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# Connectedness of AI and Islamic Stocks: Evidence from Frequency-Domain Quantile Regressions

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## Abstract

*This study explores the dynamic relationship between artificial intelligence (AI)-based stocks and Islamic stock indices. Motivated by the rising prominence of AI in global finance and the ethical appeal of Islamic investing, the study investigates whether AI stocks offer hedging, diversification, or safe haven potential relative to Islamic assets. Daily data from January 1, 2019, to April 13, 2024, is employed, covering the NASDAQ CTA Artificial Intelligence and Robotics Index (as the proxy for AI stocks), along with the Dow Jones Islamic Market World Index, United States and Canada. Using the Empirical Mode Decomposition (EEMD) with Quantile Regression techniques, the analysis captures the asymmetric relationships across different investment horizons and market states. The results reveal that AI stocks generally move in tandem with Islamic stock indices during stable and bullish markets, offering limited diversification benefits. However, in bearish markets, particularly over the long term, AI stocks exhibit a negative relationship with the global and U.S. Islamic indices, indicating potential safe haven or hedging roles. No such hedging benefit is observed concerning the Canadian Islamic index. Additionally, Islamic indices do not serve as effective hedges for AI stocks across any market regime. These results offer detailed insights into the asymmetric co-movement patterns between AI-related stocks and Islamic equities. It offers practical implications for ethical and tech-focused investors, suggesting that AI stocks may enhance portfolio resilience under specific market conditions. Policymakers and financial product designers can also leverage these insights to integrate emerging technologies into Shariah-compliant investment strategies better.*

## Introduction

One of the most essential parts of modern finance is evaluating the co-movement between asset returns (Mohamed Riyath & Hussainey, 2025; Sahabuddin et al., 2022). The foundation of risk reduction via international diversification is the presence of low cross-correlations across global stock markets (Saadaoui, 2022). Artificial Intelligence (AI) has transcended science fiction and become essential to everyday existence (Al-Najjar, 2022; Cao et al., 2024). As AI-driven developments extend across several sectors, companies at the forefront of this groundbreaking technology are included in the new asset class of AI stocks (Zhang et al., 2024). Concurrently, Islamic finance originates in Shariah law, has gained global recognition, and offers a unique investment opportunity that aligns with ethical and responsible conduct (Mirakhor et al., 2020; Shahimi & Zahari, 2025). Nowadays, much thought goes into how conventional, AI and Islamic stock returns interact in this fast-evolving financial landscape. Risk management strategies and investor portfolios stand to gain significantly from these asset classes' potential as diversification, hedging, or safe haven vehicles (Baur & Lucey, 2010; Bouri et al., 2017; Mensi et al., 2017). Concurrently, the Islamic finance sector has seen remarkable growth, managing over US$3.25 trillion in assets as of 2023 (IFSB, 2023), highlighting its role as an ethical investment option. AI stocks are the most traded type of conventional stock, so it is necessary to analyze the link between Islamic stocks and AI stocks under different market situations (Abakah et al., 2023; Adekoya et al., 2022; Snene Manzli et al., 2024).

Consequently, this development has increased focus on AI-related stocks and their performance in financial markets (Cao et al., 2024; Jevtic et al., 2022). The intersection of Islamic stocks and AI is a significant area of interest, given its impact on economic and technological domains. The rapid advancement of AI in recent years has transformed various industries, drawing attention from investors and policymakers worldwide. However, AI markets have also experienced significant turmoil. For instance, the AI stock market witnessed a major disruption when NVIDIA lost over US$600 billion in market capitalization following the introduction of the DeepSeek large language model (Keenan et al., 2025). This event highlights the volatile and sensitive nature of AI-driven markets, reinforcing the need to understand their interaction with more ethically grounded and regulated markets such as Islamic equities. On the Islamic finance side, several stock indices in countries like the US and Canada, have shown performance divergence under stress conditions, such as during the COVID-19 pandemic and post-2022 tech stock sell-offs (Alamgir & Cheng, 2023). These events underscore the growing interest of investors in identifying uncorrelated or weakly correlated asset classes that can protect their portfolios during market downturns. Given this context, this study investigates whether investors can benefit from cross-sector diversification between AI-based and Islamic-based stocks. Specifically, this research seeks to answer whether AI stocks as typically high-risk and high-reward assets, can be balanced by exposure to more stable and ethically governed Islamic stocks, and vice versa. This question is increasingly relevant as both institutional and retail investors diversify across non-traditional asset combinations to manage portfolio volatility and enhance long-term resilience.

Given the substantial growth of the Islamic finance sector and the high volatility in AI equities, analysing the relationship between Islamic stocks and AI stocks across varying market conditions is essential (Mohamed Riyath & Hussainey, 2025). The primary focus of this study is to examine the dynamic relationship between AI stocks and Islamic stocks across different market conditions, offering insights into how the interconnectedness between these asset classes may vary under different market regimes, such as bullish or bearish trends. Islamic stock markets, governed by Shariah compliance, may exhibit different efficiency dynamics due to their unique regulations. This research explores whether AI advancements improve the efficiency of these markets, addressing a relatively unexplored area in finance (Alshater et al., 2022; Dai et al., 2022). While conventional stock markets and AI stocks have been extensively studied (Abakah et al., 2023; Al-Yahyaee et al., 2020; Alamgir & Cheng, 2023), there is a lack of research that examines their dynamic interaction with Islamic stock returns using advanced techniques like Ensemble Empirical Mode Decomposition (EEMD), Quantile Regression (QR) and Quantile on Quantile Regression (QQR) explicitly. Traditional econometric models such as Vector Autoregression (VAR) and Generalised Autoregressive Conditional Heteroskedasticity (GARCH) are commonly used (Aslam et al., 2023; Atahau et al., 2022; Jeribi & Ghorbel, 2022). However, they often fail to explore the relationship across different frequencies and quantiles, especially concerning Islamic finance and AI stocks. Additionally, many studies focus on short-term dynamics or specific market events, neglecting long-term trends (Asutay et al., 2021, 2022; shear & Ashraf, 2022; Wang & Wang, 2023). This study aims to fill this gap by examining the long-, short-, and medium-term dynamics between AI stocks, conventional stocks, and Islamic stocks over an extended period from January 1, 2019, to April 4, 2024. The motivation behind this study stems from the limited research on the relationship between AI stocks and Islamic stock returns, despite the growing interest in the impact of AI on market efficiency.

To operationalize this analysis, we focus on the World AI Index and a set of Islamic stock indices for countries actively involved in AI development and financial innovation, specifically the United States and Canada. These nations are central hubs for AI-driven innovation and also maintain emerging Islamic finance sectors, making them ideal for studying interactions between these two distinct asset classes. By selecting these representative indices, the study aims to uncover both cross-sector and cross-market interdependencies. The decomposed return series of AI and Islamic stocks are then analyzed using EEMD and QQR techniques to examine their symmetric and asymmetric dependence structures across different market conditions and time horizons. This multiscale approach allows for a nuanced understanding of potential hedging, diversification, and safe haven benefits. The method's strength lies in its ability to effectively isolate the intrinsic modes of the series, making this study the first to analyze the dependence structure between AI and Islamic stocks using the EEMD-based QQR framework.

This study takes a global perspective and broadens its emphasis beyond a particular market by examining AI and Islamic stock indices using the world Islamic index, US and Canada. This multi-market study's findings are more generalizable and illustrate potential regional variations in the connection dynamics. This paper provides investors with invaluable information on managing the complexities of modern financial markets by establishing the safe haven, hedging, and diversification possibilities among the asset classes. As AI keeps upending traditional industries and Islamic finance gains greater recognition, understanding how various asset classes interact becomes essential for well-informed decision-making and robust portfolio creation. By comparing the returns of AI and Islamic stocks, investors may understand the potential diversification benefits, risk mitigation strategies, and investment opportunities these asset classes offer. Dissecting the connection dynamics allows investors to take advantage of fresh opportunities, fortify their portfolios against potential threats, and make well-informed decisions. Fundamentally, by addressing the intersection of ethical investing, technological disruption, and financial market dynamics, this research offers a contemporary and comprehensive analysis that contributes to the growing body of knowledge in this area. Investors may better understand, confidently, and resiliently handle the complexity of the modern financial environment by illuminating the linkages between different asset classes.

The theoretical foundation of this research is informed by the Adaptive Market Hypothesis (AMH), the Capital Mobility Hypothesis (CMH), and the Human Market Hypothesis (HMH), which offer distinct lenses through which market efficiency, adaptability, and investor behaviour can be understood (Munir et al., 2022; Rönkkö et al., 2024). AMH, in particular, posits that market behaviour evolves as investors adapt to new technologies, information, and circumstances. This makes it suitable for analyzing AI-driven market behaviour, where innovation continuously alters investment dynamics. HMH further supports the premise that human cognition, emotion, and ethical preferences play a role in asset pricing, particularly relevant for Islamic finance. These frameworks together support the expectation of non-linear, time-varying, and regime-sensitive relationships between AI and Islamic stocks. This justifies the methodological choice of EEMD and QR in the current study, which are designed to capture these complexities in financial time series.

