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BANKING SECTOR DOMINANCE AND CROSS-SECTORAL DEPENDENCIES IN THE IRAQI STOCK EXCHANGE: A MACHINE LEARNING AND NETWORK ANALYSIS APPROACH

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Abstract
This study investigates the behavior of different economic sectors, the accuracy of forecasting models, and the interlocking relationships among firms in the Iraqi Stock Exchange 60-index (ISX60)-an effort to fill a major gap in scholarship on emerging markets. Using daily closing prices from 57 firms drawn from seven sectors between January 2015 and December 2024, we combine sector-contribution decomposition, machine-learning and time-series forecasting, and graph-based network analysis into a unified empirical framework. The results reveal a heavily concentrated structure, with the banking segment alone holding nearly 30 percent of total capitalization, followed by industry at 18 percent and services at 15 percent, underscoring both the prominence of financial intermediaries in the country's growth agenda and the systemic exposures they generate. Forecasting accuracy varies sharply across sectors, and three benchmark models-ARIMA, long short-term memory (LSTM) networks, and random forests-yield distinctly different outcomes. LSTM dominates in highly turbulent groups, achieving a mean absolute error of 0.15 for banks and 0.08 for industry, and shows an ability to learn non-linear, long-horizon dependency. Random forests shine in intermediate-volatility categories, whereas ARIMA still holds ground only in calm, low-dispersion arenas. Network metrics confirm a tight coupling between banking and manufacturing (Pearson r equals 0.8), suggesting that shocks originating in financial losses could spread quickly across key productive nodes during downturns. The evidence presented here enhances the understanding of portfolio diversification, showing that agriculture and insurance can act as effective hedges because their returns move independently of larger sectors. For regulators, the results highlight the need to supervise tightly interlinked industries and, at the same time, to bolster modest-performing fields that matter for long-run stability. By focusing on Middle Eastern emerging markets, this study adds to scarce regional literature and provides actionable insights for investors, policymakers, and analysts who work in frontier-market settings.

Keywords: *Iraqi Stock Exchange; ISX60; sectoral analysis; predictive modeling; network interdependencies; emerging markets.*

JEL Classification: *G11, G15, G17, C53, C58, O16*

INTRODUCTION

The Iraq stock exchange ISX is an important barometer and exchange for stocks in Iraq's economy as it is heavily influenced by the international stock market. This influences trade and investment correlations (Bilaus & Garcia-Feijóo, 2022). ISX60 index tracks the best-performing stocks on the stock exchange and thus indicates the economic performance and productivity of the sectors of Iraq's economy. The interrelationship among stakeholders and business sectors are extremely complicated and provide diverse opportunities and challenges not only to investors but also to researchers and policymakers.

Like Iraq, emerging markets pose distinct opportunities along with few challenges because of the changing economic dynamics (Bekaert et al., 2005). Such markets tend to have a less developed economic infrastructure, reduced market activity, and are more prone to political disturbances than advanced economies (Rubinstein, 2002). Thus, studying sectoral contributions and interrelations within the ISX60 index can be revealing in regard to the determinants of market performance and systemic risks. The banking sector, for example, has persistently been

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one the most active constituents of the ISX60 and has greatly changed its value over the years (Caporale et al., 2015). This financial supremacy indicates the role of these institutions in the economic development of Iraq.

An examination of various sectors shows that some sectors have a greater effect on ISX60 than others. The index contains Agriculture, Industry, Services and Banking as the primary sectors, which differs in their contribution to the whole index (Hassan et al., 2011). The banking sector's contribution by far is the largest as it represents about 30% of the total market capitalization (Bilaus & Garcia-Feijóo, 2022). On the other hand, the agricultural and insurance sectors contribute to a lesser extent, perhaps due to their small market shares or low trading volume. This is in line with trends noted in many emerging economies where, as of the study, developed countries the financial institutions are at the forefront of activity (Demirguc-Kunt & Levine, 1996).

The intricate relations among various components of the ISX60 index makes it harder to analyze the economic fundamentals of the market. Strong correlations among sectors may indicate certain dependencies, likely due to common economic policies or prevailing market sentiments (Kenett et al., 2010). For instance, the banking sector is often highly correlated with the industrial sector, meaning that movements within a certain industry will have a corresponding effect on another industry (Mantegna, 1999). Insurance and service sectors show moderate correlations, indicating the presence of dependence which may derive from the same regulatory framework or similar clientele (Billio et al., 2012). Understanding these relationships is vital while evaluating systemic risks because if one highly interconnected sector suffers a downturn, many others are bound to follow, resulting in greater market turbulence (Adrian & Brunnermeier, 2016).

