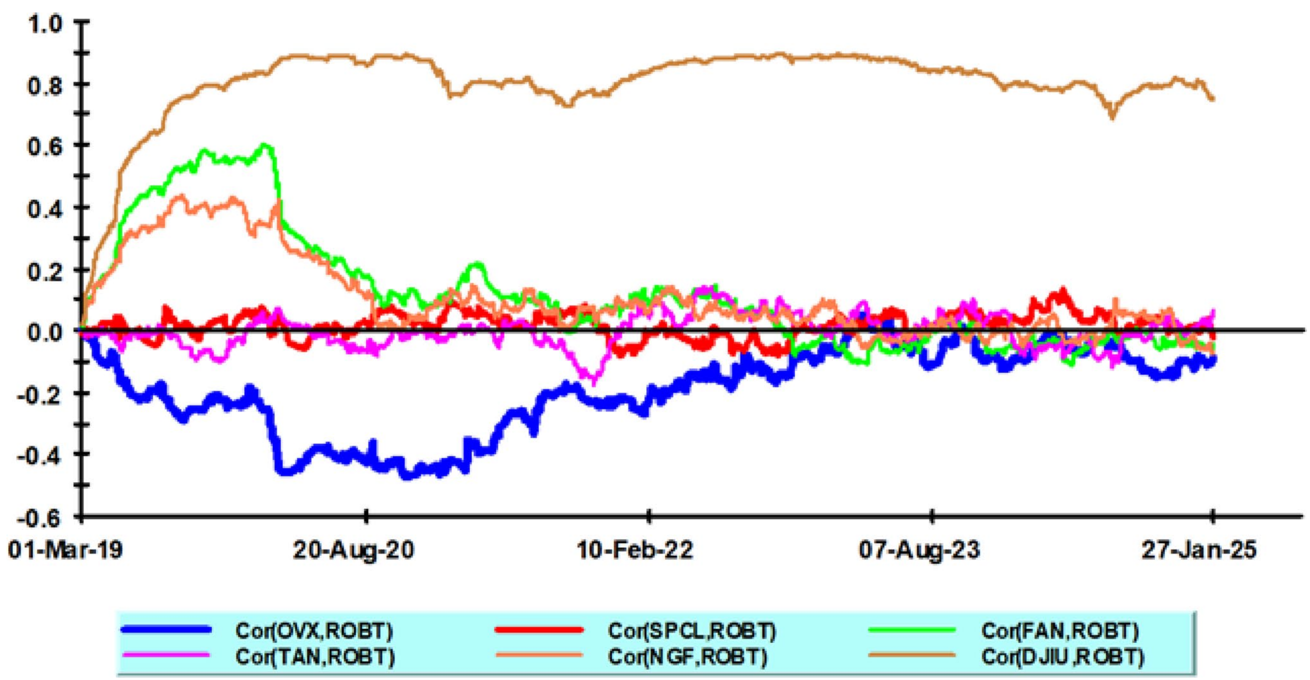


Fig. 2 The conditional correlations between Artificial Intelligence ETF and other assets

[10] determined that the Islamic stock index acts as a net recipient of spillovers. The low volatilities of Islamic investment are due to ethical foundations such as the exclusion of the financial sector, highly leveraged companies, toxic assets, and financial derivative products [74].

Additionally, we can see that the conditional volatilities are high between 2019 and 2020 and in February 2022, due to the COVID-19 pandemic and the Ukraine-Russia conflict. Our findings are supported by Taera et al. [83], who found increased volatility in almost all financial and alternative assets.

