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Exploring the predictive power of artificial neural networks in linking global Islamic indices with a local Islamic index

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This study aims to analyze the correlations and information flow between a local Sharia-compliant index and global Sharia-compliant indices using Artificial Neural Network (ANN) models, shedding light on the integration of international and national Sharia-compliant markets. Given recent market conditions and uncertainties at both local and global levels, the research investigates the predictive power of ANNs and examines the relationship between the Dubai Financial Market Sharia Index (DFMSI) and three well-known global Islamic indices: the Dow Jones Islamic Market World Index, the Standard and Poor's Global Sharia Index, and the Financial Times Stock Exchange Sharia All World Index. By incorporating data from multiple global Sharia indices, the study expands data sources beyond the local market, providing a comprehensive analysis of factors influencing the DFMSI's price. This approach reduces reliance on a single dataset and strengthens the robustness of the research findings. Additionally, the inclusion of the three global Sharia indices offers benefits such as access to global market insights, risk management, and practical applications for investors. The study demonstrates that ANNs, particularly the Nonlinear Autoregressive with External Input Neural Network (NARX), outperform classical models in accurately predicting the DFMSI. This research contributes significantly to the understanding of Sharia-compliant investments by providing a comprehensive analysis of how multiple global indices affect a local market index. It also offers valuable insights for investors and portfolio managers, suggesting that the integration of advanced machine learning models can enhance decision-making processes and improve risk management strategies.

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Introduction

Financial markets play a crucial role in a country's financial system by facilitating the flow of savings and investment decisions. They are both profitable and risky for investors, requiring accurate expectations of stock indices to make profitable investment decisions (Chen et al. 2021). However, predicting stock market movements is complex due to the interaction of macroeconomic variables and international factors that can lead to unforeseen fluctuations (Assous et al. 2020).

The process of financial deepening and integration in global stock markets has led to increased co-movement among world stock indices. To make informed decisions, investors must anticipate the direction in which other stock exchanges will move following the decline or rise of a particular market (D. Al-Najjar, 2022). This knowledge is essential for investors to act promptly and make effective decisions.

Researchers have explored the relationship between international stock indices to understand correlations and information flow. The objective is to analyze linkages between different financial exchanges enabling easier prediction of market movements and informed decision-making by investors and policymakers. This interest grew stronger in the aftermath of the global financial crisis of 2007–08, as there was a heightened focus on evaluating the interconnectedness between different exchanges(D. Al-Najjar, 2022).

Empirical research in this area is abundant (Kartal et al. 2022; Sandoval Junior et al. 2015). For instance, in a recent investigation conducted by Kartal et al. (2022), the focus was on investigating the co-movements of 11 global stock indices between 2001 and 2019 using data mining techniques. Their research aimed to identify which indices exhibit co-movement patterns and shed light on the nature of this co-movement. The findings of their study provided compelling evidence that co-movements exist among world stock indices, and these co-movements tend to occur in a cyclical manner.

Methodologically, a range of statistical models, including regression models, decision tree, fractional cointegration, ARIMA models and GARCH models (Alamro et al. 2019; Assous et al. 2020; Caporale et al. 2022), have been used to predict stock market indices. However, artificial neural networks (ANNs) have shown to be the most effective prediction models, providing high accuracy and aiding stakeholders in making informed decisions as shown by a number of recent studies including H. Al-Najjar et al. (2021); Selvamuthu et al. (2019); Siami-Namini and Namin (2018).

The study of Sharia-compliant (SC) indices has gained importance with the growth of Islamic finance (Antar and Alahouel, 2020; Boulanouar et al. 2024; Trabelsi and Naifar, 2017). SC indices comply with Islamic law, which prohibits interest-based transactions and investments in certain industries (Alqahtani and Boulanouar, 2017). These indices are used for several reasons: they provide investors the opportunity to invest in companies that align with Sharia law guidelines while excluding those that fail to meet these criteria (Addou et al. 2024; A. Hassan et al. 2022a). Moreover, they encourage observant Muslim investors to invest in listed companies that adhere to Sharia principles.

Numerous index providers and financial markets have introduced Islamic indices since 1999 in both Muslim and non-Muslim countries. These indices include the Dow Jones Islamic Market World Index (DJIMWI) in 1999, the Global Islamic Index Series (GIIS) of FTSE Group at the London Stock Exchange in 1999, and the Sharia indices of Standard and Poor's since 2006 (A. Hassan et al. 2022a). Furthermore, Turkey, Saudi Arabia, Pakistan, Malaysia, India, and Bahrain are among the financial markets that have established their own local indexes (Trabelsi and Naifar, 2017). The indices are built using different Sharia screening methodologies based on activity (qualitative) and financial (quantitative) screens. The former concerns companies engaged in non-SC activities such as manufacturing alcohol, gambling, and pork,; whereas the latter concerns enterprises whose debt, liquidity, and interest metrics exceed a predetermined cutoff point (Derigs and Marzban, 2009).

Given the cross-country co-movements due to globalization and the dominance of financial exchanges like those in the U.S. and the UK, this study proposes to analyze the linkages between a local SC index and global SC indices to understand the integration between global and domestic SC markets. Islamic finance is particularly significant in the context of the Fourth Industrial Revolution and the COVID-19 post-pandemic era, as it offers resilience and sustainability in financial practices Islamic finance is particularly significant in the context of the Fourth Industrial Revolution and the COVID-19 post-pandemic era, as it offers resilience and sustainability in financial practices (Sahabuddin et al. 2023). Specifically, considering the recent uncertainties and risks experienced by local and global markets, the aim of this study is to analyze the linkages between the Dubai Financial Market Shari'a Index (DFMSI), which demonstrates the performance of the Dubai Financial Market SC listed companies (Bloomberg, 2024) and three international Sharia indices: the Dow Jones Islamic Market World Index (DJIMWI) that is based in the United States and is developed and maintained by S&P Dow Jones Indices; the Standard and Poor's Global Sharia Index (SPGSI), which is also based in the United States and is part of the S&P Global Shariah Index Series designed to track the performance of Shariah-compliant stocks globally, and finally the Financial Times Stock Exchange Sharia All World Index (FTSESAWI), which is based in the United Kingdom, created and managed by FTSE Russell, and covers Shariah-compliant companies from various countries worldwide.