In consideration of predicting stock price movements as well as analyzing market risks of the ISX60 index, different predictive modeling techniques prove to be useful. An array of models has already been used to anticipate stock prices, including ARIMA, LSTM, and Random Forests (Box et al., 2015; Breiman, 2001; Hochreiter & Schmidhuber, 1997). ARIMA models have been successfully used in capturing linear dependencies with stable trends, but often fail with increasingly volatile stocks that portray non-linear behavior (Zhang, 2003). LSTM, on the other hand, has an edge when identifying complex temporal dependencies and is beneficial for sectors experiencing volatile behavior like banking and industry (Krollner et al., 2010). Simultaneously, Random Forests do not tend to overfit and manage non-linear relationships capably, though they tend to lag behind their peers in highly volatile markets (Andy & Matthew, 2002).

Recognizing the sectoral contributions and efficacies of the predictive model's analysis enables investors to develop effective strategies for portfolio management. Prudent approaches to reduce risk exposure include diversification across less correlated sectors (Rubinstein, 2002). The banking sector may provide excellent returns, but these are offset by high sectoral volatility, which makes it necessary to balance investments in the services and industrial sectors (Patel et al., 2015). Furthermore, network analysis will offer strategies for diversified investments by showing peripheral nodes that are many interconnected sectors and, as a result, have systemic risk potential (Diebold & Yılmaz, 2023).

From a policy perspective, sectoral dynamics analysis can enable policies aimed at supporting critical yet underperforming sectors to achieve more balanced economic growth(Levine, 1997). For instance, less intervention in the agricultural sector may worsen its contribution to the ISX60 and therefore becomes the structural change which may improve the economy's diversification and resilience(Stiglitz, 2010). Additionally, policy measures aimed at supervising and controlling more interconnected sectors could reduce systemic risks and lead to a stable financial environment (Gai & Kapadia, 2010a).

There has been considerable work done to understand stock market patterns as well as predictive modeling, however, numerous gaps still exist especially for newer markets such as Iraq. Most studies emphasize on developed economies which receive a lot of attention, and very few concentrate on the emerging economies(Bekaert et al., 2005). Also, there has been significant application of predictive models, however, their use between different industries in one market is known to be untested (Patel et al., 2015). There is limited research on network interconnections of sectors in emerging economies which leaves hidden systemic dangers(Diebold & Yılmaz, 2023). Through this study, we seek to address these gaps by performing an in-depth study about the ISX60 index in which we analyze the sectoral contributions, predictive modeling results, and network interdependencies within the Iraqi stock market.

In Closing, the ISX60 is a crucial measure of the economic status of Iraq, as it illustrates the many interrelations and interactions of the different sectors. This research integrates sectoral and intersectional analysis, predictive modeling, and network interdependence analysis to depict the entire picture of the stock market dynamics in Iraq. Such an understanding is beneficial and necessary in the context of strategic policymaking and investment decision making while demonstrating the need for further research. Further investigation regarding the external impacts of the sectoral performances like geopolitical changes, oil prices, and macroeconomic indicators is necessary. These kinds of studies may greatly improve predictive assessment models, enhance the accuracy of risk estimation frameworks, and lead to stronger, more prosperous markets.

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I. LITERATURE REVIEW

In order to analyze stock market indices like ISX60 in Iraq, it is important to have considerable knowledge of both domestic and international economic trends. The literature review seeks to cover all relevant existing studies on stock market activity, sectoral performance, forecasting methods, and networks relations analysis. This section more or less defines and outline the objectives and directions for future work based on the insights from previous studies and emphasizes the limitations which the current study aims to fulfill.

The stock market is a complex system that is affected by many factors such as economic factors, geopolitical developments, and investor attitudes (Malkiel & Fama, 1970). Performance of stock indices is greatly influenced by institutional sector contributions which is very significant for emerging markets like Iraq. Some studies show that the indices are usually led by some sectors like banking and finance because of their large market capitalization and trading volumes (Levine, 1997). For example, Caporale et al. (2015) noted that the banking sector is one of the sectoral contributors to the volatility and stability of emerging market indices, thus its importance. Iraq's ISX60 index illustrates the dominance of the banking sector, which is continually responsible for approximately 30% of the total market capitalization of the index (Bilaus & Garcia-Feijóo, 2022). This is consistent with other emerging economies where financial institutions have increasingly been regarded as the engines of economic activity (Demirguc-Kunt & Levine, 1996). In addition, other sectors such as industry and services are also important but to a lesser extent than banking (Hassan et al., 2011). The contribution of agricultural, insurance, and hospitality industries seems to be lower, perhaps because of their smaller market share or low trading activities (AL-Saadi et al., 2022). Such results indicate that the Iraqi stock market, although multi-faceted is, heavily dependent on a few sectors, which can be a problem if these sectors collapse (Bekaert et al., 2005).