While prior studies have extensively employed traditional econometric models such as VAR, GARCH and their quantile-based or time-varying parameter extensions (e.g., TVP-VAR, quantile VAR, and cross-quantilogram) to examine financial connectedness and spillovers, these approaches primarily aim to identify directional causality and shock transmission. In contrast, this study adopts EEMD combined with QR and QQR to explore the nonlinear, asymmetric dependence structure across frequency domains and quantile distributions, which are less emphasised in existing literature. Although methods like CEEMDAN and cross-quantilogram offer enhanced robustness for specific purposes, our integration of EEMD and QR techniques enables a granular understanding of how Islamic and AI-based stock returns interact under different market regimes and investment horizons.

This methodological design fills a unique gap not merely in terms of the asset classes considered but also in how their interdependencies are dissected across time scales and conditional distributions. Unlike many previous studies that assess market-wide financial integration using broader asset categories, this research provides a focused, multiscale view of two emerging and ethically divergent investment streams, namely, Islamic equities and AI-driven stocks.

The remaining sections of the paper are organised as follows. The next section presents the theoretical framework and reviews relevant literature. Section three outlines the methodology employed for data collection and analysis. Section four highlights the main findings of the study. Lastly, section five concludes the paper and provides recommendations.

## Literature Review

The AMH integrates elements of the Efficient Market Hypothesis (EMH) and Behavioural Finance, suggesting that market efficiency is not static but adapts over time based on changing conditions and investor behaviour (Cruz-Hernández & Mora-Valencia, 2024; Ghazani & Jafari, 2021). EMH is a fundamental concept in financial economics, asserting that financial markets are informationally efficient, meaning asset prices fully reflect all available information at any given time (Fama, 1970; Nyakurukwa & Seetharam, 2023). This theory posits that it is challenging to consistently outperform the market on a risk-adjusted basis, as stock prices quickly incorporate new information, rendering traditional stock selection methods like technical and fundamental analysis ineffective over time. EMH is supported by several vital premises: many rational investors participate in the market, using available information to drive prices closer to their fundamental values; information is randomly distributed and rapidly reflected in stock prices; and arbitrage opportunities are quickly seized, ensuring prices revert to their fair value. This study holistically builds on the theories to investigate the relationship between conventional AI stock and Islamic stock returns (Ali et al., 2022).

Empirically, the intersection of AI and Islamic finance remains underexplored in empirical finance literature. While various studies have examined Islamic stock performance and the dynamics of AI-related assets independently, few have systematically analysed their interaction across market regimes and time horizons. Existing literature tends to treat these domains in isolation or within limited methodological frameworks, leaving significant empirical and conceptual gaps. For example, Abakah et al. (2023) examined the dynamic effects of Bitcoin, fintech, and AI stocks on eco-friendly assets, Islamic stocks, and conventional markets using quantile-based methods. Although their study employs a quantile framework, it focuses primarily on the contemporaneous impact of multiple disruptive assets without distinguishing between time horizons or decomposing return dynamics. They also do not explore bidirectional causality or frequency-varying relationships. By contrast, our study applies EEMD with QR, enabling a richer, multi-horizon perspective on the interconnectedness between AI and Islamic assets.

Adekoya et al. (2022) analysed investor attention and its effect on Fourth Industrial Revolution assets like AI and FinTech stocks, using Google trends data. While valuable in capturing behavioural dynamics, their analysis is unidirectional and limited to investor sentiment proxies, without evaluating the structural relationship between Islamic and AI stocks. Our approach moves beyond behavioural proxies to explore direct co-movement patterns and tail dependencies, offering more actionable insights into portfolio risk management. Snene Manzli et al. (2024) investigated the safe haven properties of energy and agricultural commodities during periods of financial stress but did not focus on AI or Islamic stocks. Their wavelet coherence approach is well suited for non-linear analysis, yet their study bypasses the AI-Islamic nexus. We extend this methodological tradition by employing EEMD-based QR to uncover nonlinear, asymmetric relationships between AI and Islamic indices. Several studies have examined Islamic finance and its comparative performance vis-à-vis conventional stocks. For instance, Al-Yahyaee et al. (2020) assessed whether Islamic stocks outperform conventional sectors during crises. They employed extreme co-movement and portfolio analyses but did not isolate the effects of specific disruptive technologies such as AI. Our study bridges this gap by focusing on AI stocks as a new asset class in relation to Islamic indices across multiple regions and periods. Similarly, Ashraf et al. (2022) compared Islamic and conventional bank resilience during COVID-19 using stock data, revealing performance advantages for Islamic institutions. However, their firm-level and banking-sector focus limits the applicability of their findings to broader equity markets, especially those driven by technological innovation like AI. We address this by using aggregate Islamic stock indices and AI sector indices to explore asset class-level dynamics.

Bossman et al. (2023) applied EEMD-based techniques to model asymmetric interrelations in Islamic stock-bond markets, offering a relevant methodological precedent. However, their focus remains on Islamic financial instruments, without accounting for new market entrants like AI stocks. We adapt their methodological rigour to a broader asset class comparison, emphasising the diversification and hedging potential of AI in Islamic portfolios. The fintech landscape in Islamic finance has been reviewed by Alshater et al. (2022) and Setyowati & Rahayu (2023), both of whom highlight the conceptual alignment between AI-based systems and Shariah-compliant advisory tools. However, these are narrative reviews without empirical data or econometric analysis. Our study responds by providing the first large-scale, empirical investigation of return co-movements between AI and Islamic indices, thus grounding these conceptual claims in real market behaviour. Umar et al. (2023) examined network connectedness between sukuk (Islamic bonds) and other financial instruments. While offering insights into structural interdependence in Islamic finance, their study excludes AI or technological equities. Similarly, Cecconi (2023) discussed AI's financial market applications but did not integrate Shariah-compliant asset classes. Our study uniquely captures the joint behaviour of these two emerging fields, offering insights into ethical technology-aligned investing. Studies such as Tuysuz (2020) and Mathlouthi and Bahloul (2022) used regime-switching and dynamic models to capture the evolving relationships between Islamic and conventional stock markets. However, these works treat AI as part of conventional equities without recognising its unique volatility and innovation-driven dynamics. Additionally, they do not adopt a frequency-domain or quantile-based framework, limiting their ability to capture extreme market behaviours. Our use of EEMD and QQR overcomes these limitations by isolating patterns at specific return quantiles and time scales.

Fianto et al. (2022) applied quantile ARDL models to Indonesian Islamic stock returns, revealing short-term causality with macroeconomic variables. However, their study is market-specific and does not address global or cross-asset interdependencies. Our global sample (U.S., Canada, and world Islamic indices) provides a broader and more generalizable view of Islamic-AI linkages. Jawadi et al. (2019) documented volatility spillovers between Islamic and conventional markets using wavelet techniques, yet their study predates the recent rise of AI investing and does not explore technological influences on Islamic markets. Danila et al. (2021) and Tauseef (2020) demonstrated that market sentiment affects Islamic stocks in region-specific ways, often diverging from conventional markets. These findings underscore the distinct behavioural and regulatory characteristics of Islamic assets. We extend this insight by showing how these dynamics interact with AI-driven assets, particularly under stress regimes. The comparative study by Liu & Chang (2021), which found that interest rates and industrial production affect Islamic stocks differently from conventional ones, further highlights the distinct drivers of Islamic finance. Yet again, the role of AI remains unexplored. By isolating AI-specific indices and examining their relationships with Islamic assets across quantiles, we capture dynamics that remain invisible in symmetric or linear models. Lastly, studies such as Raza & Ye (2025) and Ali et al. (2022) evaluated the risk-adjusted performance of Islamic indices and gold-backed cryptocurrencies, respectively. These studies suggest the rising interest in ethical financial innovation but do not explore how disruptive technologies like AI interact with Islamic equities.

Recent literature has seen a shift toward more advanced decomposition techniques designed to address the limitations of traditional methods like Empirical Mode Decomposition (EMD) and its ensemble variant, EEMD. Notably, methods such as Variational Mode Decomposition (VMD), Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), and its improved version, ICEEMDAN, have been introduced to reduce mode mixing and improve decomposition stability (Cui et al., 2025; Xu & Wang, 2023; Asafo-Adjei et al., 2022). These techniques have shown promise in disciplines such as engineering, seismology, and energy forecasting, and are gradually gaining attention in financial market analysis. Despite these advancements, EEMD remains widely applied in financial economics, particularly in studies focusing on asset price dynamics, volatility spillovers, and multiscale relationships due to its non-parametric nature and adaptability to non-linear and non-stationary time series (Bouri et al., 2017; Owusu Junior et al., 2020b). The method's continued relevance, alongside newer alternatives, warrants careful methodological justification in context-specific applications. Given the exploratory nature of the current study, which involves decomposing asset returns to examine asymmetric relationships through quantile-based approaches, EEMD remains a theoretically and empirically justified tool, especially when integrated with advanced techniques like QQR to uncover frequency-specific nonlinear dependencies.