The linkages are studied by investigating the predictive power of the three SC global indices in predicting the DFMSI. This is useful to SC investors, especially in the DFMSI market, as they need to accurately predict the subsequent movements of the DFMSI following the upturn or downturn of the SC global indices(D. Al-Najjar, 2022). This plays a crucial role in enabling investors to take timely and impactful actions, ensuring that their decisions are effective and yield positive outcomes.

Utilizing the aforementioned three global SC indices provides numerous advantages, including the diversification of data sources, access to global market insights, effective risk management, and practical applications for investors. Incorporating these indices enhances understanding, aids in decision-making processes, and facilitates performance evaluation specifically within the domain of Sharia-compliant investments (Al-Yahyaee et al. 2021; Antar and Alahouel, 2020; Ashraf et al. 2022; Bossman et al. 2022; Haddad et al. 2020; Nasreen et al. 2020; Sahabuddin et al. 2022).

For example, with regard to the diversification of data sources, by incorporating data from multiple global Sharia indices, the research expands its data sources beyond the Dubai local market. This diversification allows for a broader and more comprehensive analysis of factors that influence the DFMSI's price, and enhances the robustness of the research findings. Furthermore, the three global Sharia indices provide valuable insights into the performance and characteristics of SC companies on a global scale. Their inclusion enables our study to capture trends and factors that are relevant to SC investments worldwide. Consequently, this global perspective enhances the understanding of the DFMSI and can help identify interdependencies and correlations between different markets.

As for risk management, incorporating data from these three SC global indices can contribute to effective risk management strategies by enabling the identification and analysis of risks associated with SC investments across different markets. This information can be used to assess the potential impact of global events, market trends, or regulatory changes on the DFMSI, allowing investors to make more informed decisions and manage their portfolios effectively.

To achieve the study's goal and with data on DFMSI, DJIMWI, SPGSI, and FTSESAWI, we first experimented with a linear regression model and a Least-Square Regression (LSR) Kernel model. Second, we applied a decision tree model, and third, we used two ANN models, which have emerged as highly effective tools that contribute significantly to the accuracy of predictions and support decision-making processes (H. Al-Najjar et al. 2021; Benrhmach et al. 2022; Selvamuthu et al. 2019). These two models are the Back Propagation Neural Network (BPNN) and the Nonlinear Autoregressive neural network with external input (NARX). Our findings clearly show the superiority of the NARX over the BPNN and the other proposed models as per the three standard and robust evaluation criteria which are the root mean square error, the mean absolute error, and the coefficient of determination.

The rest of the paper is organized as follows: Section "Literature Review " presents a literature review, focusing on the Sharia-compliant screening methodologies, the differences between the indices used in the empirical analysis, and a summary of previous studies comparing index performances. Section "Methodology" details the data and variables used, along with the description of the predictive models employed in the study. Section "Empirical Results and Analysis" reports and discusses the empirical results, highlighting the performance of the models in predicting the DFMSI. Finally, Section "Conclusion" concludes the paper, providing a summary of the findings and implications for policy-makers and investors.

Literature Review

The study of financial market integration and co-movement is grounded in several key theories. The Efficient Market Hypothesis (EMH) posits that asset prices fully reflect all available information, making it impossible to consistently outperform the market on a risk-adjusted basis (Fama, 1970). This theory has been foundational in understanding market behavior and the flow of information across markets. However, the existence of co-movements among global stock indices suggests that markets are interconnected and that information dissemination can lead to predictable patterns, which partially challenges the EMH.

Financial contagion theory further elaborates on how financial shocks can spread from one market to another. Forbes and Rigobon (2000) describe contagion as a notable rise in interconnectedness between markets after a shock affects one country or a group of countries. This concept is crucial for understanding the interconnectedness of global financial markets, especially during periods of economic instability.

Empirical research on international stock market linkages and predictive models for financial indices is extensive. Several studies have explored the relationships between different markets using various methodological approaches.

Correlation and causality analyses have been extensively used to examine the relationships between stock markets. Ferreira et al. (2022) investigated dynamic correlations between major stock indices during financial turmoil. Their findings suggest that correlations between markets increase during economic instability, emphasizing the need for understanding these linkages for risk management and investment strategies.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models and Vector Autoregressive (VAR) models are commonly used to model the volatility and interdependence of stock indices. Li et al. (2023) utilized a GARCH model to analyze volatility spillover effects between the US and Chinese stock markets, demonstrating significant volatility spillovers and highlighting the interconnectedness of these markets.

Machine learning, particularly ANNs, has emerged as a powerful tool for stock market prediction due to its ability to model complex, non-linear relationships. Chung and Shin (2020) found that optimized multi-channel convolutional neural networks outperform traditional statistical methods in terms of prediction accuracy, demonstrating the potential of advanced machine learning techniques in financial forecasting. Kumar et al. (2021) also demonstrated that deep learning techniques significantly improve stock price forecasts over classical approaches, highlighting the advancements in predictive accuracy achieved through computational intelligence.

The study of Sharia-compliant indices has gained importance with the growth of Islamic finance. Sharia indices comply with Islamic law, which prohibits interest-based transactions and investments in certain industries (Naouar et al. 2024). Abdul Rahman et al. (2010) reviewed Sharia indices, discussing their screening methodologies and performance, and emphasized the need for standardized criteria to improve the reliability and comparability of these indices.