The usage of predictive models has rapidly gained importance for predicting stock prices and estimating market risk. Each of these models is associated with a different market and has its own strengths and weaknesses. Autoregressive Integrated Moving Average (ARIMA) models are one of the most frequently used for time series forecasting because they capture the existence of linear dependencies (Box, 2013). However, the accuracy of ARIMA models is relatively low for highly volatile stocks that display non-linear dependencies (Zhang, 2003).

Long Short Term Memory networks (LSTMs) are a special kind of recurrent neural networks. They are good at capturing complex temporal dependencies which is beneficial in dealing with sectors that have fluctuating patterns(Hochreiter & Schmidhuber, 1997). As an example, LSTMs achieved a MAE of 0.15 as compared 0.25 for ARIMA models in the banking sector (Krollner et al., 2010). As an ensemble learning technique, Random Forests defend against overfitting and capture the non-linearity present in the data with ease (Breiman, 2001). The technique involves the construction of several decision trees which are combined in order to obtain improved prediction results. Random Forests proved to be more effective than ARIMA and LSTM models in the industrial sectors with an MAE 0.10 which clearly defines their effectiveness in dealing with non-linear data patterns (Andy & Matthew, 2002).

In addition to this, these models serve as important instruments in predicting stock price shifts and evaluating market risks. On the other hand, the choice of a model is dictated by the distinct feature and volatility characteristics of different sectors (Patel et al., 2015).

Translation of entire economic model necessitates realization of linkages among different sectors for the purpose of identifying a systemic risk in stock exchanges. Escribano (2023) and others have utilized correlation analysis and network theory to structural these relationships identifying central nodes – sectors from edge (many strong connections) to center (straightforward construction) which rest on potential systemic risks. Economically policy driven for mutual interdependencies or market psychology share strong positive correlations between banking and industrial. Weak correlation among sectors insurance and services reflects existence of a dependency probably due to the common regulatory framework or clientel (Billio et al., 2012).

As an example, a computed value of a correlation coefficient for banking and industrial sectors lends support to the 0.8 value confirming strong relationship(Mantegna, 1999). Central nodes areas in which the size is beyond obtrusively interconnected represent iceberg top; a plunge in one implies other accompanying and highlighting investments to attain diversification towards these risks (Tobias & Brunnermeier, 2016). This linkage implies that has to be for risk management purpose beyond each one singular ability in the sector towards their collective approach (Gai & Kapadia, 2010b). This could help nations embed low performing important areas to ensure development towards self sustained economy. The other side, these (Allen & Gale, 2000) provide fundamental bases towards pulsation strategy.

Levine (1997) notes that, from a policy point of view, why an economy performs the way it does could help policymakers to devise plans to address important sectors that are performing poorly. For investors, understanding the predictive model efficacies aids in selecting appropriate tools for portfolio management. Rubinstein (2002) argues that diversification around sectors that are less correlated is a sensible approach to reducing risk exposure.

Moreover, network analysis indicates that some systemic risks could be more easily dealt with through monitoring and regulation of certain highly connected sectors (Stiglitz, 2010). With these analyses together, we provide a comprehensive picture of the Iraqi stock market and its complexities and offer suggestions for

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participants while pointing out aspects which require further examination.

Even though the stock market and its behavior as well as predictive modeling has been done quite extensively, there are still gaps that need to filled. For one, there is little to no work done on emerging markets such as Iraq, on which most studies focus on developed markets (Bekaert et al., 2005). Also, while predictive models have been tested deeply, there is lack of exploration on their application across different industries within a single market (Patel et al., 2015). And lastly, there is little network analysis of interdependencies between emerging markets sectors which leaves systemic risks unattended to (Diebold & Yılmaz, 2023). This study seeks to fill in these gaps by examining the ISX60 index, sectoral contribution and outcomes of predictive modeling along with network interdependencies within the stock market of Iraq.