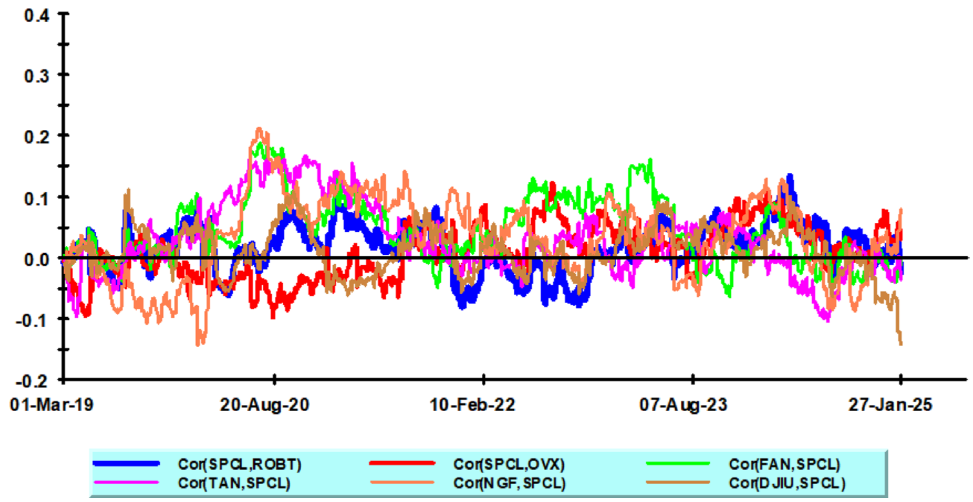


Fig. 3 The conditional correlations between Global Clean Energy and other assets

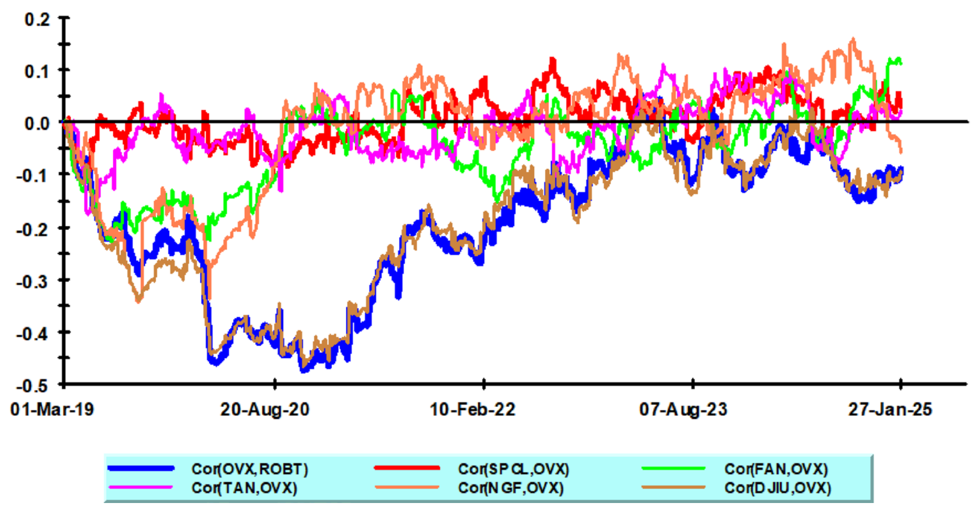


Fig. 4 The conditional correlations between Crude oil and other assets

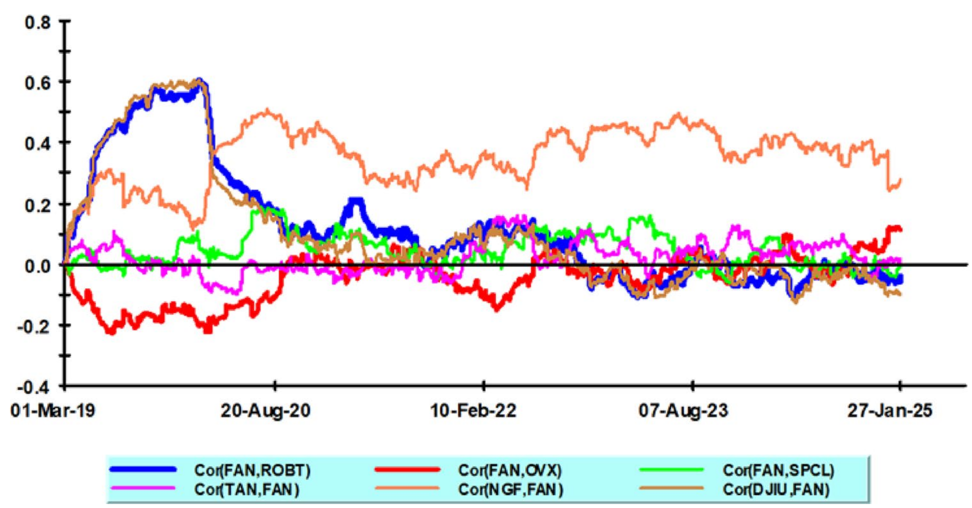
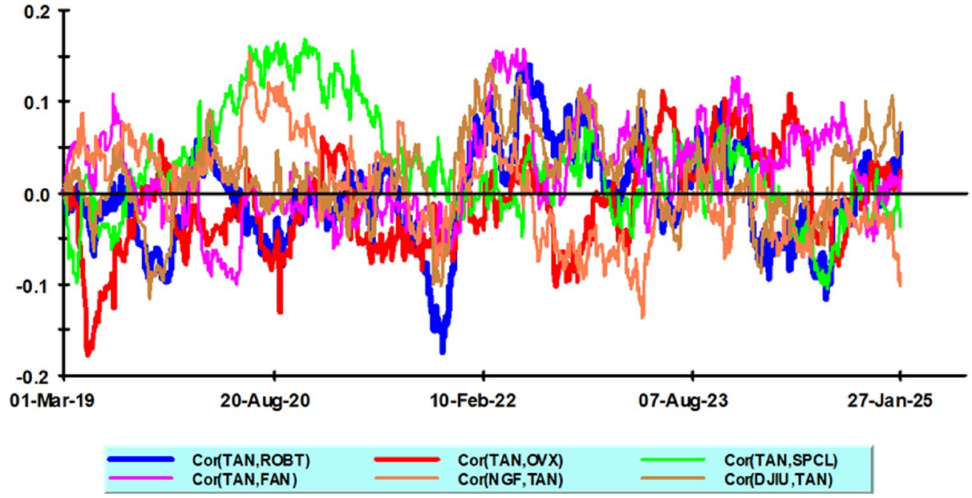


Fig. 5 The conditional correlations between Global Wind Energy ETF and other assets

Conditional Correlations of Selected Asset Classes

One can observe that the Artificial Intelligence ETF has the highest correlation with the Islamic Market US Titans 50 Index during all time periods, as presented in Fig. 2. During the COVID-19 health crisis, the correlations between ROBT and the Global Wind Energy ETF and Natural gas have increased. On the other hand, there is a decreasing trend in the correlation between ROBT and crude oil. This suggests that crude oil can provide diversification benefits to

