Modeling the Dynamics of Financial Markets Using Artificial Intelligence Approaches

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Citation: Jafari, S. S., Fallah Shams, M., Kordlouie, H., & Rahnamae Roodposhti, F. (2027). Modeling the Dynamics of Financial Markets Using Artificial Intelligence Approaches. *Business, Marketing, and Finance Open*, 4(11), 1-20.

Received: 07 July 2026
Revised: 01 November 2026
Accepted: 08 November 2026
Initial Publication: 09 November 2026
Final Publication: 01 November 2027

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Abstract: This study aimed to model the dynamics and interdependence of the Tehran Stock Exchange, Iran Fara Bourse, Iran Mercantile Exchange, and Iran Energy Exchange and to evaluate the predictive capacity of artificial intelligence-based LSTM models for forecasting financial returns. This applied quantitative study was based on financial time-series analysis. Weekly data from 2015 to 2025 were collected for four return series, including the Tehran Stock Exchange Overall Index, Iran Fara Bourse Index, Iran Mercantile Exchange Company stock, and Iran Energy Exchange Company stock, yielding 492 synchronized observations per series. Logarithmic returns were calculated after data preprocessing and calendar synchronization. Stationarity was assessed using the Augmented Dickey–Fuller test. Volatility regimes, directional intermarket relationships, impulse response functions, and time-varying dependencies were examined using regime-based analysis, causality tests, and DCC-GARCH modeling. Univariate and multivariate long short-term memory models were then developed. The first 70% of observations were used for training and the final 30% for out-of-sample testing. Forecast performance was evaluated using RMSE, MAE, MAPE, and R^2. Significant bidirectional causality was observed between the Tehran Stock Exchange and Iran Fara Bourse, while the Tehran Stock Exchange also significantly influenced the mercantile and energy exchange proxies. Impulse response analysis showed that shocks originating in the Tehran Stock Exchange generated the strongest responses in other markets. DCC-GARCH results indicated persistent and time-varying conditional correlations, with the strongest dependence between the Tehran Stock Exchange and Iran Fara Bourse. Multivariate LSTM models consistently outperformed univariate models across all four markets, producing lower RMSE, MAE, and MAPE values and higher R^2 values. The Iranian financial market exhibits dynamic interdependence, asymmetric shock transmission, and time-varying correlations, and incorporating cross-market information into multivariate LSTM models improves forecasting performance compared with models based only on each market's own historical returns.

Keywords: Financial Market Dynamics; Artificial Intelligence; LSTM; DCC-GARCH; Volatility; Intermarket Dependence; Tehran Stock Exchange

1. Introduction

Financial markets are complex adaptive systems characterized by continuous information flows, heterogeneous investor behavior, nonlinear price formation, volatility clustering, feedback mechanisms, and dynamic interdependence among market segments. These characteristics make financial market behavior difficult to explain through purely static or linear frameworks. Prices and returns are shaped not only by firm-specific and macroeconomic fundamentals but also by investor expectations, behavioral reactions, liquidity conditions, technological developments, regulatory changes, and shocks originating in connected markets. Consequently, the

analysis of financial market dynamics increasingly requires methodological approaches capable of identifying changing patterns, nonlinear dependencies, and complex temporal structures. In recent years, artificial intelligence and machine learning have become particularly important in this context because they can process large volumes of financial data, identify hidden relationships, and learn nonlinear patterns that may remain undetected by conventional statistical techniques. The growing use of intelligent algorithms in forecasting, risk management, accounting, auditing, investment analysis, and algorithmic trading reflects a broader transformation in the architecture of financial decision-making [1-3].

Artificial intelligence has moved from being a supplementary analytical tool to becoming an increasingly central component of modern financial systems. Financial institutions, investors, exchanges, accounting systems, and regulatory environments now use intelligent methods for prediction, classification, fraud detection, portfolio construction, automated trading, and decision support. The attraction of artificial intelligence in finance stems largely from its ability to process multidimensional data and capture nonlinearities, interactions, and temporal patterns that traditional models may fail to represent adequately. At the same time, the growing reliance on artificial intelligence introduces new questions about interpretability, robustness, market efficiency, systemic vulnerability, and the possibility that algorithmic strategies may amplify rather than reduce market instability. The financial consequences of artificial intelligence therefore extend beyond forecasting accuracy and include changes in the structure of information processing, market participation, financial reporting, audit quality, and organizational decision-making [4-6].

From a methodological perspective, one of the most important advantages of artificial intelligence is its ability to identify patterns in environments where relationships are highly nonlinear and time-varying. Financial return series rarely display constant variance, normal distributions, or stable correlations over long periods. Instead, they typically exhibit volatility clustering, asymmetric reactions to shocks, heavy tails, structural changes, and episodes in which correlations among markets rise sharply. These properties make financial market prediction particularly challenging. Traditional econometric methods remain valuable for identifying volatility, persistence, and causal transmission, but their explanatory capacity may be limited when the underlying data-generating process contains complex nonlinear dependencies. Machine learning approaches can complement econometric methods by learning higher-order interactions directly from data and by improving predictive performance when relevant patterns are difficult to specify parametrically. This complementary perspective has increasingly shaped research on stock market volatility, market risk, and financial forecasting [1, 7, 8].

Volatility is one of the central dimensions of financial market dynamics because it simultaneously reflects uncertainty, risk, information arrival, investor sentiment, and the intensity of market reactions. Accurate modeling of volatility is therefore essential for investment decisions, portfolio management, risk control, derivative pricing, and regulatory oversight. However, volatility is not constant over time and is often affected by market regimes. Periods of relative stability may be followed by episodes of sharp turbulence in which both variances and cross-market correlations rise. Recent applications of machine learning have demonstrated that predictive models can contribute to the analysis of volatility by identifying nonlinear predictors, simulating alternative market scenarios, and improving forecasts relative to simpler benchmark models [7]. In addition, advanced machine learning methods have been applied to related domains such as ESG markets and clean energy prices, where the ability to process nonlinear interactions and heterogeneous predictors is especially important [9]. These developments support the broader proposition that financial volatility should be examined through models capable of accounting for both temporal variation and complex cross-variable relationships.

The expansion of algorithmic trading has further increased the relevance of artificial intelligence for understanding financial market behavior. Automated and AI-driven trading systems can respond to information at speeds and frequencies that differ substantially from human trading behavior. Although these systems may improve price discovery and market efficiency under certain conditions, they can also influence liquidity, volatility, and systemic fragility. Research on AI-driven algorithmic trading has highlighted the possibility that algorithmic strategies may alter liquidity conditions and contribute to financial vulnerabilities, particularly when multiple systems react simultaneously to similar signals [10]. In parallel, simulation-based approaches combining machine learning with agent-based modeling have demonstrated the value of artificial financial markets for studying automated strategies, heterogeneous agents, and emergent market outcomes [11]. These findings indicate that artificial intelligence should not be viewed only as a forecasting technology; it can also be used as an analytical framework for investigating the mechanisms through which market dynamics evolve.

Another important development concerns the generation and augmentation of financial data. Financial markets are inherently affected by rare events, regime changes, and tail risks, yet historical datasets may contain only a limited number of such episodes. Generative artificial intelligence offers a possible solution by creating synthetic market data that preserve meaningful statistical and semantic characteristics. Market-GAN, for example, has demonstrated how generative adversarial networks can be used to produce financial market data while incorporating semantic context and controllable conditions [12]. This line of research is important because it expands the potential applications of artificial intelligence from pattern recognition to controlled simulation. Such capabilities can strengthen stress testing, scenario analysis, and model validation, particularly when researchers seek to understand how markets may behave under conditions that are underrepresented in historical data.