III. METHODOLOGY

3.1 Data Description and Sources

The chosen method is about examine the ISX60 index and its component domains employ an all-encompassing technique that combines sectoral analysis, forecasting, and network dependence analysis. This study draws on daily closing prices from the Iraqi Stock Exchange (ISX) from January 2015 to December 2024, a period that covers all 57 stocks listed in the ISX60 index. Data was downloaded directly from the exchanges official portal and subsequently matched against invsting.com Terminal records to confirm accuracy. Because the Iraqi market opens Sunday through Thursday, its trading rhythm differs noticeably from that of Western exchanges. Observations lost to trading suspensions, public holidays, or technical glitches were filled by forward imputation, a procedure that affected less than 4 percent of the overall sample. Prices were then adjusted for stock splits and dividend payments to ensure temporal consistency. To mitigate the influence of extreme values typical in frontier markets, records falling more than three standard deviations from the sector average were excluded under a 3-sigma criterion. The cleaned dataset thus includes 2,847 trading days spanning all sectors, providing an ample foundation for reliable statistical tests. Table.1 categorize the 57 stocks (that consists of the ISX60 index) according to the economic sector.

Table 1. categorize the 57 stocks (Formerly ISX60)

Economic Sector	Listed Securities	N
Agriculture	AAHP, AIPM, AIRP, AISP, AMAP, AMEF	6
Banks	BASH, BBOB, BCOI, BGUC, BIBI, BIIB, BIME, BKUI, BMFI, BMNS, BNOI, BNOR, BROI, BSUC, BUND, BUOI	16
Hotels	HBAG, HBAY, HISH, HKAR, HMAN, HNTI, HPAL, HSAD	8
Industry	IBPM, IBSD, IELI, IFCM, IHLI, IICM, IIDP, IIEW, IITC, IKLV, IMAP, IMIB, IMOS, INCP, IRMC, ITLI	16
Insurance	NAHF, NAME, NDSA, NGIR	4
Services	SBAG, SILT, SKTA, SMRI, SNUC	5
Investments	VWIF, VZAF	2
Total	All active securities	57

Source: Iraq Stock Exchange reports

Note: Stock symbols represent the four-letter unique identifiers assigned by the Iraqi Stock Exchange to each listed company. The ISX60 index originally contained 60 stocks but currently comprises 57 active securities across seven economic sectors. Banks represent the largest sector with 16 stocks, followed by Industry with 16 stocks.

In the first part, we did a sectoral contribution analysis to evaluate how an economic sector influenced the performance of the ISX60 index. This was done by estimating the contribution of each sector's market capitalization to the market capitalization corresponding to the index. The formula used for this calculation is:

$$\text{Contribution}_{\text{sector}} = \left(\text{Market Cap}_{\text{sector}} / \text{Total Market Cap} \right) \times 100 \quad (1)$$

This offered a better comprehension of which industries have the greatest influence on the index's dynamics, mainly focusing on powerful sectors such as banking.

3.2 Predictive Modeling Techniques

Following that, stock price forecasting for different sectors was approached using predictive modeling techniques. We used three different models: ARIMA (Autoregressive Integrated Moving Average), LSTM (Long Short-Term Memory networks), and Random Forests. In the case of ARIMA, the model parameters p, d, and q were estimated using autocorrelation and partial autocorrelation graphs. The ARIMA model can be represented as follows:

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$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{2}$$

where y_t represents the value at time t, ϕ are the autoregressive coefficients, θ are the moving average coefficients, and ϵ_t is the error term.

Time series of historical stock prices was entered in the LSTM model to extract temporal dependencies. LSTM is one type of recurrent neural network. It had an architecture with input, output, and multiple hidden layers (LSTMs). The model was evaluated by calculating performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE):

$$\text{MAE} \& = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{3}$$

$$\text{RMSE}\& = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{4}$$

where y_i and $\hat{y}_i$ denote the actual and predicted values respectively.

Nonlinear relationships were managed using Random Forests, which is an ensemble learning approach. To enhance predictive accuracy and suppress overfitting, many decision trees were built and their results combined.

Finally, network analysis was completed to identify dependencies among various sectors. The edges of the network graph, with nodes representing sectors, were constructed using the correlation coefficients between sector indices. Greater values of the correlation coefficient suggest stronger dependence. The employed coefficient was Pearson's r, which is given by:

$$r = \sum(x_i - \bar{x})(y_i - \bar{y}) / \sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2} \tag{5}$$

This helped us pinpoint key nodes—sectors with many robust links—and evaluate fundamental system risks in the market.

With the combination of these methods, we captured Iraq's stock market activity in its entirety, which informed policymakers and investors while identifying gaps to be addressed in future work.