This study distinguishes itself from prior research by applying the EEMD and QR framework to investigate the frequency-based co-movement between AI and Islamic stock indices. It further contributes by employing a bi-directional analytical approach to assess whether AI stocks serve as hedging instruments, safe havens, or diversification tools to Islamic indices, and vice versa. Unlike earlier studies that often focused on single regimes or short-term dynamics, our research examines multiple market conditions such as bearish, stable, and bullish, across various quantiles and frequency horizons, using high-frequency daily data over five years. Additionally, by incorporating the World Islamic Index alongside country-specific indices from Canada and the United States, the study captures important cross-country variations in the relationship between AI and Islamic stocks. In filling these critical gaps, the paper offers a rigorous and novel empirical foundation that enhances both theoretical understanding and practical decision-making for investors, policymakers, and scholars interested in ethical, technology-driven finance.

## Methods

This study employs Quantile Regression (QR), Quantile on Quantile (QQR) and Ensemble Empirical Mode Decomposition (EEMD). These methods are applied in a two-phase process that integrates artificial intelligence for more nuanced analysis.

### Phase 1: Decomposition and extraction

The first phase involves the decomposition of return series from the World Islamic Index and selected national indexes using EEMD. The aim here is to extract Intrinsic Mode Functions (IMFs) that capture various time scales within the data. Given the non-linear and non-stationary characteristics of the financial time series, identifying these IMFs is crucial for understanding the underlying patterns (Xu et al., 2016; Yujun et al., 2020). EEMD represents an enhancement of the traditional Empirical Mode Decomposition (EMD). Unlike EMD, which may suffer from mode mixing, EEMD introduces white noise into the data before decomposition. This approach allows the mean outcome of multiple iterations to be considered the accurate representation of the data, thus addressing the limitations of EMD (Brahmana et al., 2025; Chen et al., 2021).

#### *Theoretical underpinnings of EEMD*

EEMD's methodology begins with the premise that any time series x(t) can be decomposed into an actual signal $s(t)$ and a noise component $n(t)$, expressed as:

$$x(t) = s(t) + n(t) \qquad (1)$$

By adding white noise $\omega i(t)$ to the original data $\mathrm{x}(t)$, EEMD generates a series of artificial observations $\mathrm{x}i(t)$:

$$\mathrm{x}i(t) = \mathrm{x}(t) + \omega i(t) \qquad (2)$$

These observations are decomposed into IMFs, representing oscillatory modes at different frequencies. The process is repeated with various realisations of white noise, and the ensemble mean of these IMFs is taken as the final result. This step is crucial as it helps to avoid the mode mixing problem, providing a consistent reference in the time-frequency domain (Chen et al., 2021; F. Zhang et al., 2025).

*Process overview*

1) Add white noise to the targeted data to arrive at $xi(t)$
2) Decompose $xi(t)$ into IMFs
3) Repeat 1 and 2 with varying white noise series and
4) Obtain the (ensemble) means of corresponding IMFs of the decomposition as the final result.

The IMFs derived from EEMD are critical as they enable the analysis of financial time series across different time scales. The method's ability to cancel out the added noise in the final IMFs ensures that mode mixing is minimised, maintaining the accuracy of the results. Typically, the number of IMFs $s_i$ for a dataset, along with a residual $r$ can be approximated by $\log_2 \mathrm{N}$, where N represents the total data points. The residual is then given by the difference between the last two IMFs $s_i - (s_i - 1)$. Following previous studies such as Bossman et al. (2023) and Owusu Junior et al. (2020a) IMF1 is interpreted as representing short-term, IMF5 as medium-term movements, and the residual as long-term trends. This IMF classification enables frequency-specific assessment of interconnectedness.

### Phase 2: Regression analysis

In the second phase, the study applies QR and QQR techniques across different frequency bands to perform bi-directional regressions between the extracted IMFs. The focus here is on understanding how these relationships vary across quantiles, which is particularly important given the complex dynamics of financial markets.

*The QR and QQR approaches*

This study utilises QR and QQR methodologies to explore the complex, time-varying relationships between AI equities and Islamic stocks. The QQR approach, an extension of QR, provides a non-parametric framework ideal for capturing the conditional quantile link between variables. This framework allows us to assess asymmetric relationships, particularly those influenced by non-stationarity within financial time series. We examine the conditional quantile relationship between AI and Islamic stock returns through the standard QR model. The fundamental QR model can be expressed as:

$$AR_t = \beta^{\theta}(IR_t) + u_t^{\theta} \tag{3}$$

Where, $AR_t$ and $IR_t$ represent the AI and Islamic returns at the time $t$ respectively, while $\theta$ denotes the $\theta th$ quantile of the conditional distribution of $AR_t$. The term $u_t^{\theta}$ Is the error term, with its $\theta th$ conditional quantile assumed to be zero, and $\beta^{\theta}(.)$ indicates the slope of the relationship. We extend the model to include interactions in both directions to capture the bidirectional relationship between AI and Islamic stock returns. The bidirectional QR can be expressed as:

$$AR_t = \beta^{\theta}(IR_t) + \gamma^{\tau}(AR_t) + u_t^{\theta} \tag{4}$$

$$IR_t = \delta^{\phi}(AR_t) + \eta^{\sigma}(IR_t) + v_t^{\theta} \tag{5}$$

In these equations, $\beta^{\theta}(IR_t)$ and $\gamma^{\tau}(AR_t)$ capture the influence of Islamic returns on AI returns and vice versa, while $\delta^{\phi}(AR_t)$ and $\eta^{\sigma}(IR_t)$ describe the reverse effect. The terms $u_t^{\theta}$and $v_t^{\theta}$ are the respective error terms for each QR model.

The QR model is further expanded using a first-order Taylor series approximation of the quantile of $IR^{\tau}$ leading to:

$$\beta^{\theta}(IR_t) \approx \beta^{\theta}(IR^{\tau}) + \beta^{\theta'}(IR^{\tau})(IR_t - IR^{\tau}) \tag{6}$$

In this equation, $\beta^{\theta}$ captures the partial derivative of $\beta^{\theta}(IR_t)$ reflecting the marginal effect or slope. By representing $\beta^{\theta}(IR^{\tau})$ and $\beta^{\theta'}(IR^{\tau})$ as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$ respectively, we obtain:

$$\beta^{\theta}(IR_t) \approx \beta 0(\theta,\tau) + \beta 1(\theta,\tau)(IR_t - IR^{\tau}) \qquad (7)$$

Substituting Equation (7) into the initial QR model (Equation 3) gives us the QQR model:

$$AR_t = \frac{\beta_0(\theta,\tau)+\beta_1(\theta,\tau)(IR_t-IR^{\tau})+u_t^{\theta}}{(*)} \qquad (8)$$

Where (*) denotes the conditional quantile of the θth quantile of AI returns. This equation reveals the connection between the θth quantile of Islamic stock returns and the $\tau_{th}$ quantile of AI returns, governed by the parameters $\beta_0$ and $\beta_1$ with indices θ and τ.

The QQR model utilises a kernel density function to estimate the parameters in the neighbourhood of $IR^{\tau}$ where stationarity is relaxed, the estimation process involves minimising a loss function similar to ordinary least squares (OLS), defined as:

$$\min_{b0,b1} \sum_{i=1}^{n} \rho_{\theta}\left[AR_t - b_0 - b_1\left(\widehat{IR}_t - \widehat{IR}^{\tau}\right)\right] K\left(\frac{F_n(\widehat{IR}_t)-\tau}{h}\right) \qquad (9)$$

In this equation, ρθ (u) represents the quantile loss function K(.) is the kernel density function, and h is the bandwidth parameter. The kernel function weights the observations around $IR^{\tau}$ ensuring that minimal weights are applied to observations with lower ranks.