Artificial intelligence has also become increasingly significant in financial risk analysis and investment decision-making. AI-based financial models can combine historical prices, market indicators, firm-level variables, and broader economic information to estimate risk and support portfolio decisions. Research on U.S. companies has shown that AI-based analysis can be used to predict market risk and inform investment decisions through data-driven modeling frameworks [8]. This development is consistent with the growing literature on machine learning for financial prediction, where the objective is not merely to fit historical observations but to generate out-of-sample forecasts that can support real-world decisions. The emphasis on out-of-sample performance is particularly important because financial models can easily overfit historical data. A model that performs well in-sample may fail when market conditions change, especially if it has learned noise rather than persistent relationships. Therefore, rigorous forecasting research requires chronological training and testing procedures that preserve the temporal order of observations and prevent information leakage.

The increasing integration of artificial intelligence into financial systems is also evident in accounting and auditing. AI can improve the processing of accounting information, detect anomalies, automate repetitive tasks, and support more timely and accurate reporting. The integration of blockchain and artificial intelligence in accounting information systems has been associated with improvements in information quality, process efficiency, and the structural transformation of accounting systems [5]. Similarly, research in GCC markets indicates that artificial intelligence adoption may influence audit quality and integrated financial reporting, highlighting the broader institutional consequences of intelligent technologies in financial environments [4]. AI-based auditing models have also been proposed to enhance audit services while considering customer trust, suggesting that the effectiveness of intelligent systems depends not only on technical accuracy but also on the confidence of users and

stakeholders in automated decision processes [13]. These applications illustrate the widening scope of artificial intelligence across the financial ecosystem.

The value of AI-based analytics is also evident in fraud detection, where large, high-dimensional datasets must be processed rapidly to identify anomalous transactions. Hybrid artificial and quantum intelligence approaches have been proposed for financial fraud detection, emphasizing the potential of advanced computational methods to identify complex patterns that conventional rule-based systems may overlook [14]. Although fraud detection differs from market forecasting in its immediate objective, both fields share a common analytical challenge: relevant information may be distributed across nonlinear, high-dimensional, and dynamically changing relationships. Thus, developments in fraud detection reinforce the broader argument that intelligent analytical systems are particularly valuable in financial contexts characterized by complexity and rapid change.

The impact of artificial intelligence has also extended into financial strategy, marketing, and organizational performance. AI-based analysis can improve segmentation, prediction, resource allocation, and customer-related decision-making, thereby indirectly influencing financial outcomes. Research has linked artificial intelligence to financial performance through mechanisms such as sensory marketing effectiveness [6], while broader studies have emphasized the scope of AI applications across financial services and retail industries [15]. Machine learning has also been applied to consumer behavior analysis for optimizing marketing and financial strategies, demonstrating how behavioral data can be transformed into predictive information for strategic decisions [16]. These studies indicate that the financial implications of artificial intelligence are not limited to securities trading; rather, AI increasingly influences multiple layers of organizational and market-level decision-making.

Despite the rapid expansion of artificial intelligence research in finance, several analytical challenges remain unresolved. First, many studies focus on a single market, index, or asset class, whereas actual financial systems consist of multiple interconnected segments. Studying a market in isolation can therefore omit important information transmitted from related markets. Second, static correlation measures provide only an average estimate of association and cannot adequately represent periods in which relationships strengthen or weaken. Third, conventional forecasting frameworks may not capture interactions that vary across market regimes. Fourth, although machine learning models can achieve high predictive accuracy, their performance may depend heavily on whether they use only the historical information of the target asset or incorporate information from connected markets. A comprehensive framework should therefore combine volatility modeling, dynamic intermarket dependence, shock transmission analysis, and nonlinear forecasting rather than treating these dimensions separately.

These issues are particularly relevant for the Iranian financial market, where different capital market segments operate within a common macroeconomic and institutional environment but may respond differently to shocks. The Tehran Stock Exchange represents the largest and most visible segment of the Iranian equity market, while the Iran Fara Bourse serves as another important venue for securities trading. The Iran Mercantile Exchange and Iran Energy Exchange represent more specialized segments connected to commodity and energy-related activities. Because these markets are exposed to overlapping economic conditions, policy developments, investor expectations, and liquidity constraints, their return dynamics may be interdependent. A shock originating in one market may therefore influence other segments directly through investor reallocation or indirectly through changing expectations and risk perceptions. Consequently, understanding the Iranian capital market requires analysis not only of individual market volatility but also of the structure and evolution of intermarket connections.

Recent research has begun to demonstrate the applicability of hybrid machine learning approaches to the Tehran Stock Exchange. In particular, the predictability of the Tehran Stock Exchange total index has been examined through hybrid machine learning methods, with attention to market efficiency and the relative importance of influential variables [17]. Such findings support the use of advanced computational methods in the Iranian context, but they also point to the need for broader modeling strategies that move beyond a single index. If market segments exchange information over time, models based solely on the historical behavior of one market may ignore useful predictive signals embedded in other markets. A multivariate artificial intelligence approach can address this limitation by allowing the model to learn cross-market temporal dependencies.

Long short-term memory networks are particularly suitable for this purpose because they are designed to learn sequential dependencies and retain information across time. Unlike standard feedforward neural networks, LSTM architectures include memory mechanisms that allow them to capture relationships across multiple lags while reducing problems associated with vanishing gradients. In financial applications, this feature is valuable because the effect of market information may persist over several periods and may interact with the historical state of other variables. Comprehensive reviews of advanced artificial intelligence and machine learning methods in financial market prediction emphasize the increasing importance of recurrent and deep learning structures for forecasting and risk management [1]. Their use is particularly justified when the objective is to compare univariate models based on the target market's own history with multivariate models that incorporate information from multiple connected markets.

At the same time, predictive modeling alone cannot provide a complete understanding of market dynamics. A model may improve forecast accuracy without revealing whether the improvement is associated with stronger correlations, volatility transmission, or directional shock propagation. For this reason, econometric and artificial intelligence approaches should be treated as complementary rather than competing frameworks. Dynamic conditional correlation models can estimate how relationships among markets change over time, while GARCH-type models can characterize conditional volatility. Regime-based models can identify transitions between calm and turbulent states, and impulse response analysis can reveal the direction and persistence of shocks. Machine learning can then determine whether these intermarket structures contain predictive information that improves out-of-sample forecasting. Such an integrated design offers both interpretive and predictive advantages and is consistent with the broader evolution of financial analytics toward hybrid methodological frameworks [7, 11].

The broader literature also suggests that future financial research must simultaneously consider prediction, systemic risk, and market interconnectedness. The widespread use of algorithmic systems can affect the structure of liquidity and systemic vulnerability [10], while generative and simulation-based systems provide new tools for modeling alternative financial states [12]. Advanced machine learning has demonstrated utility across stock markets, clean energy markets, risk prediction, and behavioral analytics [9, 16]. In addition, the increasing adoption of artificial intelligence across financial reporting, auditing, fraud detection, accounting information systems, and strategic management shows that intelligent technologies are reshaping financial systems at both the institutional and market levels [4, 5, 13, 14]. This broad transformation increases the importance of empirical studies that examine how AI-based methods perform in specific market environments and whether they can meaningfully capture the complex interactions that characterize those environments.