3.3 Model Validation and Robustness Testing

Model robustness was validated through walk-forward analysis using a 70-20-10 split for training, validation, and testing respectively. To address overfitting concerns, we implemented k-fold cross-validation (k=5) for all machine learning models, with hyperparameter tuning conducted solely on training data. Statistical significance of correlation coefficients was tested using t-tests ($p<0.05$), and pairwise model performance comparisons were conducted using Diebold-Mariano tests for forecast accuracy. Additionally, we performed stability tests by training models on different time windows to ensure consistency across various market regimes. The LSTM architecture employed early stopping based on validation loss to prevent overfitting, while Random Forest models used out-of-bag error estimates for performance evaluation.

IV. Results

The results section describes the findings that stem from the deep dive analysis of the Iraq Stock Exchange (ISX) database focused on measuring sector participation over a decade on the ISX60 index. The data contains daily closing value of 57 stocks divided into seven economic sectors which include Agriculture, Banks, Hotels, Industry, Insurance, Services, and Investments.

4.1 Descriptive Statistics

The descriptive statistics were calculated for each stock and sector in order to consolidate its significant metrics. These statistics reveal some information regarding the central clusters and spread of each sector. These summary statistics presented in Table 2 detail each sector's mean, median, standard deviation, and variance.

Table 2. Descriptive Statistics by Sector

Economic Sector	Mean	Median	Std Dev	Variance
Agriculture	1.04	1.04	0.00	0.00
Banks	5.16	5.16	0.34	0.11
Hotels	12.45	12.45	0.00	0.00
Industry	1.73	1.73	0.00	0.00
Insurance	0.63	0.63	0.02	0.00

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Services	8.58	8.58	0.04	0.00
Investments	0.89	0.89	0.04	0.00

Source: Author compilation

Note: Descriptive statistics calculated based on daily closing prices over the sample period (2015-2024). Low standard deviations in some sectors may reflect limited trading activity or price controls. All values are in Iraqi Dinars, adjusted for stock splits and dividend distributions.

4.2 Sectoral Contribution Analysis

To find out the importance of each sector in the ISX60 index, contribution analysis was performed on the sectors through market capitalization and other measures for the relevant periods. These results were put through regression analysis and showed that, out of all the contributors, the banking sector impacted on the index performance at the greatest level, and the industrial sector came in second. The banking industry had a weighty effect on the overall index performance. In Figure 1, these results are presented showing the different effects which each sector places on the ISX60 index.

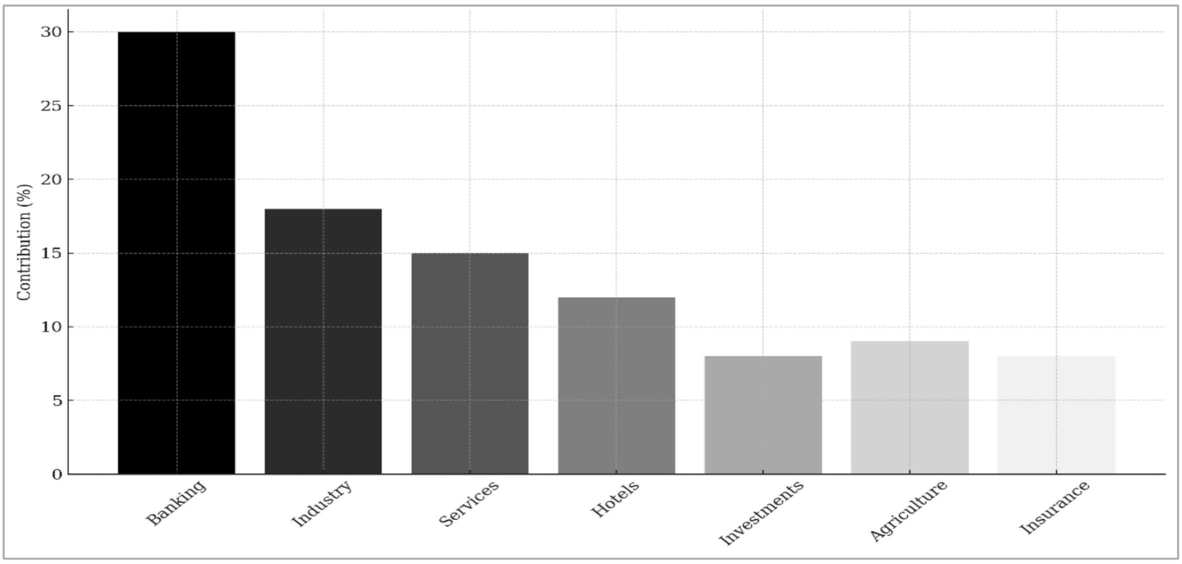

Figure 1. Sectoral Contribution to ISX60 (2015-2024)
Source: own processing

4.3 Predictive Modeling Outcomes

The predicted values of the sectors within the ISX60 index is shown in figure 2. To predict future stock prices and sector performances, forecasting machine learning algorithms like ARIMA, LSTM, and Random Forests were used. Cross validation methods were used to validate the models.