For practical implementation, the study follows the approach of Sim and Zhou (2015), using a bandwidth h ranging from 0.05 to 0.95 for empirical QQ analysis. The choice of bandwidth is crucial; larger bandwidths may introduce bias, while smaller ones ensure the smoothness of the estimates. To account for time-varying, non-linear, and non-stationary dynamics, QR and QQR are applied to analyze the relationship between AI and Islamic stocks across different return regimes bullish, bearish, and stable periods at short-, medium-, and long-term horizons. The inclusion of Intrinsic Mode Functions (IMFs) as inputs further enhances the robustness of the analysis, providing new insights into the intricate links between these markets

### *Data and Preliminary Analysis*

This study utilizes daily stock price data from two key asset groups: AI-based equities and Islamic stock indices. We represent the AI stock index, the World Islamic stock index, the United States Islamic stock index and the Canada Islamic stock index by AI, WD, US and CD, respectively. For AI stocks, we used the NASDAQ CTA Artificial Intelligence and Robotics Index sourced from Refinitiv, which tracks the performance of companies involved in artificial intelligence, machine learning, and robotics. For Islamic equities, we employ the Dow Jones Islamic Market World Index, U.S. Index and Canada Index, all of which are widely used benchmarks representing Shariah-compliant equities across global and national markets. These datasets span from January 1, 2019, to April 13, 2024. The selected assets offer distinct features that justify their inclusion. AI stocks are characterised by high growth potential but are prone to volatility and speculative bubbles, as evidenced by events like the sharp valuation drop of NVIDIA in 2024. In contrast, Islamic indices represent ethically screened, lower-leverage stocks that tend to be more stable and less exposed to conventional financial risk factors such as interest rate volatility. This contrast makes them suitable candidates for evaluating hedging, diversification, and safe haven relationships under different market conditions. The combination of these asset classes offers a unique perspective on the dynamic and non-linear interaction between innovation-driven and ethically constrained markets. However, we analyse daily stock price returns, which were decomposed into various Intrinsic Mode Functions (IMFs) to capture short-, medium-, and long-term dynamics. Specifically, IMF1, IMF5, and the IMF Residual were selected to represent short-term, medium-term, and long-term dynamics, respectively, following established literature (Owusu Junior et al., 2020a).

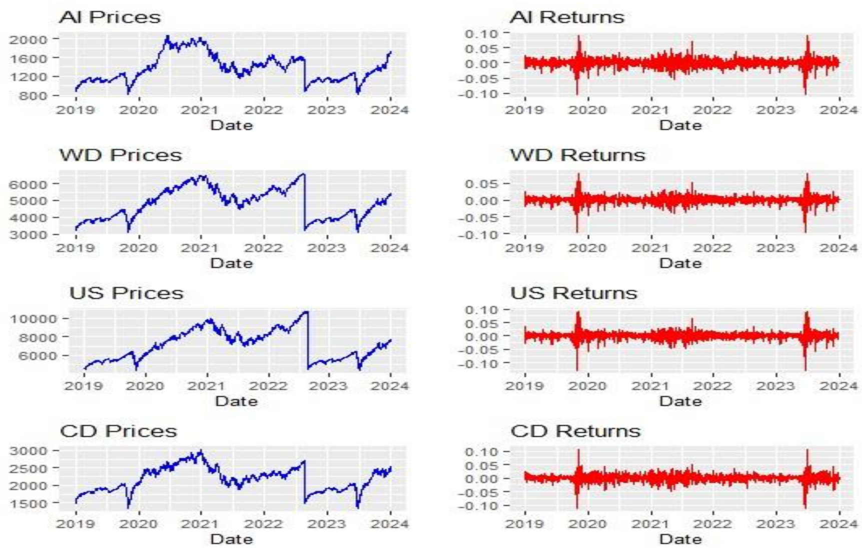



**Figure 1. Graphical Representation of Daily Raw Series (Left) and Return Series (Right).**

To start the data analysis process, the study examined the statistical distribution of the return series. This provided an overview of the patterns of movements in AI and Islamic stock prices and returns over the study period. Figure 1 shows the graphical distribution of AI stocks' prices and returns and Islamic market indexes' prices and returns. A glance at the plots reveals that the study's asset values exhibit similar tendencies. For instance, prices increased between January 2019 and January 2020 but declined between January 2020 and May 2020. From May 2020 to January 2022, prices rise significantly. Except for AI stock, which stays constant after January 2024, it is seen that asset values decreased once more after January 2022 but climbed in January 2023, dipped in the middle of the year, and then assumed a greater rising tendency through to January 2024 and beyond. In general, during times of market uncertainty, asset stocks may be observed to display comparable characteristics. Consequently, the pairwise correlations between the stock indices are shown in the research. In Figure 2, the pairwise correlation figure is summarised.

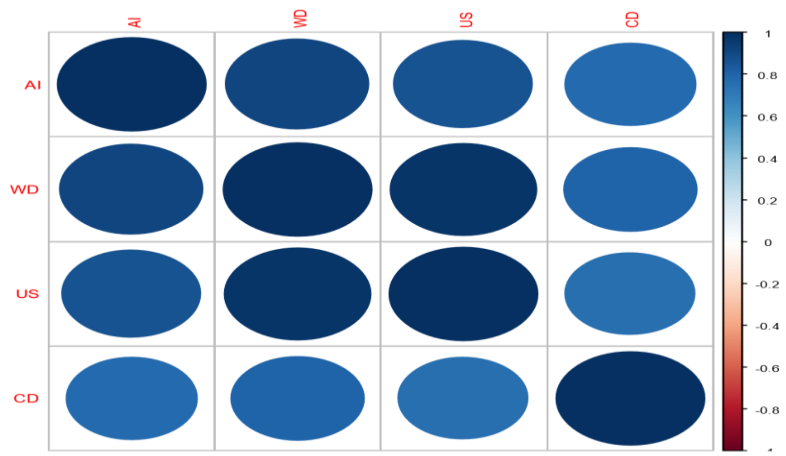



**Figure 2. Correlation Plot**.

The correlation plot in Figure 2 showed a low association with CD but a significant correlation between AI, US and WD. A moderate to high correlation was found between the Islamic indexes; however, there was no collinearity issue as the analysis was conducted for different markets. The descriptive statistics of the return series and their decomposed components (IMF1, IMF5, and IMFR) are presented in Table 1. The return series exhibits characteristics of non-normality, including skewness, excess kurtosis, and significant Jarque-Bera statistics. Given the study’s application of non-linear quantile-based models, we conducted further diagnostics. Specifically, the ADF test suggests stationarity in all series at varying significance levels while the BDS test also rejects the null hypothesis of linearity at a 1% significance level for all series, indicating strong non-linear dependence structures. In addition, we applied for the KSS test for non-linear unit roots, which confirmed stationarity under non-linear dynamics. These findings validate our use of non-linear models (QR and QQR) in the analysis. These attest to asymmetries in the series' distributions. For the IMFs, we also discover comparable trends throughout the various timescales. In addition, given the time series frequency fluctuations, IMFs appear helpful as regression approach inputs. These give us even more reason to use quantile-based regressions in our analysis of the AI-Islamic relationship.

**Table 1.** Summary statistics and stationarity tests of AI stocks and Islamic stocks returns and their IMFs

| IMF / Series | Mean | Std. Dev | Skewness | Kurtosis | Jarque-Bera | ADF Test | BDS Test | KSS Test |
|---|---|---|---|---|---|---|---|---|
| AI | 0.0004 | 0.01469 | -0.4696 | 5.7238 | 1871.48*** | -10.0280** | 0.634*** | -3.921*** |
| WD | 0.0005 | 0.01143 | -0.7808 | 10.9921 | 6851.81*** | -10.164** | 0.591*** | -3.484*** |
| US | 0.0006 | 0.01415 | -0.6747 | 11.001 | 6828.43*** | -10.244** | 0.645*** | -3.774*** |
| CD | 0.0003 | 0.01371 | -0.7196 | 9.544 | 5178.92*** | -10.102** | 0.601*** | -3.619*** |
| AI_IMF1 | 7.36E-05 | 0.0106 | -0.0732 | 4.5227 | 1139.55*** | -11.42** | 0.582*** | -3.482*** |
| WD_IMF1 | -8.38E-05 | 0.0088 | -0.1286 | 13.6078 | 10295.30*** | -11.92** | 0.506*** | -3.297*** |
| US_IMF1 | -0.00019 | 0.0115 | -0.1601 | 14.2428 | 11279.94*** | -12.10** | 0.521*** | -3.390*** |
| CD_IMF1 | 1.89E-05 | 0.0104 | -0.0523 | 4.7959 | 1280.52*** | -12.38** | 0.497*** | -3.215*** |
| AI_IMF5 | 1.19E-05 | 0.0022 | -0.2562 | 1.2693 | 104.69*** | -9.47** | 0.417*** | -2.991*** |
| WD_IMF5 | -1.68E-05 | 0.0019 | -0.1566 | 4.2542 | 1012.81*** | -9.53** | 0.394*** | -2.822*** |
| US_IMF5 | 3.83E-06 | 0.0018 | -0.1479 | 2.9941 | 504.29*** | -9.58** | 0.402*** | -2.968*** |
| CD_IMF5 | -3.05E-05 | 0.0021 | -0.0753 | 4.6278 | 1193.10*** | -7.99** | 0.376*** | -2.851*** |
| AI_IMFR | 0.0005 | 0.0011 | 0.2045 | -1.1687 | 84.57*** | 0.39** | 0.339*** | -2.718*** |
| WD_IMFR | 0.0006 | 0.0005 | 1.1853 | 0.3629 | 319.39*** | -18.46** | 0.315*** | -2.645*** |
| US_IMFR | 0.0008 | 0.0006 | 1.1801 | 0.2412 | 312.53*** | -15.17** | 0.324*** | -2.730*** |
| CD_IMFR | 0.0003 | 0.0009 | 0.967 | -0.3641 | 214.77*** | 19.58** | 0.308*** | -2.688*** |

Note: respectively. *, **, and *** signify significance in respect of 10%, 5%, and 1% levels. ADF, BDF and KSS represent Augmented Dickey-Fuller, Brock-Dechert-Scheinkman and Kapetanios, Shin, and Snell respectively

## Empirical Results and Discussions

This section presents empirical findings based on the EEMD-based QR and QQR models. We explore the non-linear dependencies between AI and Islamic stock returns across different market conditions and investment horizons. The QR model captures the asymmetric dependence between AI and Islamic stock returns across different quantiles, highlighting how relationships vary under bearish, neutral, and bullish market conditions. The QQR model extends this by evaluating nonlinear dependence across both the quantiles of Islamic stock returns and those of AI stock returns, providing a more detailed co-movement structure.