Accordingly, a major research gap lies in developing an integrated empirical framework for the Iranian financial market that simultaneously examines volatility regimes, intermarket shock transmission, time-varying conditional correlations, and the predictive value of multivariate artificial intelligence models. Such an approach can provide

a more complete representation of how different segments of the market behave independently and jointly. It can also determine whether information generated in one market improves the prediction of another, thereby offering evidence regarding the informational interconnectedness of the financial system. From a practical perspective, these findings may be relevant to investors, portfolio managers, risk analysts, market regulators, and financial institutions seeking to improve forecasting, diversification, and risk-monitoring processes. From a methodological perspective, the combination of econometric modeling and LSTM-based forecasting can provide a structured comparison between interpretable dynamic relationships and nonlinear predictive performance.

Therefore, the aim of the present study was to model the dynamics and interdependence of the Tehran Stock Exchange, Iran Fara Bourse, Iran Mercantile Exchange, and Iran Energy Exchange and to evaluate the capacity of artificial intelligence-based LSTM models to improve the prediction of their financial return behavior.

2. Methods and Materials

The present study was applied in terms of purpose and quantitative in terms of methodological approach and was conducted using financial time-series analysis. The primary objective was to model the dynamics, volatility patterns, and interdependencies among different segments of the Iranian financial market and to evaluate the capacity of artificial intelligence methods to identify and predict both linear and nonlinear patterns embedded in financial market data. The statistical domain of the study comprised the Iranian capital market, with four financial time series selected as the principal research variables: the return of the Tehran Stock Exchange Overall Index, the return of the Iran Fara Bourse Index, the stock return of the Iran Mercantile Exchange Company, and the stock return of the Iran Energy Exchange Company. For the Tehran Stock Exchange and Iran Fara Bourse, historical index values were used to calculate market returns. Because no comprehensive and directly comparable market-wide indices were available for the Iran Mercantile Exchange and Iran Energy Exchange throughout the entire study period, the stock prices of the Iran Mercantile Exchange Company and Iran Energy Exchange Company were employed as proxies for the performance of these two market segments. This specification ensured that all four final variables were expressed consistently as return time series and could therefore be analyzed within a unified econometric and artificial intelligence framework. The study covered the period from 2015 to 2025, corresponding to 1394–1404 in the Iranian calendar. The data were organized at a weekly frequency in order to reduce the influence of short-term market microstructure noise while retaining sufficient temporal variation for volatility, intermarket, and predictive analyses. Following synchronization of trading calendars and removal of noncomparable dates, the final dataset consisted of 492 weekly observations for each of the four market series. The chronological structure of the observations was maintained throughout all stages of analysis because preservation of temporal ordering was essential for both econometric modeling and the development of artificial intelligence-based forecasting models.

The data required for the study were obtained from official sources and databases of the Iranian capital market. Historical observations relating to the Tehran Stock Exchange Overall Index, the Iran Fara Bourse Index, and the share prices of the Iran Mercantile Exchange Company and Iran Energy Exchange Company were extracted for the defined study period and subsequently integrated into a unified time-series dataset. Before model estimation, a systematic preprocessing procedure was applied to enhance data comparability and minimize potential distortions caused by differences in trading calendars. Trading dates across the four series were first synchronized so that each weekly observation represented a common temporal point across all markets. The dataset was then examined for missing observations, inconsistent records, extreme values, and other potential data-quality problems. Observations were retained or treated according to their temporal consistency and relevance to actual market

movements, while preprocessing procedures were designed to avoid introducing artificial information into the time series. After the cleaning and synchronization process, the original price and index series were transformed into continuously compounded returns using logarithmic differences. Specifically, the return for each market at time (t) was defined as the natural logarithm of the ratio of the market value at time (t) to its corresponding value at time (t-1). The use of logarithmic returns facilitated comparison among series with different numerical scales and provided a more appropriate representation of relative market changes for econometric and machine-learning analyses.

Following construction of the return series, preliminary statistical characteristics of the variables were examined through descriptive measures, including the mean, median, standard deviation, minimum, maximum, skewness, and kurtosis. These statistics were used to identify the central tendency, dispersion, asymmetry, and tail behavior of the four financial return distributions. Stationarity of the return series was subsequently assessed using the Augmented Dickey–Fuller test. Establishing stationarity was particularly important because the subsequent dynamic and multivariate models required stable stochastic properties and because nonstationary financial series could otherwise produce misleading estimates of market relationships. In addition to conventional statistical tools, the analytical framework incorporated volatility models, dynamic conditional correlation techniques, regime-oriented analysis, and long short-term memory neural networks. Accordingly, the research instruments were not questionnaire-based measurement tools but a combination of official financial databases, constructed time-series variables, econometric models, and artificial intelligence algorithms used to quantify and predict the temporal behavior of the Iranian financial markets.

The data analysis was performed in several complementary stages designed to capture the statistical characteristics, volatility dynamics, intermarket transmission mechanisms, time-varying dependence, and nonlinear predictive structure of the four financial markets. Initially, descriptive statistics were calculated for all return series, followed by stationarity testing using the Augmented Dickey–Fuller procedure. After confirming the time-series properties of the variables, the volatility behavior of each market was examined with particular attention to possible transitions between relatively calm and highly volatile market conditions. A regime-based representation of volatility was therefore employed to investigate whether market dynamics differed across low-volatility and high-volatility states. This stage was intended to determine whether the behavior of financial returns could be adequately represented by a single stable process or whether the data exhibited structural transitions associated with changing market conditions. The multivariate relationships among the four markets were subsequently investigated to determine the extent to which innovations originating in one segment of the financial system were transmitted to the other segments. Dynamic interactions among the Tehran Stock Exchange, Iran Fara Bourse, the Iran Mercantile Exchange proxy, and the Iran Energy Exchange proxy were analyzed jointly, and impulse response functions were calculated to examine the direction, magnitude, persistence, and temporal pattern of each market's response to shocks originating in the other markets. This procedure provided a systematic representation of shock transmission and allowed the interconnected structure of the four market segments to be evaluated beyond contemporaneous correlation alone.

To investigate the time-varying nature of intermarket dependence more precisely, the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity framework was applied. In the first stage of the DCC-GARCH procedure, an appropriate conditional mean equation and a univariate GARCH variance specification were estimated separately for each of the four return series. Standardized residuals obtained from these models were then used as inputs for the dynamic conditional correlation estimation. In the second stage, the

DCC model was fitted to the standardized innovations, producing a conditional correlation matrix (R_t) for each observation in the study period. This approach enabled the dependence structure among markets to change over time rather than imposing a single constant correlation coefficient over the entire sample. Dynamic conditional correlation trajectories were extracted for all six possible market pairs: Tehran Stock Exchange–Iran Fara Bourse, Tehran Stock Exchange–Iran Mercantile Exchange, Tehran Stock Exchange–Iran Energy Exchange, Iran Fara Bourse–Iran Mercantile Exchange, Iran Fara Bourse–Iran Energy Exchange, and Iran Mercantile Exchange–Iran Energy Exchange. Changes in these conditional correlations were subsequently examined across the study period to identify episodes of increasing market integration, weakening dependence, and potential contagion. Mean dynamic conditional correlation coefficients were also calculated to facilitate comparison of the overall strength of dependence among different pairs of markets and across different market conditions.