Fig. 6 The conditional correlations between Invesco Solar ETF and other assets



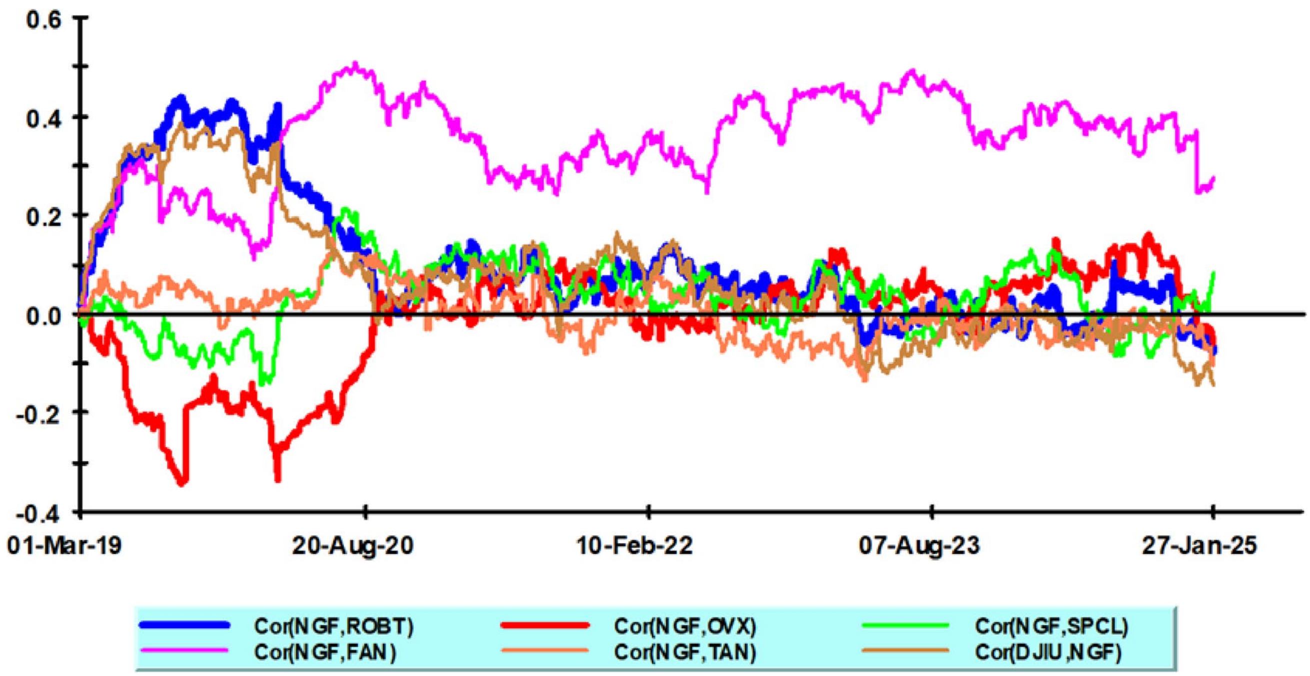


Fig. 7 The conditional correlations between Natural gas and other assets

ROBT-based investors during crisis periods. During normal market periods, asset correlations decreased. This finding aligns with the findings of Yousaf et al. [93] where they found that the total connectedness level among the assets was moderate.

Figure 3 shows us that Global Clean Energy has relatively low or negative correlations with other assets during all periods. This is supported by a study by Kuang [52], which found that clean energy has a lower risk than conventional equities. Interestingly, the Islamic Market US Titans 50 Index shows a strong negative correlation, suggesting it can provide diversification benefits for investors focused on clean energy.

During the crisis periods, crude oil has a strong negative correlation with the Artificial Intelligence and Robotics ETF and the Islamic Market US Titans 50 Index, as shown in Fig. 4. Additionally, it shows relatively low, slightly negative correlations with other selected assets. This finding aligns with a previous study by Tunc [87].

Overall, Global Wind Energy has a relatively high correlation with natural gas during all periods (Fig. 5). During the crisis period (COVID-19), Global Wind Energy has very strong positive correlations with Artificial Intelligence and Islamic investment. The first finding is supported by Zhang et al. [94] who found a significant positive relationship between AI and clean energy stocks. Furthermore,