### *QR results*

The study investigates the bi-directional relationship between AI and Islamic stock returns using QR. The estimated coefficients are reported in Tables 2 and 3. The relationships are interpreted based on direction. For instance, "AI - WD" implies AI returns are regressed on the Islamic World Index, while "WD - AI" reflects the reverse. We examine these relationships to shed light on safe havens and opportunities for diversification and hedging. In this sense, we view an inverse association, or negative coefficient, as having the possibility for diversification, whereas a positive coefficient does not (Baur & Lucey, 2010). By analyzing these correlations at different quantiles, we can determine the precise market scenarios where AI equities and Islamic stocks can effectively hedge or diversify against each other, thereby enhancing portfolio resilience. Using the QR model, the study investigates the AI–Islamic connection in 19 quantiles (0.05, 0.10, 0.15, … 0.95). The study defines three market conditions as (0.05, 0.1, 0.15, 0.20, 0.25, 0.30) for lower quantiles representing bearish market conditions. (0.35, 0.40, 0.45, 0.50, 0.55, 0.60) for intermediate quantiles representing stable market conditions and (0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95) for upper quantiles representing bullish market conditions. Tables 2 and 3 present the QR results of the relationship between AI and Islamic stocks and the bi-directional relationship.

The results presented in Tables 2, 3, and 4 highlight clear patterns of dependency between AI stocks and Islamic indices across different market conditions and time horizons. These findings provide a deeper understanding of how the connectedness between these asset classes evolves, especially under stress, stability, and growth phases. The QR results reveal that AI stocks generally exhibit positive co-movement with the Islamic indices (WD, US, and CD) during stable and bullish market conditions. This implies that during periods of market optimism or normalcy, these assets tend to move in the same direction, thereby limiting their effectiveness for diversification in those phases. This behaviour is consistent with prior observations that AI stocks, while known for their growth and innovation-led resilience (Asutay et al., 2021), may not always serve as diversification tools under normal or optimistic conditions. However, when attention shifts to bearish markets, which are represented by the lower quantiles, AI stocks begin to show distinct behaviour. The results suggest that in long-term horizons (IMF R), AI stocks exhibit negative correlations with WD and US Islamic indices, indicating potential safe haven characteristics during market downturns (Bossman et al., 2023; Umar et al., 2023). This inverse relationship implies that AI assets may act as a buffer against prolonged declines in Islamic stock performance, supporting their use as a risk management tool for long-horizon investors. Such a role is particularly important in markets where ethical compliance limits exposure to certain conventional financial instruments, making non-traditional assets like AI increasingly relevant (Al-Yahyaee et al., 2020; Ashraf et al., 2022).

The CD, however, presents a contrasting case. Across all quantiles and time horizons, its relationship with AI stocks remains consistently positive. This suggests that AI does not offer meaningful diversification or hedging value when paired with CD, reducing its usefulness for Canadian investors seeking downside protection. Conversely, none of the Islamic indices shows safe haven or hedging behaviour toward AI stocks. Their persistent positive correlations across all market conditions reinforce the view that AI stocks are becoming increasingly influential within Islamic markets but not necessarily shielded from their movements (Bossman et al., 2023). These findings provide a practical lens for investors who seek to align ethical investment principles with high-growth sectors like AI, offering strategic insights into when AI stocks can be used to stabilise portfolios and when they may amplify risk. The bidirectional analysis confirms that the influence is not one-sided. Islamic indices, especially WD and US, are also affected by fluctuations in AI stock returns, further establishing the increasing relevance of AI innovations to the broader ethical investment space. This persistent positive correlation across all market phases underscores that investors heavily exposed to Islamic indices may not find AI stocks sufficient for diversification unless their strategy is tailored to longer timeframes or downturn scenarios. Thus, the study not only demonstrates statistical significance but also offers actionable insights on how the interaction between AI and Islamic stocks can be interpreted and applied in portfolio construction and risk management strategies.

**Table 2.** QR estimates for AI and Islamic stocks.

| | WD on AI | | | US on AI | | | CD on AI | | |
|---|---|---|---|---|---|---|---|---|---|
| IMF/Quantile | IMF1 | IMF5 | IMFR | IMF1 | IMF5 | IMFR | IMF1 | IMF5 | IMFR |
| **0.05** | 1.1711*** | 1.0469*** | -2.9040*** | 0.8550*** | 1.0869*** | -1.8089*** | 0.7965*** | 0.9734*** | 1.1189*** |
| **0.1** | 1.1711*** | 1.0453*** | -2.2281*** | 0.8550*** | 1.0869*** | -1.6915*** | 0.7965*** | 0.9734*** | 1.1296*** |
| **0.15** | 1.1704*** | 1.0451*** | -1.8938*** | 0.8542*** | 1.0869*** | -1.5646*** | 0.8083*** | 0.9734*** | 1.1394*** |
| **0.2** | 1.1704*** | 1.0415*** | 1.2567*** | 0.8542*** | 1.0869*** | -0.5436*** | 0.8083*** | 0.9718*** | 1.1507*** |
| **0.25** | 1.1703*** | 1.0390*** | 1.2786*** | 0.8542*** | 1.0869*** | 0.8123*** | 0.8083*** | 0.9661*** | 1.1623*** |
| **0.3** | 1.1703*** | 1.0389*** | 1.3014*** | 0.8539*** | 1.0869*** | 1.0705*** | 0.8083*** | 0.9661*** | 1.1743*** |
| **0.35** | 1.1703*** | 1.0389*** | 1.3264*** | 0.8539*** | 1.0869*** | 1.0839*** | 0.8083*** | 0.9661*** | 1.1880*** |
| **0.4** | 1.1666*** | 1.0389*** | 1.3539*** | 0.8534*** | 1.0869*** | 1.0987*** | 0.8083*** | 0.9661*** | 1.2020*** |
| **0.45** | 1.1666*** | 1.0348*** | 1.3855*** | 0.8534*** | 1.0869*** | 1.1137*** | 0.8083*** | 0.9660*** | 1.2167*** |
| **0.5** | 1.1666*** | 1.0348*** | 1.4203*** | 0.8508*** | 1.0869*** | 1.1302*** | 0.8098*** | 0.9636*** | 1.2322*** |
| **0.55** | 1.1653*** | 1.0348*** | 1.4587*** | 0.8501*** | 1.0869*** | 1.1475*** | 0.8098*** | 0.9594*** | 1.2496*** |
| **0.6** | 1.1653*** | 1.0348*** | 1.5044*** | 0.8496*** | 1.0869*** | 1.1655*** | 0.8098*** | 0.9594*** | 1.2678*** |
| **0.65** | 1.1653*** | 1.0336*** | 1.5570*** | 0.8466*** | 1.0869*** | 1.1847*** | 0.8098*** | 0.9594*** | 1.2869*** |
| **0.7** | 1.1643*** | 1.0336*** | 1.6196*** | 0.8418*** | 1.0869*** | 1.2042*** | 0.8098*** | 0.9594*** | 1.3086*** |
| **0.75** | 1.1643*** | 1.0336*** | 1.6963*** | 0.8410*** | 1.0869*** | 1.2244*** | 0.8114*** | 0.9530*** | 1.3314*** |
| **0.8** | 1.1643*** | 1.0336*** | 1.7938*** | 0.8400*** | 1.0869*** | 1.2440*** | 0.8114*** | 0.9530*** | 1.3575*** |
| **0.85** | 1.1643*** | 1.0336*** | 1.9256*** | 0.8396*** | 1.0869*** | 1.2625*** | 0.8114*** | 0.9530*** | 1.3854*** |
| **0.9** | 1.1643*** | 1.0336*** | 2.1129*** | 0.8392*** | 1.0869*** | 1.2778*** | 0.8114*** | 0.9530*** | 1.4170*** |
| **0.95** | 1.1639*** | 1.0309*** | 2.4246*** | 0.8392*** | 1.0869*** | 1.2883*** | 0.8114*** | 0.9530*** | 1.4536*** |

Note : *, **, and *** represents 10%, 5%, and 1%  significance level respectively