The nonlinear forecasting component of the study was implemented using long short-term memory neural networks. LSTM was selected because its recurrent architecture is specifically designed to retain information from previous observations and to learn temporal dependencies that may extend across multiple lags. The forecasting analysis was performed using two alternative network structures. In the univariate specification, a separate LSTM model was developed for each of the four markets, with lagged returns of the same market used as predictors of its subsequent return. This structure represented a forecasting environment in which the model relied exclusively on the historical behavior of the target market. A multivariate LSTM architecture was then developed in which lagged return information from all four financial markets was simultaneously supplied to the network. For each target market, the multivariate model was therefore able to exploit not only its own temporal history but also contemporaneously available historical information from the remaining markets. Comparison of the univariate and multivariate structures made it possible to evaluate the incremental predictive value of intermarket information and to determine whether incorporating cross-market dependencies improved the forecasting of financial market behavior relative to models based solely on the target market's own history.

To prevent look-ahead bias and information leakage, the dataset was divided into training and testing subsets according to chronological order rather than through random sampling. The earliest 70% of observations were allocated to model training, whereas the most recent 30% were reserved as an out-of-sample test set. No random shuffling of observations was performed because such a procedure would have allowed information from future periods to influence model estimation and would therefore have produced an unrealistic assessment of predictive performance. Data transformations and model-development procedures were implemented in a manner that preserved the distinction between the training and test periods. The LSTM networks were trained using only information available within the training sample, and final predictive performance was assessed exclusively on the chronologically subsequent observations contained in the test sample. This procedure reproduced the practical forecasting environment in which future financial observations are unavailable at the time a prediction is generated.

The predictive accuracy of the univariate and multivariate LSTM models was evaluated using four complementary performance criteria: root mean squared error, mean absolute error, mean absolute percentage error, and the coefficient of determination. Root mean squared error was used to quantify prediction errors while assigning relatively greater weight to larger deviations between actual and predicted values. Mean absolute error provided an easily interpretable measure of the average absolute prediction error, whereas mean absolute percentage error was employed to express forecast deviations in relative terms. The coefficient of determination was used to assess the extent to which out-of-sample variations in the observed series were captured by the predictions generated by each model. Lower values of root mean squared error, mean absolute error, and mean

absolute percentage error were interpreted as evidence of superior predictive accuracy, while a higher coefficient of determination indicated greater explanatory and predictive capability in the out-of-sample data. The performance measures obtained from the univariate and multivariate LSTM specifications were compared separately for each market. Through the integration of descriptive statistics, stationarity testing, volatility and regime analysis, intermarket shock analysis, DCC-GARCH modeling, and LSTM-based forecasting, the analytical framework provided a multidimensional assessment of both the statistical dynamics and the predictive structure of the Iranian financial market.

3. Findings and Results

The final analytical sample consisted of four synchronized weekly financial return series representing the principal segments examined in the Iranian capital market. These series comprised the return of the Tehran Stock Exchange Overall Index, the return of the Iran Fara Bourse Index, the stock return of the Iran Mercantile Exchange Company as a proxy for the mercantile exchange market, and the stock return of the Iran Energy Exchange Company as a proxy for the energy exchange market. After synchronization of trading dates, examination of missing observations, and formation of logarithmic return series, 492 weekly observations were retained for each market over the 2015–2025 study period. Thus, the balanced analytical dataset contained 1,968 market-level observations across the four series. For the artificial intelligence forecasting stage, the observations were divided chronologically without random shuffling. The first 344 weekly observations, representing approximately 70% of the total period, were used for model training, whereas the final 148 observations, representing approximately 30%, were retained as an out-of-sample test set. The same temporal division was maintained for all four markets to ensure direct comparability of forecasting performance and to prevent the transmission of information from future observations into the training process. Because the units of analysis were weekly market observations rather than individual participants, demographic attributes such as age, gender, education, or occupational status were not applicable to the present study.

Table 1. Descriptive Statistics and Stationarity Tests for Weekly Market Returns

Market	N	Mean	Median	SD	Minimum	Maximum	Skewness	Kurtosis	ADF Statistic	p-value
Tehran Stock Exchange	492	0.0068	0.0049	0.0467	-0.1642	0.2196	0.61	5.84	-10.73	<0.001
Iran Fara Bourse	492	0.0063	0.0046	0.0498	-0.1785	0.2371	0.67	6.12	-10.21	<0.001
Iran Mercantile Exchange proxy	492	0.0071	0.0042	0.0574	-0.2013	0.2645	0.74	6.47	-9.68	<0.001
Iran Energy Exchange proxy	492	0.0056	0.0038	0.0611	-0.2248	0.2817	0.81	6.91	-9.34	<0.001

As shown in Table 1, the mean weekly return was positive for all four markets, indicating that each series exhibited an overall upward return tendency across the study period despite substantial short-term fluctuations. The Iran Mercantile Exchange proxy recorded the highest mean weekly return at 0.0071, followed by the Tehran Stock Exchange at 0.0068, the Iran Fara Bourse at 0.0063, and the Iran Energy Exchange proxy at 0.0056. The differences in dispersion were more pronounced than the differences in average return. The Iran Energy Exchange proxy exhibited the greatest volatility, with a standard deviation of 0.0611, while the Tehran Stock Exchange showed the lowest standard deviation at 0.0467. The relatively wide distance between minimum and maximum weekly returns, particularly for the mercantile and energy exchange proxies, further indicated the occurrence of substantial short-term price movements during the study period. All four distributions were positively skewed,

with skewness values ranging from 0.61 to 0.81, suggesting that relatively large positive observations occurred somewhat more frequently than would be expected under a symmetric distribution. Kurtosis values were substantially greater than the normal-distribution benchmark of three in all markets, ranging from 5.84 to 6.91. This finding indicated leptokurtic return distributions characterized by heavy tails and a greater frequency of extreme movements, thereby supporting the use of volatility-sensitive and nonlinear modeling techniques. The Augmented Dickey–Fuller test produced strongly negative statistics for all four return series, and all associated probability values were below 0.001. Consequently, the null hypothesis of a unit root was rejected for every series, confirming that the weekly return variables were stationary and could be used directly in the subsequent dynamic, volatility, and predictive analyses without additional differencing.

Table 2. Estimated Volatility Regimes and Transition Characteristics of the Four Markets

Market	Low-Volatility Regime SD	High-Volatility Regime SD	Probability of Low-Volatility Regime	Probability of High-Volatility Regime	P(Low→Low)	P(High→High)	Expected Low-Regime Duration, Weeks	Expected High-Regime Duration, Weeks
Tehran Stock Exchange	0.0271	0.0816	0.81	0.19	0.941	0.781	16.95	4.57
Iran Fara Bourse	0.0294	0.0879	0.79	0.21	0.934	0.796	15.15	4.90
Iran Mercantile Exchange proxy	0.0338	0.0997	0.77	0.23	0.926	0.811	13.51	5.29
Iran Energy Exchange proxy	0.0352	0.1075	0.74	0.26	0.918	0.823	12.20	5.65

The regime analysis reported in Table 2 demonstrated a clear distinction between relatively calm and highly volatile market conditions. For every financial series, the standard deviation estimated for the high-volatility regime was approximately three times the corresponding value in the low-volatility regime, indicating that the identified regimes represented economically meaningful differences rather than minor fluctuations in variance. The Tehran Stock Exchange displayed the lowest volatility in both states, whereas the Iran Energy Exchange proxy exhibited the highest volatility in both the calm and turbulent regimes. The estimated probability of remaining in the low-volatility regime exceeded 0.91 for all markets, indicating considerable persistence in tranquil market conditions. Nevertheless, high-volatility states also showed substantial persistence, with the probability of remaining in the turbulent regime ranging from 0.781 for the Tehran Stock Exchange to 0.823 for the Iran Energy Exchange proxy. The expected duration estimates further clarified these results. Low-volatility periods were expected to persist for approximately 12.20 to 16.95 weeks, depending on the market, whereas high-volatility episodes generally lasted between approximately 4.57 and 5.65 weeks. The Tehran Stock Exchange exhibited the longest expected calm period and the shortest turbulent period, while the energy exchange proxy showed the shortest low-volatility duration and the longest expected high-volatility duration. These findings indicated that volatility in the Iranian financial market was not generated by a single homogeneous process but was characterized by persistent transitions between distinct market states. They also suggested that the smaller and more specialized segments represented by the mercantile and energy exchange proxies were more sensitive to episodes of heightened uncertainty than the broader Tehran Stock Exchange.