Several studies have investigated the performance of SC indices and artificial intelligence (AI)-based forecasting models during crises such as the COVID-19 pandemic and geopolitical conflicts (Rabbani et al. 2023). Understanding the performance of Sharia-compliant indices and the efficacy of AI-based forecasting during these crises is essential for investors seeking to navigate turbulent times.

On one hand, advancements in AI have revolutionized predictive models and forecasting methodologies, offering new tools for analyzing financial market trends. AI and machine learning techniques have gained popularity in financial forecasting due to their ability to analyze large datasets and identify complex patterns (Anjum and Qaseem, 2019). They can reduce investors' risks, empower them with data-driven decisions, and identify current and future trends in multi-class forecasting techniques employing profitability analysis to identify highly profitable stock indices (Khattak et al. 2023).

On the other hand, the integration of SC stocks with AI-based forecasting presents promising opportunities for Islamic finance and enhancing investment decision-making during crises (M. K. Hassan et al. 2022b; Karim et al. 2022). The COVID-19 pandemic and geopolitical tensions, such as the Russian-Ukraine war, have significantly impacted financial markets worldwide. During the COVID-19 pandemic, AI-based forecasting models faced challenges due to the unprecedented nature of the crisis and rapid market fluctuations. Several researchers found that Sharia-compliant indices exhibited resilience during the COVID-19-induced market downturn compared to conventional indices (Hasan et al. 2022; Mirza et al. 2022). Similarly, geopolitical events have a significant but short-lived impact on Sharia-compliant indices, highlighting their relative stability compared to conventional indices during such periods (Hasan et al. 2023).

Furthermore, AI-based forecasting can provide valuable insights into market reactions and investor sentiment. However, research specifically examining the performance of AI-based forecasting models during the Russian-Ukraine war is limited. Future studies could explore how AI techniques can capture the impact of geopolitical events on Islamic financial markets and identify profitable trading and investment strategies.

Table 1 Islamic Indices Information.

Islamic indices	Period considered	Local currency	Currency considered
DJIMWI	27/10/2019-3/1/	USD	USD
SPGSI	2024	USD	USD
FTSESAWI		GBP	USD
DFMSI		AED	USD

Despite significant advancements, several limitations remain in the existing literature. Many studies rely on traditional econometric models, which may not fully capture the complexity and non-linearities of financial markets. Although machine learning techniques such as ANNs have shown promise, their application is still relatively new and further research is needed to validate their robustness across different contexts (Kumar et al. 2021).

Most research focuses on developed markets, particularly the US and Europe. There is a need for more studies on emerging markets and their interactions with global indices. (Alamro et al. 2019) highlighted this gap, suggesting that emerging markets might exhibit different dynamics not well captured by models developed for advanced economies.

Many studies analyze data over relatively short periods, constrained by the availability of high-frequency data. Long-term studies are essential to understand how market relationships evolve, particularly in response to structural changes such as financial crises and regulatory reforms (Kartal et al. 2022).

The proposed study addresses two critical gaps in the literature: predicting local indices using international SC indices and the application of artificial neural networks. Most previous research has focused on interactions and co-movements between international indices or between local indices. However, no study has examined the use of international SC indices to predict a local SC index. Understanding these linkages is essential for SC investors, as it provides insights into how global market movements influence local SC indices, thereby aiding in more informed investment decisions (Ashraf et al. 2022).

While traditional econometric models have been widely used, the application of ANNs in predicting stock indices, especially within the context of SC investments, remains underexplored. ANNs offer the potential to capture complex, non-linear relationships that traditional models might miss, thereby improving prediction accuracy and aiding stakeholders in making more effective decisions (Kumar et al. 2021).

The proposed study aims to fill these gaps by examining the linkages between the DFMSI and three global Sharia indices: the DJIMWI, the SPGSI, and the FTSESAWI. By employing advanced machine learning models, specifically ANNs, this research will provide a comprehensive analysis of these relationships, offering valuable insights for investors and policymakers alike.

Methodology

Data. This study used daily closing prices of DJIMWI, SPGSI, FTSESAWI and DFMSI covering the period from October 27, 2019 until January 3, 2024, with a base date for market capitalization on December 31, 2009. All data were collected from the Bloomberg database. It is worth noting that the study sample is limited by the availability of data since DFMSI was launched only on October 27, 2019, which determines the start date of the data sample. Table 1 presents information on the SC indices included in our study.

Modeling. The study experimented with predictive models: (1) Linear Regression, (2) LSR Kernel, (3) Fine Tree, (4) BPNN, and (5) NARX. These five models were tested and compared in terms of their R-Squared (R^2 or coefficient of determination) to determine the proportion of variance in the independent variables (X_i), which are the three global Islamic indices that can explain and predict the dependent variable (the local DFMSI, Y). R^2 indicates how well the observed data fit the model or the model's "goodness of fit". Generally, a higher R^2 indicates a better fit for the model. Additionally, we compared the statistical models in terms of their Mean Absolute Error (MAE) and Mean Squared Error (MSE) to measure the "erroneousness" of the model's predictions and how inaccurate those predictions are compared to actual observed data. Generally, a lower MSE indicates a better model's prediction. The formulas used for R^2, MAE and MSE are as follows, respectively:

$$R^2 = 1 - \frac{SSR}{SST}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|,$$

$$MSE = \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{n}.$$

where SSR represents the sum of squared residuals (also known as the sum of squared errors) and SST represents the total sum of squares with

$$SSR = \sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2$$

And

$SST = \sum_{i=1}^{N}\left(y_i - \bar{y}_i\right)^2$ with $\hat{y}_i$ and $\bar{y}_i$ are the predicted and mean values, respectively.

We used cross-validation to examine the predictive accuracy of the fitted models, with a number of folds equal to five.