**Table 3.** Bidirectional QR estimates for AI and Islamic stocks.

| | | **AI on WD** | | | **AI on US** | | | **AI on CD** | |
|---|---|---|---|---|---|---|---|---|---|
| IMF/Quantile | IMF1 | IMF5 | IMFR | IMF1 | IMF5 | IMFR | IMF1 | IMF5 | IMFR |
| **0.05** | 0.6970*** | 0.6483*** | 0.3645*** | 0.8520*** | 0.6987*** | 0.7744*** | 0.7257*** | 0.6194*** | 0.4920*** |
| **0.1** | 0.6970*** | 0.6483*** | 0.3851*** | 0.8520*** | 0.6987*** | 0.7758*** | 0.7257*** | 0.6194*** | 0.5194*** |
| **0.15** | 0.6990*** | 0.6512*** | 0.4092*** | 0.8520*** | 0.6987*** | 0.7778*** | 0.7262*** | 0.6194*** | 0.5446*** |
| **0.2** | 0.6990*** | 0.6512*** | 0.4326*** | 0.8520*** | 0.7006*** | 0.7807*** | 0.7262*** | 0.6194*** | 0.5694*** |
| **0.25** | 0.6990*** | 0.6514*** | 0.4552*** | 0.8520*** | 0.7006*** | 0.7843*** | 0.7312*** | 0.6219*** | 0.5930*** |
| **0.3** | 0.6990*** | 0.6514*** | 0.4762*** | 0.8531*** | 0.7006*** | 0.7884*** | 0.7312*** | 0.6219*** | 0.6164*** |
| **0.35** | 0.6990*** | 0.6514*** | 0.4962*** | 0.8531*** | 0.7011*** | 0.7932*** | 0.7312*** | 0.6219*** | 0.6375*** |
| **0.4** | 0.6994*** | 0.6514*** | 0.5156*** | 0.8531*** | 0.7028*** | 0.7984*** | 0.7333*** | 0.6300*** | 0.6580*** |
| **0.45** | 0.6997*** | 0.6514*** | 0.5329*** | 0.8534*** | 0.7028*** | 0.8039*** | 0.7333*** | 0.6318*** | 0.6777*** |
| **0.5** | 0.6997*** | 0.6526*** | 0.5502*** | 0.8534*** | 0.7028*** | 0.8098*** | 0.7345*** | 0.6318*** | 0.6958*** |
| **0.55** | 0.7010*** | 0.6526*** | 0.5661*** | 0.8542*** | 0.7028*** | 0.8159*** | 0.7345*** | 0.6318*** | 0.7135*** |
| **0.6** | 0.7011*** | 0.6526*** | 0.5820*** | 0.8542*** | 0.7028*** | 0.8220*** | 0.7354*** | 0.6327*** | 0.7304*** |
| **0.65** | 0.7011*** | 0.6526*** | 0.5963*** | 0.8542*** | 0.7028*** | 0.8287*** | 0.7354*** | 0.6327*** | 0.7470*** |
| **0.7** | 0.7011*** | 0.6526*** | 0.6107*** | 0.8542*** | 0.7041*** | 0.8352*** | 0.7354*** | 0.6347*** | 0.7622*** |
| **0.75** | 0.7011*** | 0.6526*** | 0.6242*** | 0.8542*** | 0.7041*** | 0.8419*** | 0.7412*** | 0.6347*** | 0.7772*** |
| **0.8** | 0.7014*** | 0.6534*** | 0.6378*** | 0.8554*** | 0.7075*** | 0.8482*** | 0.7412*** | 0.6359*** | 0.7916*** |
| **0.85** | 0.7014*** | 0.6534*** | 0.6505*** | 0.8555*** | 0.7086*** | 0.8552*** | 0.7412*** | 0.6359*** | 0.8059*** |
| **0.9** | 0.7026*** | 0.6537*** | 0.6625*** | 0.8563*** | 0.7086*** | 0.8618*** | 0.7412*** | 0.6366*** | 0.8190*** |
| **0.95** | 0.7026*** | 0.6537*** | 0.6744*** | 0.8563*** | 0.7105*** | 0.8686*** | 0.7418*** | 0.6366*** | 0.8318*** |

**Note :** *, **, and *** represents 10%, 5%, and 1% significance level respectively

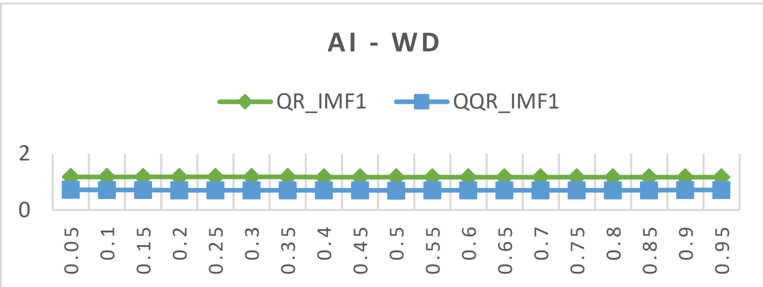
**Table 4.** Summary co-movements between AI Stocks and WD, US, and CD Islamic Stocks

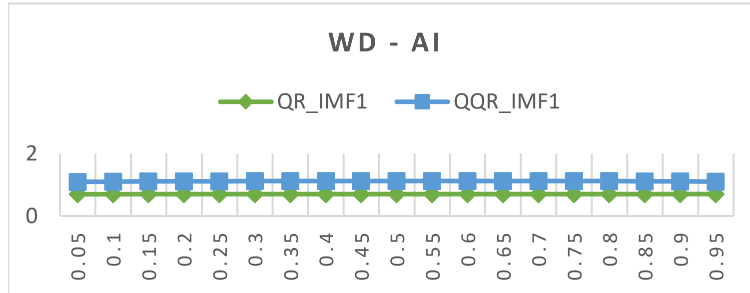
| Co movements | Quantile Range | IMF 1 | IMF 5 | IMF R |
|---|---|---|---|---|
| AI → WD | (Bearish) 0.05 – 0.30 | (+) | (+) | (−) |
| | (Stable) 0.35 – 0.60 | (+) | (+) | (+) |
| | (Bullish) 0.65 – 0.95 | (+) | (+) | (+) |
| AI → US | 0.05 – 0.30 | (+) | (+) | (−) |
| | 0.35 – 0.60 | (+) | (+) | (+) |
| | 0.65 – 0.95 | (+) | (+) | (+) |
| AI → CD | 0.05 – 0.30 | (+) | (+) | (+) |
| | 0.35 – 0.60 | (+) | (+) | (+) |
| | 0.65 – 0.95 | (+) | (+) | (+) |
| WD → AI | 0.05 – 0.30 | (+) | (+) | (+) |
| | 0.35 – 0.60 | (+) | (+) | (+) |
| | 0.65 – 0.95 | (+) | (+) | (+) |
| US → AI | 0.05 – 0.30 | (+) | (+) | (+) |
| | 0.35 – 0.60 | (+) | (+) | (+) |
| | 0.65 – 0.95 | (+) | (+) | (+) |
| CD → AI | 0.05 – 0.30 | (+) | (+) | (+) |
| | 0.35 – 0.60 | (+) | (+) | (+) |
| | 0.65 – 0.95 | (+) | (+) | (+) |

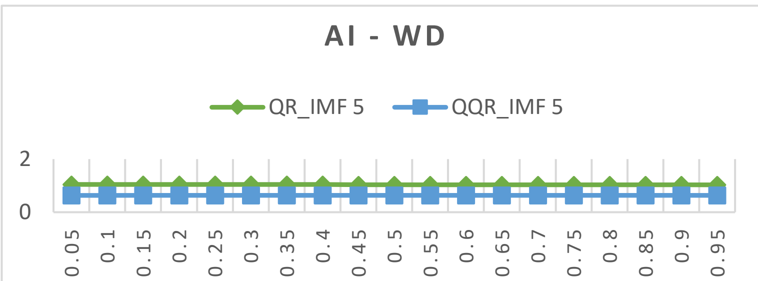
Note: (AI → WD) means AI is the Dependent and WD is the Independent. Whereas (WD → AI) is the bidirectional relationship. (+) and (−) represent positive and negative relationships respectively.