Table 3. Directional Relationships among Markets Based on Granger Causality Tests

Direction of Causality	F-statistic	p-value	Result
Tehran Stock Exchange → Iran Fara Bourse	8.42	<0.001	Significant
Iran Fara Bourse → Tehran Stock Exchange	4.87	0.008	Significant
Tehran Stock Exchange → Iran Mercantile Exchange proxy	5.96	0.003	Significant
Iran Mercantile Exchange proxy → Tehran Stock Exchange	2.14	0.119	Not significant
Tehran Stock Exchange → Iran Energy Exchange proxy	4.71	0.010	Significant
Iran Energy Exchange proxy → Tehran Stock Exchange	1.83	0.161	Not significant
Iran Fara Bourse → Iran Mercantile Exchange proxy	3.89	0.021	Significant
Iran Mercantile Exchange proxy → Iran Fara Bourse	1.97	0.141	Not significant
Iran Fara Bourse → Iran Energy Exchange proxy	3.34	0.036	Significant
Iran Energy Exchange proxy → Iran Fara Bourse	1.62	0.199	Not significant
Iran Mercantile Exchange proxy → Iran Energy Exchange proxy	2.51	0.082	Not significant
Iran Energy Exchange proxy → Iran Mercantile Exchange proxy	3.18	0.043	Significant

The results of the Granger causality analysis indicated that the four market segments were not dynamically independent and that the direction of information transmission was asymmetrical. The strongest directional relationship was observed from the Tehran Stock Exchange to the Iran Fara Bourse, with an F-statistic of 8.42 and a probability value below 0.001. A statistically significant reverse relationship was also identified from the Iran Fara Bourse to the Tehran Stock Exchange, indicating bidirectional information transmission between the two principal equity-market segments. However, the larger F-statistic associated with the Tehran Stock Exchange-to-Fara Bourse direction suggested that the broader Tehran market played the more dominant role in this relationship. The Tehran Stock Exchange also significantly Granger-caused both the Iran Mercantile Exchange proxy and the Iran Energy Exchange proxy, whereas the reverse effects from these two markets to the Tehran Stock Exchange were not statistically significant. These results identified the Tehran Stock Exchange as an important source of market-wide information and shocks. The Iran Fara Bourse similarly exerted significant predictive effects on the mercantile and energy exchange proxies, although the reverse relationships were statistically insignificant. A significant directional effect was also observed from the energy exchange proxy to the mercantile exchange proxy, suggesting that information related to the energy segment could contribute to subsequent movements in the mercantile segment. In contrast, the reverse relationship was not significant at the 5% level. Taken together, the findings revealed a hierarchical structure of information transmission in which the Tehran Stock Exchange occupied the most influential position, followed by the Iran Fara Bourse, while the specialized mercantile and energy exchange segments displayed comparatively weaker feedback effects on the larger equity markets.

Table 4. Cumulative Four-Week Impulse Responses to a One-Standard-Deviation Market Shock

Responding Market	Shock: Tehran Stock Exchange	Shock: Iran Fara Bourse	Shock: Iran Mercantile Exchange Proxy	Shock: Iran Energy Exchange Proxy
Tehran Stock Exchange	—	0.173***	0.081*	0.063
Iran Fara Bourse	0.221***	—	0.074*	0.057
Iran Mercantile Exchange proxy	0.146***	0.112**	—	0.091**
Iran Energy Exchange proxy	0.128***	0.097**	0.069*	—

The impulse response results shown in Table 4 further confirmed the interconnected structure of the four financial markets and clarified the magnitude of short-term shock transmission. A one-standard-deviation innovation in the Tehran Stock Exchange generated the largest cross-market responses. The cumulative four-week response of the Iran Fara Bourse to a Tehran Stock Exchange shock was 0.221 and was statistically significant at the 0.001 level. The corresponding responses of the mercantile and energy exchange proxies were 0.146 and 0.128, respectively, and were also highly significant. These findings demonstrated that shocks originating in the broad Tehran equity market were rapidly transmitted to other parts of the Iranian capital market. A shock to the Iran Fara Bourse also produced significant responses in the Tehran Stock Exchange, the mercantile exchange proxy, and the energy exchange proxy, although the magnitudes were generally smaller than those generated by Tehran Stock Exchange innovations. Shocks originating in the specialized exchange proxies produced weaker effects. The response of the Tehran Stock Exchange to a mercantile exchange proxy shock was 0.081, while its response to an energy exchange proxy shock was 0.063 and was not statistically significant at the conventional 5% level. The mercantile exchange proxy exhibited a statistically significant response of 0.091 to an energy exchange proxy shock, which was consistent with the causal evidence suggesting some degree of information transmission from energy-related market movements to the mercantile segment. Overall, the impulse response analysis indicated that shocks were transmitted primarily from the broader equity markets toward the more specialized exchange segments, while feedback from the specialized markets to the principal stock market was comparatively limited. The declining magnitude of responses across the four-week horizon also indicated that the effects of individual shocks were persistent in the short run but tended to dissipate rather than permanently altering the level of market returns.