It is worth noting that ANNs are used in the literature across several domains. They are recognized for their usefulness in predicting and forecasting stock prices, financial market indices and trends (De Oliveira et al. 2013; Di Persio and Honchar, 2016; Olatunji et al. 2013; Qiu and Song, 2016). ANNs are increasingly favored as a fitting tool due to their superior predictive accuracy compared to traditional linear statistical methods and other computational intelligence approaches. They include several techniques, some of which are more popular than others. ANNs are recognized as flexible nonlinear regression techniques that outperform traditional regression methods in modeling both linear and nonlinear relationships (Al Shami et al. 2015). ANNs are typically classified based on the type of training algorithms they employ, namely supervised and unsupervised algorithms. The BPNN is an algorithm for supervised training of feed-forward ANNs using gradient descent of the error function with respect to the neural network's weights. In applications where a set of inputs needs to be fitted to specific targeted outputs, a feed-forward neural network is commonly employed (Al Shami et al. 2015).

Panel data or Time Series Cross Section (TSCS) analysis is widely regarded as a prominent method in advanced econometric modeling. It involves studying a specific object or entity over a defined period. By gathering repeated observations across different cross-sections, panel analysis enables the examination of dynamic changes with short time series (Al Shami et al. 2015; Yaffee, 2003). In general sense, a panel data regression can be represented as follows:

$$Y_{i,t} = \alpha_{i,j} + \beta' X_{i,t,j} + \varepsilon_{i,t} \text{ with } i = 1, \ldots, n; t = 1, \ldots, T; \text{and } j = 1, \ldots, J$$

In our context, the dependent variable to be predicted, denoted as $Y_{i,t}$, corresponds to the local DFMSI. The independent variable, $X_{i,t,j}$, represents one of the three global Islamic indices and serves as an explanatory variable. The coefficient vector, β',

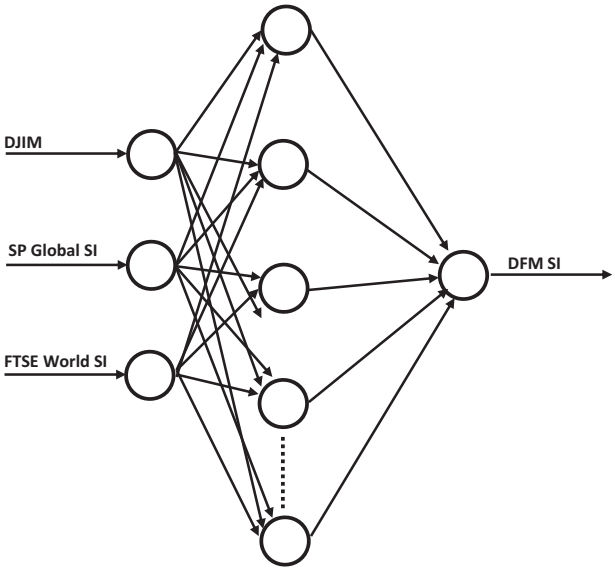

Fig. 1 Proposed model architecture.

has dimensions $Jx1$, where J refers to the number of explanatory variables. $X_{i,t,j}$ denotes the i^{th} observation on the J explanatory variables, specifically the price of the index in this case. The subscript i indicates the entities, representing the cross-section dimension, which pertains to the Sharia market index. The subscript t represents the time, signifying the time-series dimension. The estimated residual for the panel model is denoted as $\varepsilon_{i,t}$ and is represented by the MSE value.

It is worth noting that an initial 70% of the data were utilized to train the models (from 27/10/2019 to 29/09/2022), and the remaining 30% were used to test the performance of the five models (from 30/09/2022 to 03/01/2024). The choice of 30% as a testing set was to ensure a robust evaluation of the model's performance. This proportion provides a sufficient sample size for reliable performance metrics while retaining enough data for training the model.

Empirical Results and Analysis

Models

Linear Regression. In the first part of the analysis, we used the linear regression model to predict the DFMSI given the three independent variables: FTSESAWI, DJIMWI, and SPGSI.

$$DFM = \beta_0 + \beta_1 * FTSE + \beta_2 * DWJ + \beta_3 * SP$$

Least Squares Regression Kernel. Regression Kernel is a trained model object for Gaussian kernel regression using random feature expansion (Sahoo et al. 2019). Regression Kernel is more practical for big data applications that have large training sets but can also be applied to smaller data sets that fit in memory.

$$DFM = T(x)\beta + b$$

Where :

- x is an observation (row vector) from p predictor variables.
- $T(\cdot)$ is a transformation of an observation (row vector) for feature expansion. T(x) maps x in $\mathbb{R}^p$ to a high-dimensional space ($\mathbb{R}^m$).
- β is a vector of coefficients.
- b is the scalar bias.

Decision Tree. A decision tree is a basic and effective supervised machine learning structure that uses a tree-like model to make predictions (Rady et al. 2021). The fine tree model provided in Matlab's models pane will be used in this work to predict the DFMSI.

Table 2 Performance of Linear Regression, LSR Kernel, Fine Tree, BPNN, and NARX Models.

	Linear Regression	LSR Kernel	Fine Tree	BPNN	NARX
MSE	0.0181174	0.009216	0.008338	0.006594	0.000388
MAE	0.10556	0.071824	0.059855	0.056302	0.022613
R^2	0.7226	0.8172	0.8391	0.8661	0.9905

First, the variance of the root node is computed, then the variance of features is computed to create the tree model.

$$\sigma^2 = \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}{n},$$

$$\sigma_X^2 = \sum_{c \in X} P(C)\sigma^2$$

where X is the input variables and $P(C)$ is the probability of the distinct values of this feature.

$$Vr_x = \sigma^2 - \sigma_X^2.$$

Leaves indicate the mean values of instances using the bootstrapping method. This method is repeated until the variance of leaves is less than a threshold or all input variables are used.