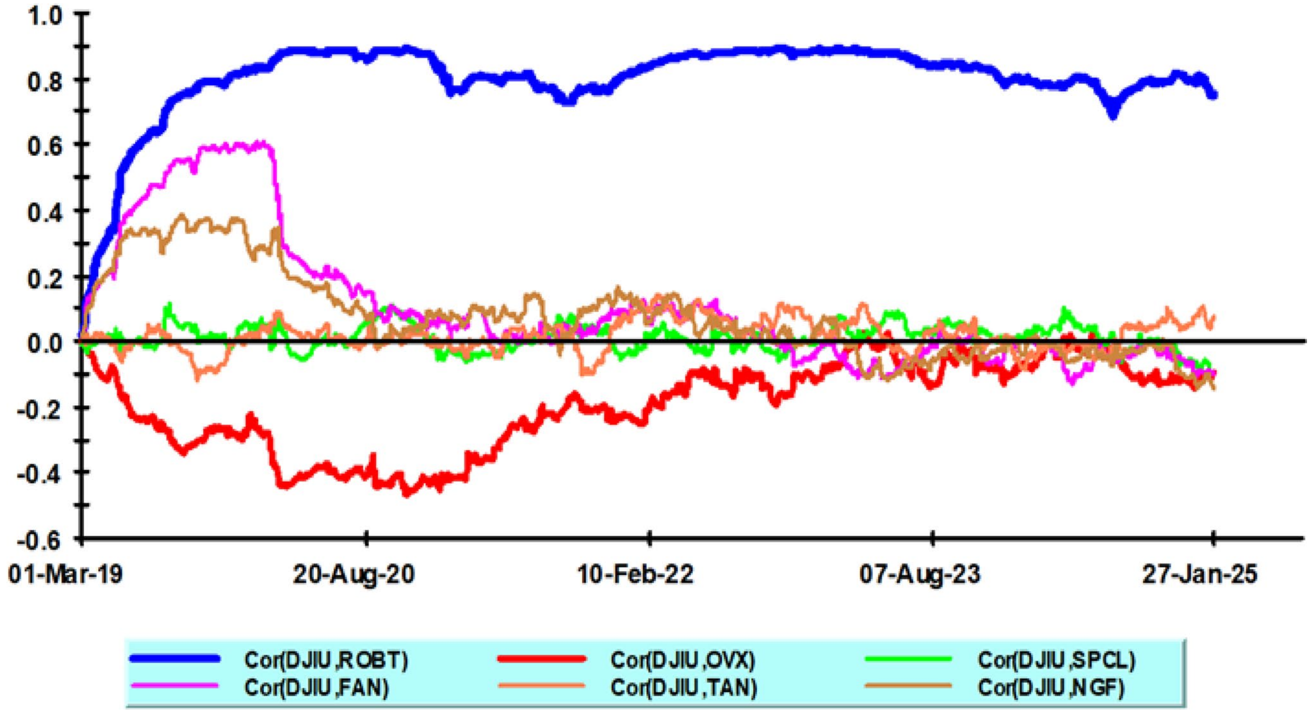


Fig. 8 The conditional correlations between Islamic Investment and other assets

Table 5 Ranks of conditional correlations among selected asset classes (from lowest to highest)

Artificial intelligence ETF	Global clean energy	Crude oil	Global wind energy ETF	Solar ETF	Natural gas	Islamic investment
Crude oil	Islamic investment	Islamic investment	Crude oil	Artificial intelligence ETF	Crude oil	Crude oil
Global clean energy	Artificial intelligence ETF	Artificial intelligence ETF	Islamic investment	Crude oil	Islamic investment	Global clean energy
Invesco solar ETF	Crude oil	Global wind energy ETF	Solar ETF	Islamic investment	Solar ETF	Natural gas
Global wind energy ETF	Invesco solar ETF	Natural gas	Artificial intelligence ETF	Global wind energy ETF	Artificial intelligence ETF	Global wind energy ETF
Natural gas	Global wind energy ETF	Solar ETF	Global clean energy	Natural gas	Global clean energy	Solar ETF
Islamic investment	Natural gas	Global clean energy	Natural gas	Global clean energy	Global wind energy ETF	Artificial intelligence ETF

Global Wind Energy has a negative correlation with crude oil, suggesting possible diversification benefits for investors in Global Wind Energy relative to crude oil. During normal periods, Global Wind Energy has relatively low or weak negative correlations with other assets except natural gas.

From Fig. 6, one can observe that Solar ETF has relatively low or negative correlations with other selected assets. This finding is supported by D'Ecclesia et al. [27], who found that Solar ETF has relatively low correlations with other assets. In particular, the solar ETF has a negative correlation with crude oil during COVID-19, as well as with the Artificial Intelligence and Robotics ETF and the Ukraine-Russia conflicts. The correlations between Solar ETF and Global Clean Energy and Natural Gas have a decreasing trend towards the end of the data period.

In general, natural gas showed a strong, positive correlation with the Global Wind Energy ETF throughout (see Fig. 7). Our results are consistent with the findings of Saeed et al. [72], who found that the return connectedness between clean energy stocks and crude oil was higher. During the crisis period (COVID-19), natural gas has a positive correlation with Artificial Intelligence and Robotics ETF and Islamic investment, while it had a negative correlation with Crude oil and Global Clean Energy. This implies that crude oil and Global Clean Energy can provide some degree of diversification benefits during crisis periods. However, during periods of normalcy, natural gas has relatively low or negative correlations with all selected asset classes except the Global Wind Energy ETF, as stated earlier.

From Fig. 8, we can see that Islamic investment has a strong, positive correlation with the Artificial Intelligence and Robotics ETF at all times, as explored earlier. However, it shows a negative correlation with crude oil, suggesting a potential diversification benefit for Islamic investors. This result is consistent with similar studies that investigated the relationship between Islamic stocks and crude oil [2, 4, 36, 63]. During the crisis period (COVID-19), Islamic investment was found to have positive correlations with the Global Wind Energy ETF and natural gas, but the correlations are weakened during the normal periods. Overall, Islamic investment can benefit from the selected assets during the normal periods, with the exception of the Artificial Intelligence and Robotics ETF.