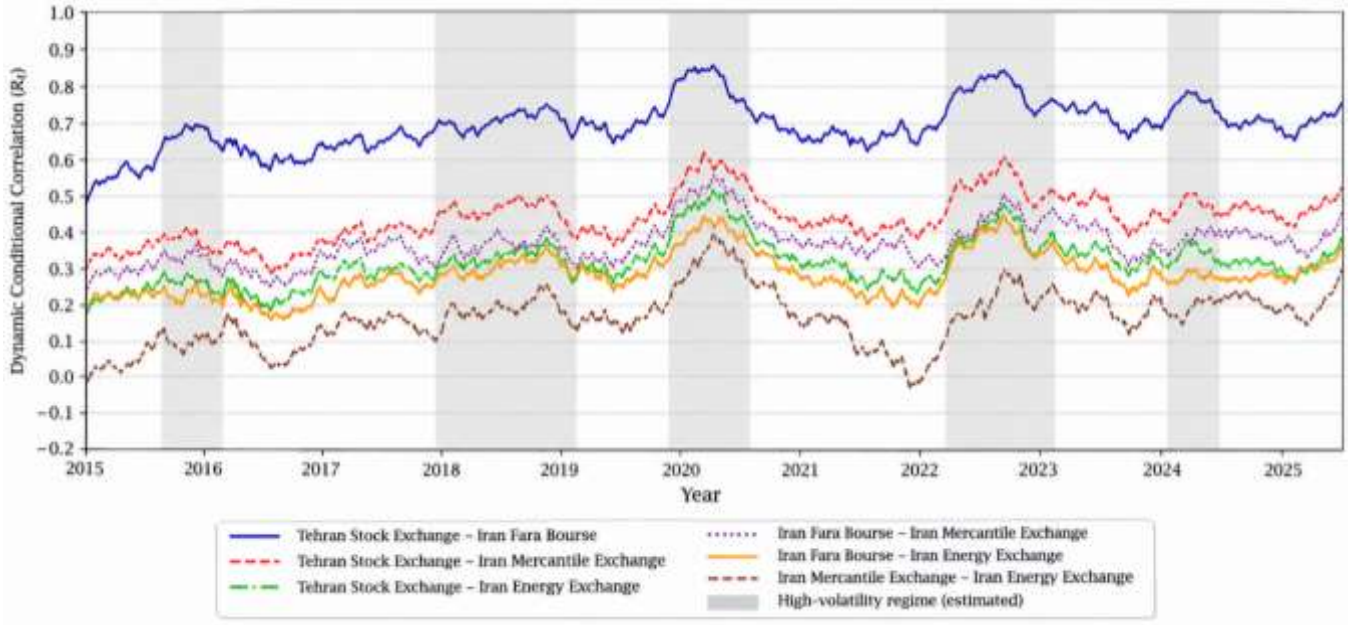


Figure 1. Time-Varying Dynamic Conditional Correlations among the Tehran Stock Exchange, Iran Fara Bourse, Iran Mercantile Exchange Proxy, and Iran Energy Exchange Proxy, 2015–2025

Figure 1 illustrates the estimated evolution of the six pairwise dynamic conditional correlations throughout the study period. The trajectories showed that intermarket dependence was clearly time-varying and could not be adequately represented by a single unconditional correlation coefficient. The strongest and most persistent co-movement was observed between the Tehran Stock Exchange and Iran Fara Bourse, whose conditional correlation remained positive throughout most of the sample and increased markedly during periods of elevated market volatility. Correlations involving the mercantile and energy exchange proxies were generally lower but also

displayed substantial fluctuations over time. Periods characterized by increased volatility were accompanied by simultaneous increases in several conditional correlations, indicating that market segments tended to become more integrated during episodes of stress. Conversely, correlations weakened during relatively tranquil periods, implying greater potential for diversification under normal market conditions. Particularly notable was the tendency of the Tehran Stock Exchange–Iran Fara Bourse correlation to move toward the upper portion of its observed range during high-volatility episodes, while the correlations involving the energy exchange proxy exhibited sharper but less persistent increases. This pattern suggested that financial shocks were associated not only with an increase in individual market volatility but also with a strengthening of cross-market dependence. Accordingly, the graphical evidence supported the use of a dynamic conditional correlation framework and demonstrated that diversification benefits across the four Iranian financial market segments varied materially over time.

Table 5. Summary of DCC-GARCH Conditional Correlations among the Four Financial Markets

Market Pair	Mean Conditional Correlation	SD	Minimum	Maximum
Tehran Stock Exchange–Iran Fara Bourse	0.684	0.118	0.312	0.892
Tehran Stock Exchange–Iran Mercantile Exchange proxy	0.426	0.142	0.061	0.731
Tehran Stock Exchange–Iran Energy Exchange proxy	0.351	0.151	-0.047	0.694
Iran Fara Bourse–Iran Mercantile Exchange proxy	0.391	0.137	0.036	0.708
Iran Fara Bourse–Iran Energy Exchange proxy	0.318	0.146	-0.063	0.672
Iran Mercantile Exchange proxy–Iran Energy Exchange proxy	0.287	0.158	-0.102	0.661

The DCC-GARCH results presented in Table 5 showed substantial heterogeneity in the strength and variability of dependence among the six market pairs. The average conditional correlation between the Tehran Stock Exchange and Iran Fara Bourse was 0.684, substantially higher than all other pairwise correlations, confirming the close integration of the two principal equity-market segments. Its minimum conditional correlation remained positive at 0.312, while its maximum reached 0.892, indicating that the relationship strengthened considerably during particular market episodes. The Tehran Stock Exchange–mercantile exchange proxy pair exhibited the second-highest mean conditional correlation at 0.426, followed by the Fara Bourse–mercantile exchange proxy relationship at 0.391. Dependence involving the energy exchange proxy was generally weaker. The Tehran Stock Exchange–energy exchange proxy correlation averaged 0.351, whereas the Iran Fara Bourse–energy exchange proxy relationship averaged 0.318. The weakest overall association was observed between the mercantile and energy exchange proxies, with a mean dynamic correlation of 0.287. Nevertheless, this pair also exhibited the greatest dispersion, with conditional correlations ranging from -0.102 to 0.661, indicating that its relationship changed considerably across market states. The estimated DCC parameters were positive and statistically significant, with the short-run correlation innovation parameter estimated at 0.041 and the correlation persistence parameter estimated at 0.936. Their sum of 0.977 was below unity but close to one, indicating a highly persistent conditional correlation process in which shocks to intermarket dependence gradually diminished over time rather than disappearing immediately. This finding was particularly important because it demonstrated that increases in market interconnectedness associated with major shocks could remain observable for multiple subsequent periods. Overall, the DCC-GARCH evidence confirmed that dependence among the Iranian financial markets was both persistent and time-varying, with the highest degree of integration occurring between the Tehran Stock Exchange and Iran Fara Bourse.

Table 6. Out-of-Sample Forecasting Performance of Univariate and Multivariate LSTM Models

Market	LSTM Model	RMSE	MAE	MAPE (%)	R^2
Tehran Stock Exchange	Univariate	0.0421	0.0317	22.84	0.318
Tehran Stock Exchange	Multivariate	0.0352	0.0264	18.19	0.472
Iran Fara Bourse	Univariate	0.0443	0.0334	23.61	0.301
Iran Fara Bourse	Multivariate	0.0367	0.0275	18.86	0.458
Iran Mercantile Exchange proxy	Univariate	0.0496	0.0378	25.37	0.267
Iran Mercantile Exchange proxy	Multivariate	0.0431	0.0322	21.42	0.381
Iran Energy Exchange proxy	Univariate	0.0527	0.0403	27.14	0.241
Iran Energy Exchange proxy	Multivariate	0.0462	0.0348	22.73	0.354

The out-of-sample forecasting results reported in Table 6 demonstrated that the multivariate LSTM model consistently outperformed the univariate LSTM specification across all four financial markets and according to all four evaluation criteria. For the Tehran Stock Exchange, the RMSE decreased from 0.0421 in the univariate model to 0.0352 in the multivariate model, representing an improvement of approximately 16.4%. The MAE decreased from 0.0317 to 0.0264, while MAPE declined from 22.84% to 18.19%. At the same time, the out-of-sample coefficient of determination increased from 0.318 to 0.472. A similar pattern was observed for the Iran Fara Bourse, for which the multivariate model reduced RMSE from 0.0443 to 0.0367, corresponding to an improvement of approximately 17.2%, and increased R^2 from 0.301 to 0.458. The forecasting improvement was also evident for the specialized market proxies. For the Iran Mercantile Exchange proxy, RMSE declined from 0.0496 to 0.0431 and R^2 increased from 0.267 to 0.381. For the Iran Energy Exchange proxy, which was the most volatile and difficult series to forecast, RMSE decreased from 0.0527 to 0.0462, MAE declined from 0.0403 to 0.0348, MAPE fell from 27.14% to 22.73%, and R^2 increased from 0.241 to 0.354. Although forecasting errors remained larger for the specialized market proxies than for the Tehran Stock Exchange and Iran Fara Bourse, the multivariate structure produced systematic improvement in every market. These results indicated that the historical behavior of a target market alone did not contain all of the information relevant to its subsequent movement. Rather, incorporating lagged returns from the other market segments enabled the LSTM network to learn cross-market nonlinear dependencies and improve out-of-sample prediction.