Neural Networks. Recent research has pointed out that ANNs may enhance the accuracy of financial data's long-term behavior prediction (Cao et al. 2019; Guresen, 2011). Following this, we built an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the DFMSI according to the rules taken from the three global indices. When the values (normalized values of the three indices) change in one or all of the three global indices, the DFMSI output values change as well.

The DFMSI is predicted to perform less than the global markets of DJIMWI, SPGSI and FTSESAWI when the global markets perform at 0.5 values meaning that it follows the trends of the three global markets. The fuzzy representation of the three inputs used as inputs to the neural network in this study is still premature.

A neural network is composed of three distinct layer types: the input layer, which receives the initial data, one or more hidden layers that perform intermediate computations, and the output layer, which produces the final results. With the exception of those found in the last layer, every neuron in a given layer is linked to every neuron in the layer underneath it.

The BPNN: In this study, we employ a BPNN for predicting the DFMSI. Sako et al. (2022) used BPNN and different neural network models for financial time series prediction and found that recurrent neural networks are very powerful tools. The architecture of our BPNN contains three neurons in the input layer, one hidden layer containing ten neurons, and one neuron in the output layer. In this model, the hidden layer plays a fundamental role in mapping the weights and biases to achieve the desired outcome in the output layer. It iteratively adjusts and refines its calculations until it arrives at a prediction, continuously iterating between the layers to optimize the overall performance of the neural network.

Figure 1 is a representation of the BPNN. Notice there are three inputs (three indices), ten hidden layers, and one output (DFMSI) that have been mapped, w_{ij} are the weights for each of the inputs, and b is the bias. The hidden layers are the black box that computes all the permutations by considering different weights and biases for the different inputs. The architecture (3-10-1) was

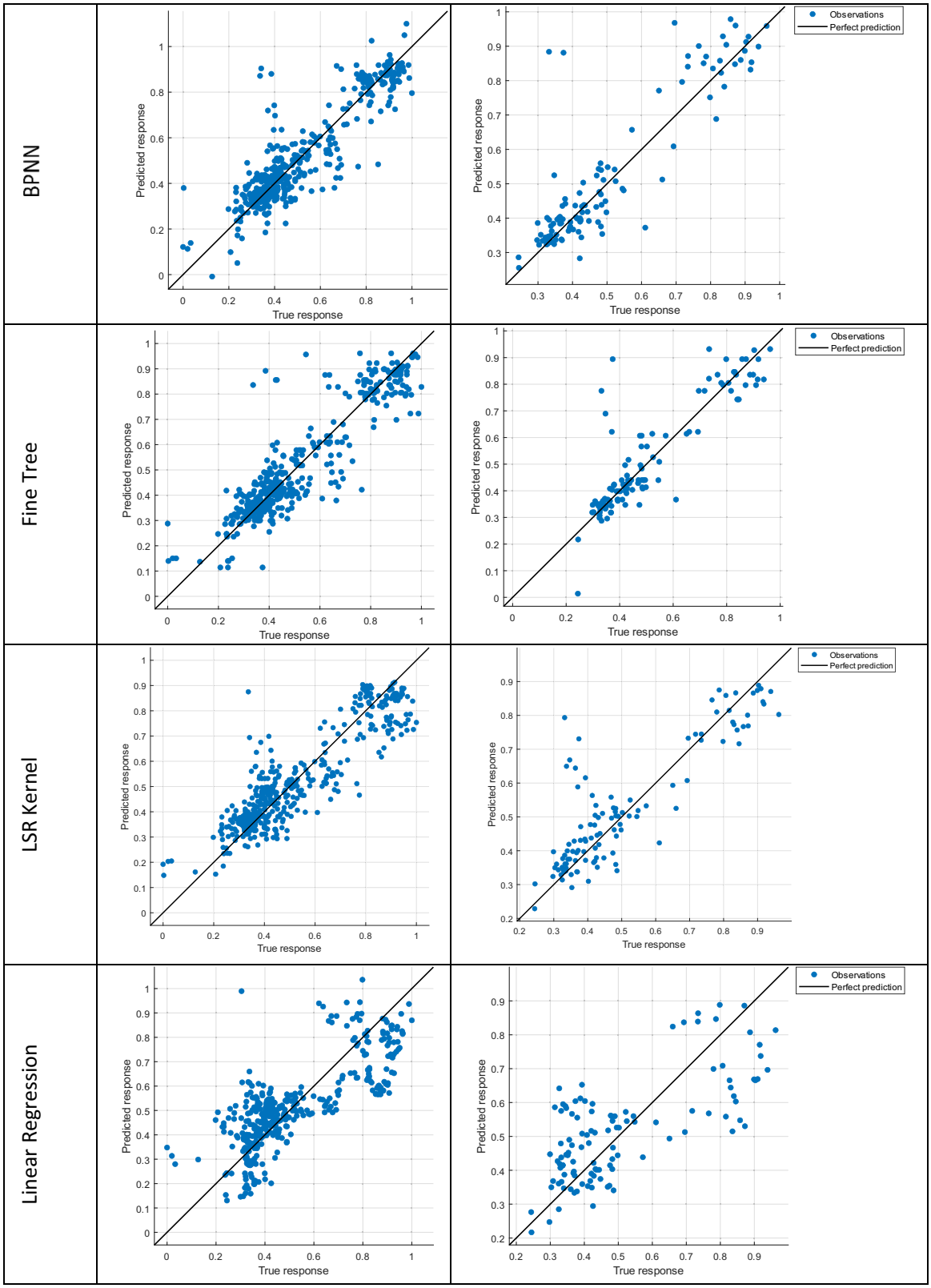

Fig. 2 Coefficient of Determination for Proposed Models.

found to be the best balance between underfitting and overfitting in our case.