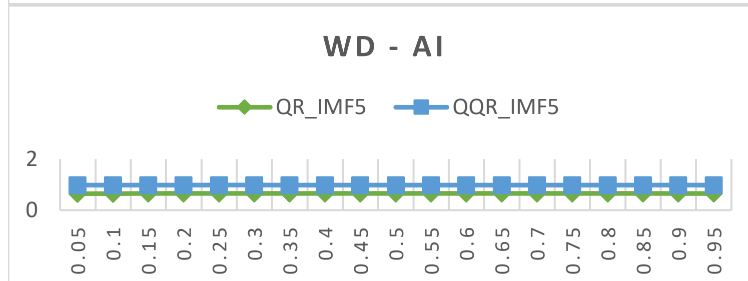
*QQR results*

Next, we illustrate the QQR results in three-dimensional plots (Figure 4) see appendix. Like their QR counterparts, the results show that across all quantiles of both AI and Islamic stock returns, positive slopes are found. This pattern confirms the limited diversification potential of AI stocks in portfolios that are already exposed to Islamic indices, particularly during upward or stable market conditions. The close match between the QR and QQR line plots in Figure 3 confirms the robustness of the QQR results. Using QR to cross-check the QQR estimates is a common way researchers test how reliable the findings are, and it's a method supported by past studies (Yeboah et al., 2025a; Agyei et al., 2025; Yeboah et al., 2025b)


AI - WD
QR_IMF1
QQR_IMF1
2
0
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95

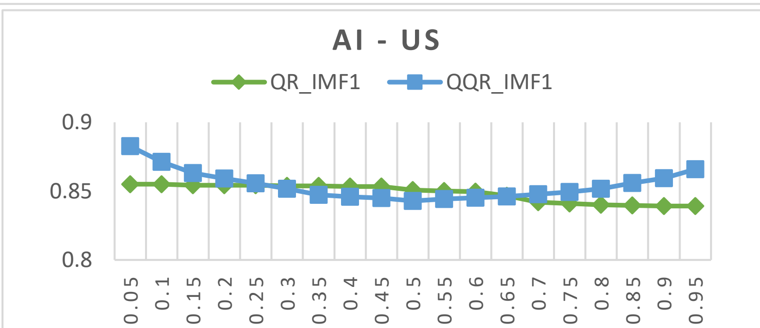

WD - AI
QR_IMF1
QQR_IMF1
2
0
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95

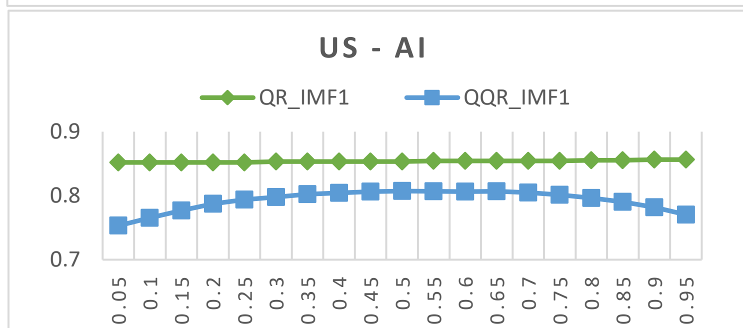

AI - WD
QR_IMF 5
QQR_IMF 5
2
0
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95

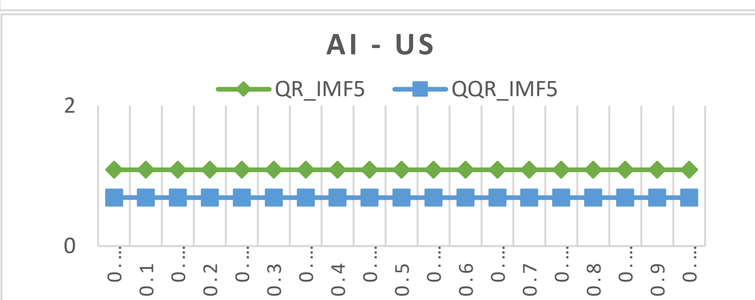

WD - AI
QR_IMF5
QQR_IMF5
2
0
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95

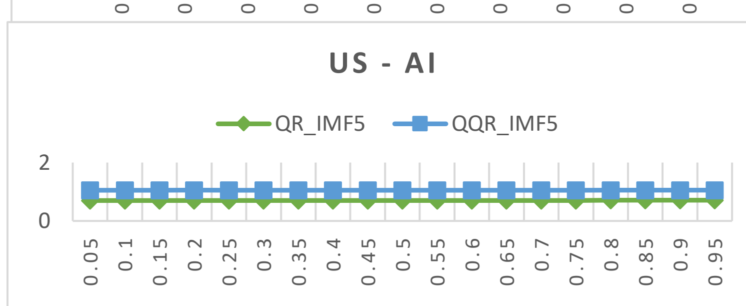

AI - WD
QR_Residual
QQR_Residual
5
0
-5
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95


WD - AI
QR_Residuals
QQR_Residuals
2
1
0
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95


AI - US
QR_IMF1
QQR_IMF1
0.9
0.85
0.8
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95


US - AI
QR_IMF1
QQR_IMF1
0.9
0.8
0.7
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95


AI - US
QR_IMF5
QQR_IMF5
2
0
0.… 0.1 0.… 0.2 0.… 0.3 0.… 0.4 0.… 0.5 0.… 0.6 0.… 0.7 0.… 0.8 0.… 0.9 0.…


US - AI
QR_IMF5
QQR_IMF5
2
0
0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95

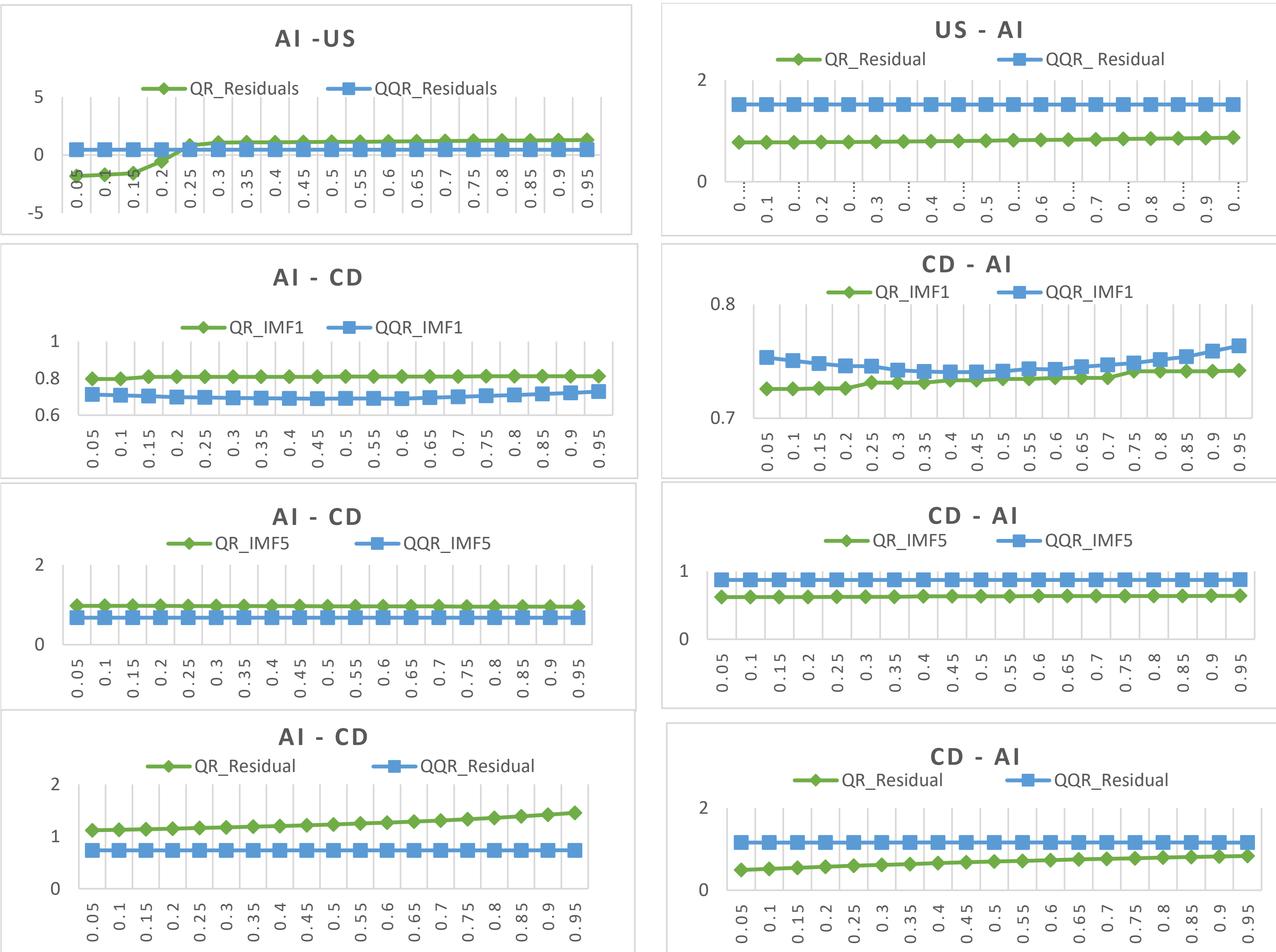



**Figure 3.** Bi-directional AI and Islamic stock returns QR and QQR

## Conclusion

Using QR and QQR combined with EEMD we examine the connectedness between AI-based stocks and Islamic stock indices (World, US, and Canada) across different market conditions and time horizons. The findings reveal meaningful asymmetries and time-varying dependencies, particularly in bearish and long-term settings. AI stocks generally exhibit strong co-movement with all Islamic indices during stable and bullish markets, suggesting limited diversification opportunities in such phases. However, negative correlations emerge between AI and the WD and US indices during bearish conditions in the long term, indicating potential hedging value. Unexpectedly, AI stocks failed to offer any diversification or safe haven benefits against the Canada Islamic Index across all market phases and horizons. This anomaly may reflect structural differences in the Canadian Islamic equity space, such as sectoral concentration, market depth, or limited overlap with AI-intensive industries. Likewise, none of the Islamic indices served as a hedge or safe haven for AI stocks, which was initially hypothesized given their ethical and low-volatility nature. This deviation implies that AI-driven markets may be more autonomous in behaviour, increasingly shaping rather than being shaped by broader ethical indices.