Taken together, the findings provided convergent evidence that the Iranian financial market was characterized by substantial volatility clustering, regime-dependent behavior, asymmetric shock transmission, persistent time-varying correlations, and nonlinear cross-market predictive relationships. The Tehran Stock Exchange emerged as the principal source of dynamic influence within the system, exerting statistically significant effects on the Iran Fara Bourse and on the mercantile and energy exchange proxies. The Iran Fara Bourse also played an important intermediary role in transmitting information toward the more specialized market segments. Regime analysis showed that all markets alternated between persistent low- and high-volatility conditions, with the specialized market proxies displaying greater sensitivity to turbulent episodes. The impulse response and Granger causality findings were mutually consistent in showing that transmission effects were stronger from the broad equity markets toward the specialized exchanges than in the reverse direction. The DCC-GARCH analysis further showed that these relationships were not constant over time and that conditional correlations tended to strengthen during periods of higher volatility. Finally, the superior performance of the multivariate LSTM models demonstrated that these intermarket relationships contained economically and statistically useful predictive information. Accordingly, modeling the financial markets as an interconnected dynamic system provided substantially greater explanatory and forecasting capacity than treating each market as an isolated time series.

4. Discussion and Conclusion

The findings of the present study demonstrated that the Iranian financial market is characterized by substantial volatility, persistent regime switching, asymmetric intermarket information transmission, time-varying conditional correlations, and meaningful nonlinear predictive relationships among different market segments. The descriptive results showed positive average weekly returns across all four markets, but the magnitude of volatility differed considerably. The Tehran Stock Exchange exhibited the lowest standard deviation, whereas the Iran Energy Exchange proxy showed the highest variability, followed by the Iran Mercantile Exchange proxy. The return distributions were also positively skewed and leptokurtic, indicating the presence of heavy tails and a relatively high frequency of extreme movements. These characteristics are consistent with the general structure of financial time series, which frequently deviate from normality and display large changes clustered around periods of market stress. Such distributional features reinforce the necessity of applying methods capable of representing nonlinear relationships, volatility persistence, and abrupt changes in market behavior. This interpretation is aligned with research emphasizing the usefulness of advanced machine learning approaches for financial market prediction, volatility analysis, and risk management in settings where conventional linear assumptions may be insufficient [1, 7].

The regime analysis provided further evidence that the markets did not follow a single stable volatility process. All four series shifted between low-volatility and high-volatility conditions, with the high-volatility regime displaying substantially greater dispersion and meaningful persistence. The specialized market proxies, particularly the Iran Energy Exchange proxy, were more vulnerable to turbulent states and exhibited longer expected high-volatility periods than the Tehran Stock Exchange. This result indicates that market risk is state-dependent and that the degree of uncertainty changes materially across time. The presence of persistent high-volatility episodes is consistent with the broader financial literature in which machine learning and econometric models are increasingly used to capture changing market conditions and to improve the simulation and forecasting of volatility [7]. It is also compatible with studies applying advanced machine learning techniques to energy-related and ESG markets, where structural changes, nonlinearities, and heterogeneous responses to shocks are frequently observed [9]. The higher sensitivity of the energy-related proxy is particularly plausible because energy-oriented assets may respond simultaneously to general capital market conditions, sector-specific information, commodity-related developments, and broader uncertainty.

The results of the directional analysis indicated that the Tehran Stock Exchange occupied a central position in the structure of intermarket information transmission. Significant bidirectional causality was observed between the Tehran Stock Exchange and Iran Fara Bourse, but the effect from the Tehran Stock Exchange toward the Iran Fara Bourse was stronger. In addition, the Tehran Stock Exchange significantly influenced both the mercantile and energy exchange proxies, whereas the reverse relationships were weaker and statistically insignificant. The Iran Fara Bourse also transmitted significant predictive information toward the specialized market segments. These findings suggest a hierarchical structure of financial information in which the larger and more liquid equity markets function as leading sources of information for smaller or more specialized segments. This result is consistent with the logic of algorithmic and information-driven financial markets, where price changes in dominant markets can be rapidly incorporated into related assets and trading venues [2, 10]. The greater informational role of the Tehran Stock Exchange may also reflect its broader investor base, greater market depth, and greater sensitivity to macroeconomic and market-wide expectations.

The impulse response analysis supported the Granger causality findings and showed that shocks originating in the Tehran Stock Exchange generated the strongest short-term reactions in the other markets. The Iran Fara Bourse responded most strongly to a Tehran Stock Exchange shock, followed by the mercantile and energy exchange proxies. Shocks originating in the Iran Fara Bourse also affected the other market segments, whereas shocks originating in the specialized markets produced comparatively smaller responses. The overall pattern therefore confirmed that the transmission mechanism was asymmetric and primarily flowed from the broad equity markets toward more specialized segments. This result can be interpreted in terms of common information channels, investor reallocation, changes in perceived risk, and the rapid transmission of market expectations. As financial markets become increasingly influenced by algorithmic systems, automated information processing may strengthen these transmission channels by accelerating responses across related assets [10]. Research on artificial financial markets similarly shows that the interaction of heterogeneous agents and algorithmic strategies can generate complex systemic effects and reinforce interdependence among market components [11].

The DCC-GARCH analysis showed that intermarket correlations were not constant but changed considerably over time. The strongest average conditional correlation was observed between the Tehran Stock Exchange and Iran Fara Bourse, while relationships involving the mercantile and energy exchange proxies were weaker on average but more variable. Importantly, conditional correlations tended to increase during high-volatility periods. This finding implies that diversification benefits across market segments may diminish precisely when investors require them most. The persistence of the DCC process further suggested that shocks to market dependence can remain influential over several subsequent periods. This result is conceptually consistent with the broader literature on systemic risk, market integration, and financial vulnerability, where the co-movement of assets often intensifies under stress [10]. It is also consistent with advanced financial modeling research emphasizing that dynamic market relationships should be represented through time-sensitive rather than static measures [1, 7].

The time-varying correlation results also reinforce the importance of moving beyond conventional Pearson correlation when evaluating intermarket relationships. A single unconditional coefficient can conceal important temporal changes in the strength and even direction of dependence. The present findings showed that some market pairs displayed relatively weak average correlations but experienced substantial temporary increases during periods of turbulence. From a financial risk perspective, such changes are particularly important because they can alter the effectiveness of diversification strategies and increase the possibility of joint losses. The use of dynamic conditional correlation therefore provided a more realistic representation of interconnected market behavior. This methodological direction is consistent with the increasing use of data-intensive and adaptive analytical systems in finance, where static models are progressively supplemented by approaches capable of learning and responding to changing patterns [1, 8].