The NARX: The second neural network used in this study is the NARX. The NARX has been found to be an excellent tool for predicting noisy time series with high volatility, particularly financial time series (Benrhmach et al. 2021; Benrhmach et al. 2020). The NARX network was be trained to predict the DFMSI time series. The network is initially constructed and trained in an open loop manner, where the target variables are used as

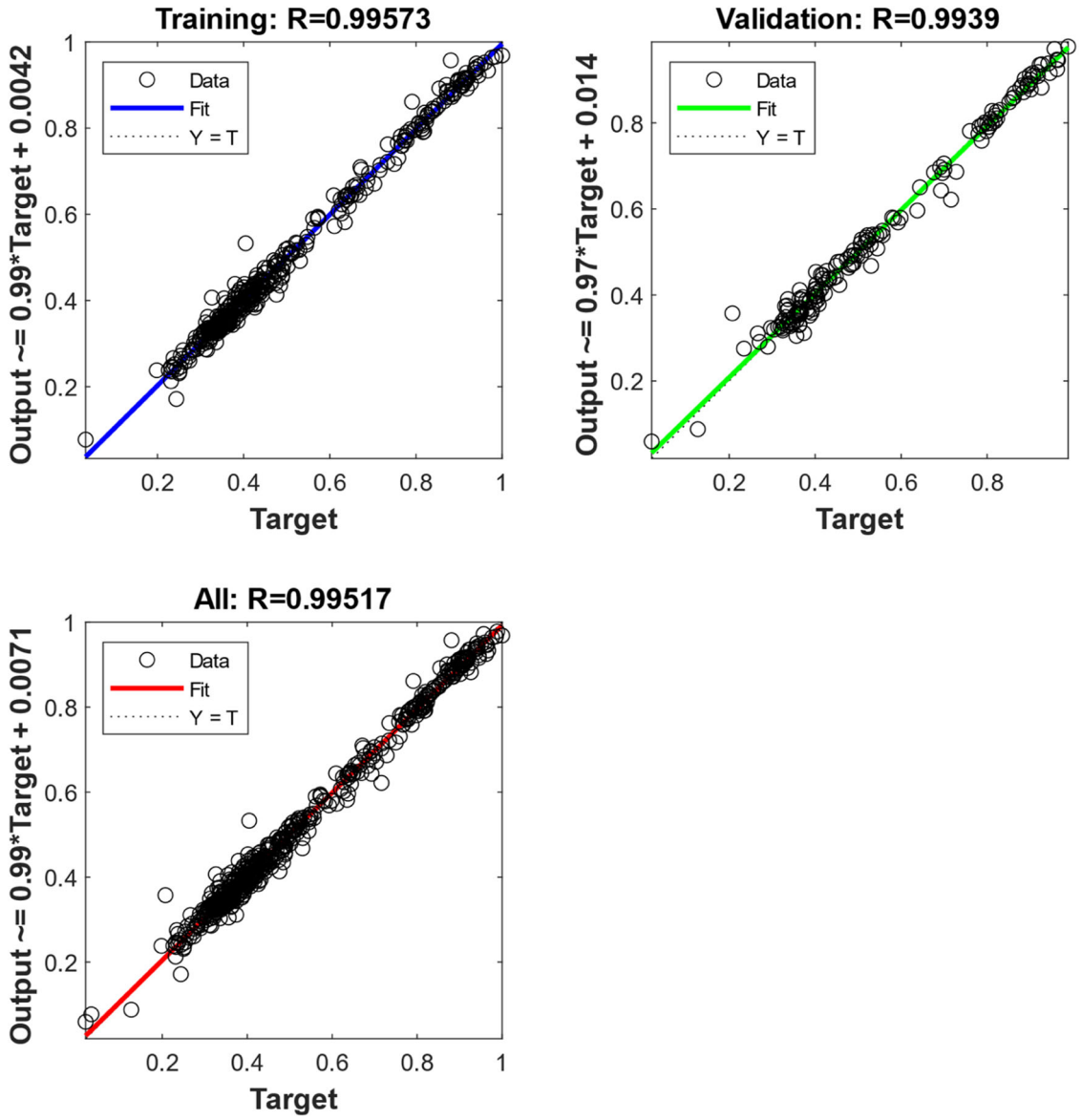

Fig. 3 Coefficient of Determination for NARX Model.

responses to optimize the training process and achieve high-quality results. Once the training is complete, the network transitions into a closed loop configuration, where predicted values are employed as inputs to continuously provide new responses, ensuring ongoing and dynamic functionality. The NARX model may be expressed in the following way:

$$X_t = \alpha_0 + \sum_{j=1}^{k} \alpha_j \varphi \left(\sum_{i=1}^{a} w_{ij} X_{t-1} + w_{0j} \right) + \varepsilon_t,$$

where a is the number of neurons in the layer, k is the number of hidden layers, φ is the activation function, w_{ij} is the weight of the connection between the neuron i in the input layer and j in the hidden layer, α_j is the weight linking the hidden neuron j and the output neuron, and the constants w_{0j} and α_0 represent the specific values associated with the hidden neuron j and the output neuron, respectively.

Analysis of Models' Outputs. Turning to the outputs from the above models and their analysis using the three performance measures stated earlier, Table 2 reports results, and Figs. 2 and 3 represent the coefficients of determination of the five proposed models according to the training set, the testing set, and all the data for the NARX model.

The linear regression model, while useful, showed limitations during the COVID-19 pandemic period (from approximately time steps 300 to 350), where it failed to accurately predict the DFMSI. This is evident in Fig. 2, where some points deviate significantly from the perfect prediction line (X = Y), resulting in a moderate coefficient of determination ($R^2 = 0.7226$).