These findings provide important implications for investors and portfolio managers. First, the usefulness of AI stocks as a hedge is highly context-specific, effective only in long-term bearish scenarios and primarily against the WD and US indices. Second, Islamic investors seeking to diversify portfolios with AI assets must consider not just general co-movement patterns but also market conditions and investment horizons. The persistent positive correlations during stable and bullish phases suggest that AI stocks, while enhancing returns, offer limited downside protection during short-term market shocks. From a policy standpoint, financial regulators and portfolio strategists in Islamic markets should monitor the increasing influence of AI-related stocks on Islamic equity behaviour. The growing alignment between these markets underscores the need for ethical screening frameworks that consider not only financial compliance but also technological and systemic risk exposure. Encouraging the development of Shariah-compliant AI indices or investment vehicles could serve as a forward-looking strategy to balance innovation with compliance and risk management. While this study provides useful insights into the connectedness between AI and Islamic stocks, it is limited by its focus on global, U.S., and Canadian Islamic indices. Key Islamic markets in the Middle East and Southeast Asia are not directly represented. Future research could incorporate region-specific indices from countries such as Malaysia, Saudi Arabia, or the UAE to broaden the geographical relevance and test the robustness of these findings.

## Declaration of Statement

The authors state that none of their known conflicting financial interests or personal connections could have impacted the work published in this publication.

## Data Availability Statement

Data will be made available upon request from the corresponding author

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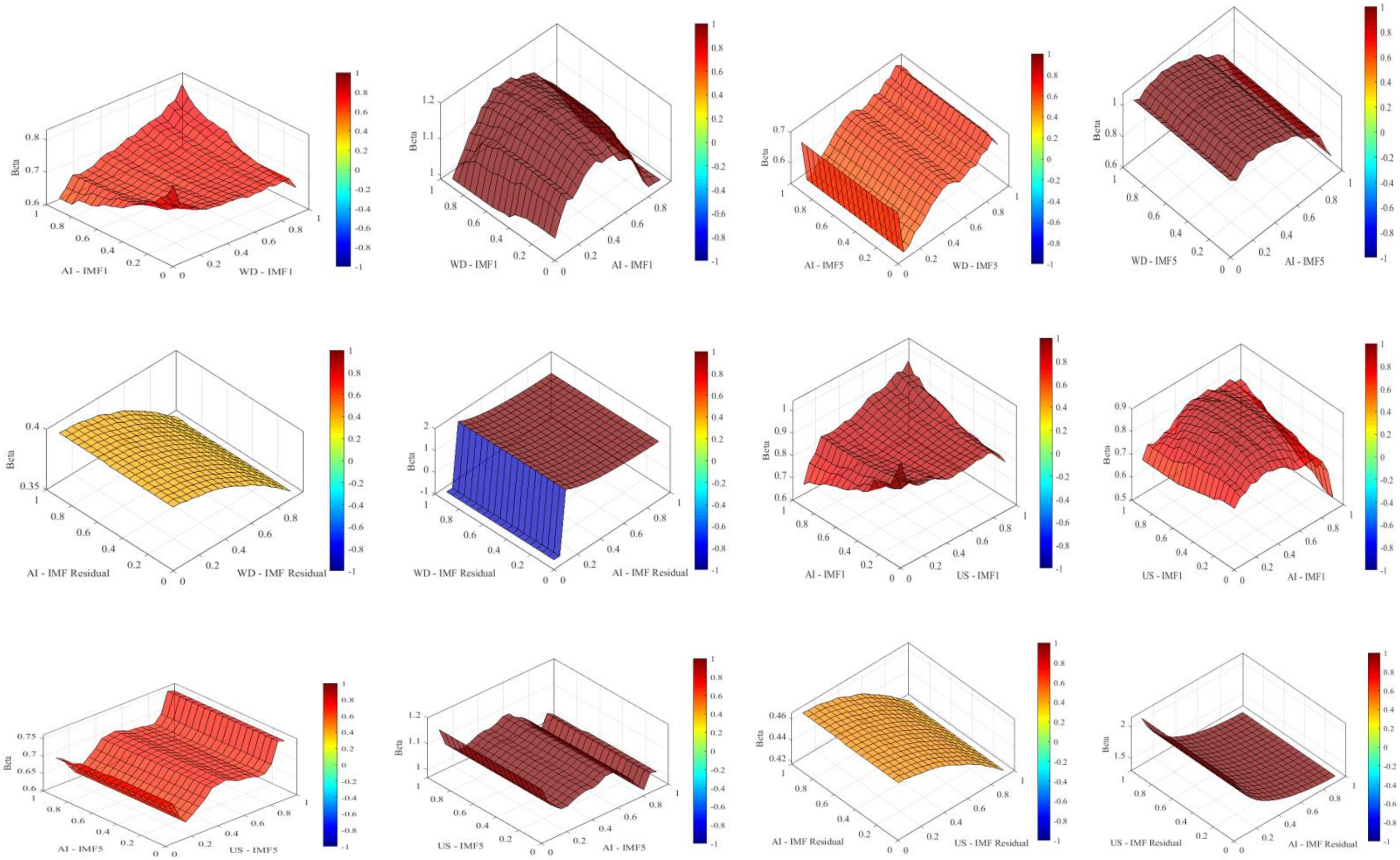
## Appendix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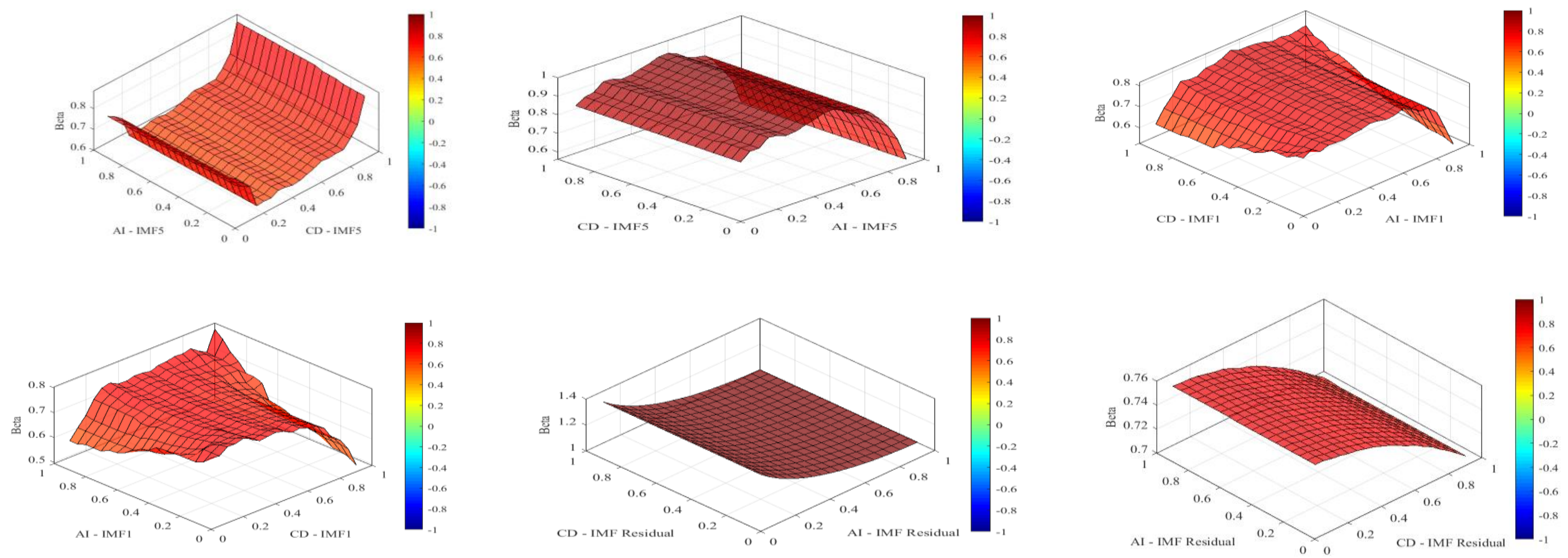


**Figure 4.** Bi-directional AI and Islamic stock returns QQR plots