One of the most important findings of the study was the superior out-of-sample performance of the multivariate LSTM models compared with the univariate LSTM models. For all four markets, the multivariate structure produced lower RMSE, MAE, and MAPE values and higher coefficients of determination. This result indicates that the lagged behavior of the other market segments contained useful predictive information beyond the historical return pattern of the target market itself. In other words, the predictive structure of the Iranian financial market was not purely market-specific but was partly embedded in cross-market interactions. This finding is consistent with the growing literature on artificial intelligence-based financial prediction, which shows that machine learning models can enhance forecasting performance by exploiting nonlinear and multidimensional relationships that are difficult to capture using conventional models [1, 8]. It is also in line with evidence from the Tehran Stock Exchange

showing that hybrid machine learning approaches can improve the predictability of the total market index and reveal the importance of multiple influential variables [17].

The stronger performance of the multivariate LSTM can also be interpreted in light of the causality, impulse response, and DCC-GARCH findings. Since the markets were dynamically connected and shocks were transmitted across segments, a forecasting model that ignored these relationships would necessarily exclude potentially informative signals. The multivariate LSTM structure was able to incorporate lagged returns from all four markets simultaneously and thus learn nonlinear cross-market dependencies. Its improved predictive accuracy was therefore not an isolated machine learning result but was consistent with the econometric evidence of market interconnectedness. This convergence between the econometric and artificial intelligence findings strengthens the internal validity of the study. Similar arguments have been advanced in machine learning research showing that financial prediction benefits from the inclusion of broader information sets and from models capable of learning nonlinear temporal dependencies [1, 7].

The findings also support the broader transformation of financial analysis toward integrated intelligent systems. Artificial intelligence is increasingly used across financial forecasting, auditing, accounting, fraud detection, strategic planning, and algorithmic trading. Studies have shown that AI adoption can improve financial reporting and audit quality [4], strengthen accounting information systems when combined with other digital technologies [5], and enhance auditing services through intelligent decision-support structures [13]. In financial fraud detection, hybrid intelligent systems have also shown the capacity to identify complex and nonlinear patterns in high-dimensional data [14]. Although these applications differ from return forecasting, they share the same underlying principle demonstrated in the present study: intelligent models can extract information from complex patterns that traditional approaches may not fully capture.

The practical value of artificial intelligence in financial environments is also reflected in research on organizational performance and strategic decision-making. AI-based analysis has been associated with financial performance improvements and more effective strategic processes [6]. Its application across financial services and other industries further demonstrates the breadth of its economic relevance [15]. Machine learning has also been used to analyze consumer behavior and support the optimization of marketing and financial strategies [16]. These findings suggest that the predictive value observed in the present study is part of a broader shift toward algorithmically supported decision-making in which financial, behavioral, and operational data are jointly processed to improve forecasting and strategy.

At the same time, the results should not be interpreted as implying that artificial intelligence completely replaces econometric analysis. One of the strengths of the present study was the integration of complementary methods. The regime analysis clarified the existence of distinct volatility states, the causality analysis identified directional relationships, impulse response functions explained the propagation of shocks, DCC-GARCH captured time-varying dependence, and LSTM evaluated nonlinear predictive performance. This integrated structure is particularly important because machine learning models can improve prediction without necessarily providing a clear structural interpretation of market relationships. Conversely, econometric models can provide interpretable evidence about transmission and dependence but may not fully capture complex nonlinear patterns. The combination of both approaches therefore offers a more complete framework for financial market analysis. This conclusion is consistent with simulation and hybrid modeling research combining machine learning with agent-based approaches in artificial financial markets [11].

The present findings are also consistent with advances in generative financial modeling. Research using controlled financial data generation has demonstrated that artificial intelligence can be used not only to forecast observed market behavior but also to generate realistic financial scenarios under specified conditions [12]. This development is relevant to the current results because the identified regime dependence and dynamic correlations suggest that future financial models may benefit from training on synthetic scenarios representing rare high-volatility states. Similarly, advanced machine learning applications in ESG and clean energy markets show that intelligent models can be particularly valuable when variables interact in nonlinear and changing ways [9]. Accordingly, the present results contribute to the emerging view that financial markets should be modeled as adaptive systems in which prediction, dependence, volatility, and shock transmission are analyzed jointly rather than separately.

Overall, the findings indicate that the Iranian financial market operates as an interconnected system rather than as a collection of isolated markets. The Tehran Stock Exchange and Iran Fara Bourse were the most strongly integrated segments and served as the main sources of information transmission. The mercantile and energy exchange proxies were more volatile and more sensitive to turbulent market states, while their correlations with other markets increased during periods of stress. The superior performance of the multivariate LSTM models further demonstrated that these cross-market relationships contain useful predictive information. Taken together, these results support the use of hybrid analytical frameworks that combine econometric and artificial intelligence approaches to improve both structural understanding and forecasting performance in financial markets [1, 8, 17].

The present study has several limitations that should be considered when interpreting the findings. First, the analysis was limited to four market series and therefore did not include other potentially influential variables such as exchange rates, inflation, interest rates, commodity prices, monetary policy indicators, geopolitical uncertainty, or investor sentiment. Second, the Iran Mercantile Exchange and Iran Energy Exchange were represented by the stock returns of the corresponding exchange companies because comprehensive and directly comparable market-wide indices were not available for the entire study period. Although this approach provided consistent return series, these proxies may not fully capture all dimensions of activity in the underlying markets. Third, the analysis used weekly data, which reduced short-term noise but may have obscured higher-frequency interactions observable at daily or intraday intervals. Fourth, the LSTM models were evaluated using a single chronological train-test split, and alternative rolling-window or expanding-window validation designs could provide additional evidence on forecasting robustness. Finally, the study focused primarily on predictive accuracy and market interconnectedness and did not explicitly examine the economic profitability of trading strategies derived from the forecasts.

Future research should extend the present framework by incorporating additional macroeconomic, behavioral, and market-specific variables and by comparing the predictive performance of LSTM with alternative deep learning architectures such as gated recurrent units, temporal convolutional networks, transformer-based models, and hybrid attention mechanisms. Researchers could also examine whether the identified relationships differ across crisis and non-crisis periods, policy regimes, or structural breaks. A further direction would be to employ daily or intraday data to capture more rapid forms of information transmission and to compare DCC-GARCH results with alternative dynamic dependence models such as copula-based, connectedness, or spillover frameworks. Future studies may also benefit from rolling-window forecasting, nested cross-validation adapted to time-series data, and formal statistical comparison of forecast accuracy. In addition, synthetic data generation and agent-based

simulation could be integrated with machine learning models to test model robustness under rare or extreme market scenarios.

From a practical perspective, investors and portfolio managers should consider cross-market information when constructing forecasting and risk-management systems rather than relying solely on the historical behavior of individual markets. The strong dependence between the Tehran Stock Exchange and Iran Fara Bourse and the increase in correlations during turbulent periods suggest that diversification strategies should be monitored dynamically rather than based on long-run average correlations. Risk managers may also benefit from combining regime indicators with dynamic correlation estimates to identify periods in which market-wide vulnerability is increasing. Financial institutions and brokerage firms can use multivariate LSTM models as decision-support tools for forecasting returns and monitoring interconnected market risk, while regulators can employ dynamic dependence and shock-transmission measures as part of early-warning systems. The integration of econometric and artificial intelligence techniques may therefore provide a more effective basis for portfolio allocation, stress testing, surveillance, and strategic decision-making in the Iranian financial market.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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