The LSR Kernel and Fine Tree models showed improvements over the linear regression model, with higher R^2 values and lower MSE and MAE values. The LSR Kernel model achieved an R^2 of 0.8172, while the Fine Tree model reached 0.8391, indicating better predictive power and model fitting.

The BPNN model further improved the predictions with an R^2 of 0.8661, demonstrating the effectiveness of neural networks in capturing the complex relationships within the data. The MSE and

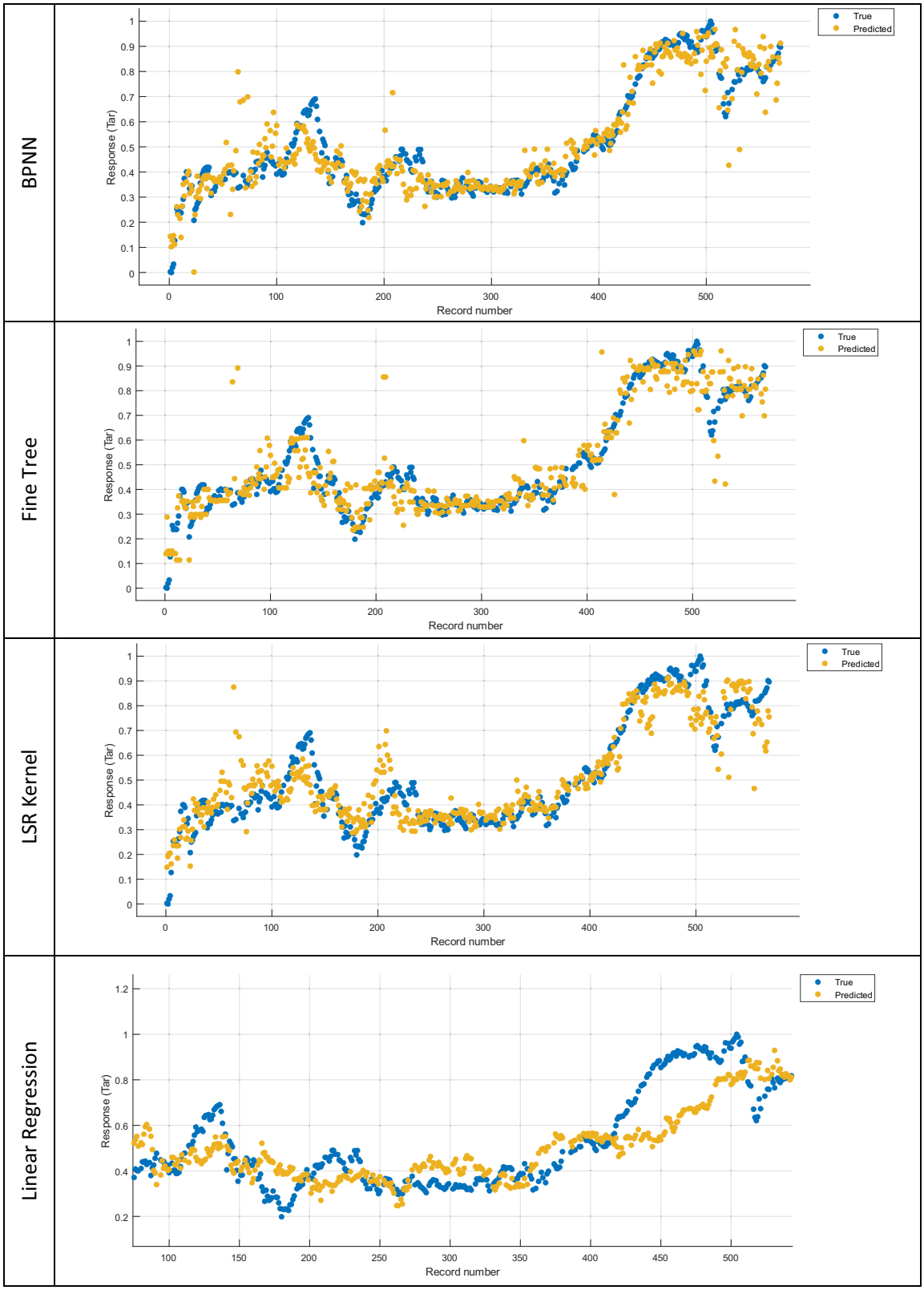

Fig. 4 Original Vs Predicted DFM Using Proposed Models.

MAE values also decreased, suggesting higher accuracy and lower prediction errors compared to the previous models.

However, the NARX model outperformed all the other models significantly, with an impressive R^2 of 0.9905, an MSE of 0.000388, and an MAE of 0.022613. This indicates that the NARX model is highly accurate in predicting the DFMSI, capturing almost all the variability in the data.

The visual representation in Fig. 4, where blue dots represent the original time series of the DFMSI and yellow ones the output of the models, shows that the NARX model's predictions closely