Portfolio Implications

Table 5 presents the levels of conditional correlations between the chosen asset classes, from lowest to highest. It shows some compelling portfolio implications:

1. Crude oil provides diversification benefits to all classes of assets that are under investigation. This is a fact attested by numerous studies, including those of Mensi et al. [63, 73], and others.
2. Notably, diversification benefits might be achieved by all types of investors under Islamic investment except those investing in the Artificial Intelligence ETF. This is testified to by studies available illustrating that Islamic investment has the potential to provide diversification benefits to multiple types of investors [1, 15, 39, 45]; Nasreen, Naqvi, et al., [67]; Saiti et al., [75, 76].
3. The Artificial Intelligence ETF can provide diversification advantages to all types of investors under study except Islamic investment-based investors. The above conclusion supports Yousaf et al. [93], who argued that AI tokens can yield diversification benefits over traditional assets.
4. The Artificial Intelligence ETF can provide diversification benefits to all types of investors under study except Islamic investment-based investors. This finding is consistent with Yousaf et al. [93], who concluded that AI tokens may offer diversification benefits to traditional assets.
5. In general, natural gas failed to show diversification benefits to all asset classes under study, except for Islamic investment. Lambert et al. [55] found a similar result, concluding that the EU may face diversified gas challenges in the short and medium term.
6. Global clean energy can provide diversification benefits to both the Artificial Intelligence ETF and Islamic investment-based investors. This finding aligns with Henriques and Sadorsky [41], who found that clean energy does provide diversification benefits to technology-based investors.

Conclusion

This study examines the dynamic relationships between Artificial Intelligence (AI) and other alternative investments, including sustainable energy, commodities, and Islamic investments, using Engle's (2002) DCC-GARCH model. The sample period spans from March 1, 2019, to January 27, 2025. This study contributes by incorporating an AI ETF into a diversification framework alongside sustainable energy, commodities, and Islamic investments, an under-explored area in prior research, and guides portfolio diversification strategies for interested parties.

Firstly, during normal periods, Artificial Intelligence ETF-based investors may include all asset classes under study in their portfolios, except Islamic investments. This is evident in both unconditional and conditional correlations. The correlation between the Artificial Intelligence ETF and Islamic investment (0.865) was high through both crisis and non-crisis periods. Islamic investment-based investors may also include all alternative asset classes under investigation to obtain some degree of diversification benefits, except for the Artificial Intelligence ETF, due to its high correlation with other asset classes.

Secondly, crude oil-based investors can obtain diversification benefits across almost all asset classes due to the low and negative correlations among them. In particular, Islamic investment (-0.214) and the Artificial Intelligence ETF (-0.211) appear to offer the greatest diversification benefits due to their strong negative correlation with crude oil.

Thirdly, Global Wind Energy ETF-based investors may invest in all asset classes, except for natural gas, during the normal period. During the crisis period, investors in the Global Wind Energy ETF may avoid investing in Artificial Intelligence and Islamic investments due to their strong correlations. Both Solar ETF and Global Clean Energy-based investors may obtain diversification benefits from all asset classes under study during both crisis and non-crisis periods.

Lastly, during normal periods, natural gas-based investors can obtain diversification benefits from all asset classes under investigation, except for the Global Wind Energy

ETF, due to the high correlation between them. During the crisis period, as evidenced by conditional correlation, they may avoid investing in Artificial Intelligence ETFs and Islamic investments while obtaining the greatest diversification benefits from crude oil and Global Clean Energy.

Our findings are important and valuable to financial analysts, various types of investors, and portfolio managers who seek to understand the dynamic linkages between AI and other alternative investments. Furthermore, financial integration across asset classes is significant for portfolio diversification, as it helps maximize returns and minimize financial risk. Due to the continuous emergence of alternative asset classes, such as digital assets, and the dynamic evolution of the world's financial markets, it is essential to understand how these asset classes are integrated and to gain insights into the dynamics driving these relationships.

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Data Availability The dataset used in this study is available upon reasonable request via email to Dr. Burhan Uluyol (borhanseti@gmail.com).

Declarations

Conflict of interest The authors declare no conflict of interest.

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