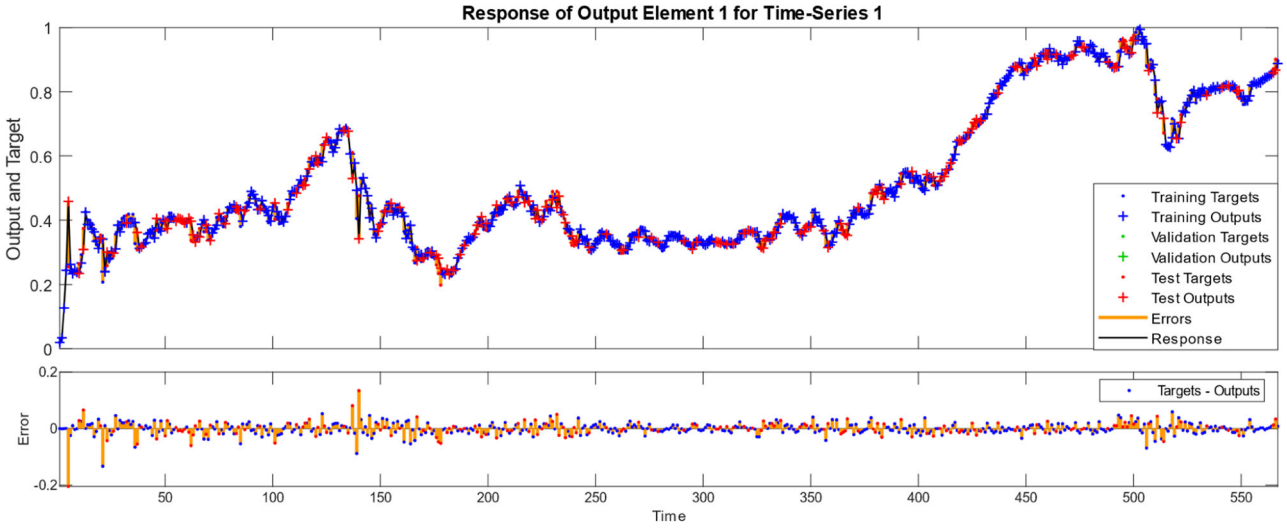

Fig. 5 The first plot shows the original data with the predicted data, and the second plot show the error between the output and target data.

follow the actual data, even during the volatile COVID-19 pandemic period.

The error analysis in Fig. 5 further confirms the superior performance of the NARX model. The plot shows the original data against the predicted data and the error between the output and target data. The NARX model consistently demonstrates minimal error, indicating its robustness in various market conditions.

The comparative analysis between traditional models and ANNs reveals significant differences in predictive performance. Traditional models, such as linear regression, often fall short in capturing the intricate, non-linear relationships present in financial data. On the other hand, ANNs, particularly hybrid models, excel in this aspect. As demonstrated in the study by Mousapour Mamoudan et al. (2023), hybrid neural network-based metaheuristics significantly improve the prediction accuracy for financial markets, exemplified by their application to the global gold market. This study underscores the enhanced capability of ANNs to model complex market behaviors, providing a robust alternative to traditional approaches.

Conclusion

This study addresses the complexity of predicting the DFMSI by analyzing its correlations with three global Islamic indices: the DJIMWI, the SPGSI, and the FTSESAWI. Utilizing advanced predictive models, including LSR Kernel, Fine Tree, BPNN, and NARX, this study aimed to understand the integration of international and national Sharia-compliant markets.

The main research problem was the accurate prediction of DFMSI movements, a critical task given the market conditions and uncertainties at both local and global levels, particularly highlighted during the COVID-19 pandemic. The study incorporated multiple global Sharia indices to diversify data sources and enhance the robustness of findings. Methodologically, it employed advanced machine learning models, particularly focusing on ANNs.

The results showed that the NARX model significantly outperformed other models, with an R^2 of 0.9905 and MSE of only 0.000388, indicating its superior predictive accuracy for DFMSI. This finding underscores the potential of ANNs in capturing complex, non-linear relationships within financial data, which is especially crucial during periods of heightened market volatility such as the COVID-19 pandemic.

The originality and value of this study lie in its demonstration of the effective application of ANNs, particularly the NARX model, in predicting a local Sharia-compliant index using international SC indices. This approach not only enhances prediction accuracy but also provides valuable insights into the interconnectedness of global Islamic financial markets, a perspective that proved critical during the global financial disruptions caused by COVID-19.

The implications of this study are profound for both practical and theoretical perspectives. For investors and portfolio managers, the superior performance of the NARX model implies that they can rely on ANNs for more accurate predictions of SC indices, enhancing decision-making processes, improving risk management strategies, and optimizing portfolio allocations. Policymakers can leverage these findings to integrate data from multiple global indices, providing a more comprehensive market view and aiding in the formulation of policies that ensure market stability and resilience. Encouraging the adoption of advanced predictive models in financial analysis can better anticipate market movements, especially during unprecedented events like the COVID-19 pandemic.

From a theoretical standpoint, this study supports the EMH by demonstrating that market behavior can be better understood and predicted using advanced machine learning models, which capture the complexities and irrationalities inherent in financial markets. It also underscores the relevance of financial contagion theory, highlighting how financial shocks and information flow between interconnected global markets can be effectively analyzed using these models. Additionally, insights from behavioral finance are reinforced, showing that psychological factors influencing market behavior can be better incorporated into predictive models through machine learning techniques.

In terms of policy recommendations, regulators should consider establishing guidelines for the use of AI and machine learning models in financial forecasting, ensuring transparency, accuracy, and ethical considerations. Financial institutions should invest in these technologies to enhance their predictive analytics capabilities, improving their competitiveness and contributing to the overall stability and efficiency of financial markets.

Despite its contributions, the study has limitations. It primarily focuses on the DFMSI and three global Islamic indices, which may not capture all factors influencing Sharia-compliant markets. Future research could explore additional indices and factors, such as geopolitical events and other global crises like the COVID-19

pandemic, to provide a more holistic view of market dynamics. Moreover, while the application of ANNs is promising, it requires further validation across different contexts and longer time periods. Future studies should aim to refine these models and test their robustness in various market conditions.

Data availability

The data that support the findings of this study are available from Bloomberg but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the corresponding author upon reasonable request and with permission of Bloomberg.

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Author contributions

ZB handled all tasks, including most of the writing and editing, GB focused on methodology and data analysis, RG, SA, and MA contributed to the literature review, all except GB secured funding, ZB and RG supervised the research, and all authors initiated and discussed the ideas of the research.

Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval was not required as the study did not involve human participants.

Informed consent

This article does not contain any studies with human participants performed by the authors.

Additional information

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