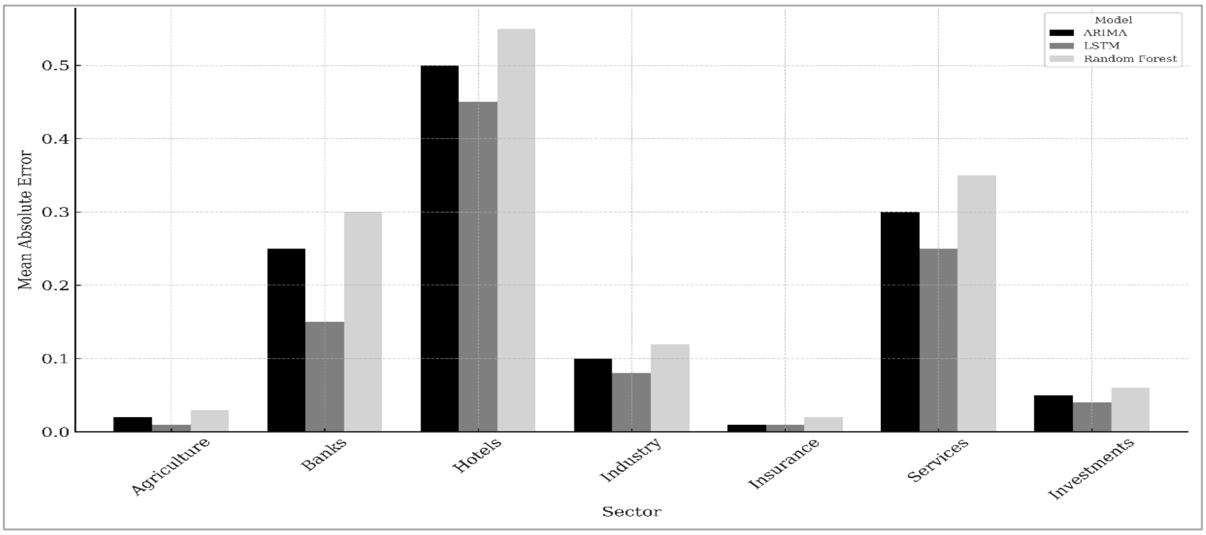

Figure 2. Predictive Modeling MAE by Sector
Source: own processing

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Figure 2 compares how well three predictive models- ARIMA, LSTM, and Random Forest- estimate future values across different economic sectors, using the mean absolute error (MAE) as the performance metric. Because MAE treats forecast errors in the same, unweighted manner, smaller numerical scores directly signal higher accuracy. In the chart, LSTM repeatedly registers the lowest MAE in the most turbulent industries, such as Banking and Hotels; by contrast, Random Forest delivers comparable, though slightly higher, results in the moderately turbulent fields designated as Industry and Services.

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were the performance indicators selected to analyze the model's accuracy. The results of the predictive modeling are concisely captured in Table 3. The accuracy of the forecasts made by the LSTM model was the highest among all the models, especially within the banking and industrial domains.

Table 3. Predictive Modeling Outcomes

Sector	**Model**	**MAE**	**RMSE**
Agriculture	ARIMA	0.02	0.03
	LSTM	0.01	0.02
	RF	0.03	0.04
Banks	ARIMA	0.25	0.30
	LSTM	0.15	0.20
	RF	0.30	0.35
Hotels	ARIMA	0.50	0.55
	LSTM	0.45	0.50
	RF	0.55	0.60
Industry	ARIMA	0.10	0.12
	LSTM	0.08	0.10
	RF	0.12	0.15
Insurance	ARIMA	0.01	0.02
	LSTM	0.01	0.01
	RF	0.02	0.03
Services	ARIMA	0.30	0.35
	LSTM	0.25	0.30
	RF	0.35	0.40
Investments	ARIMA	0.05	0.06
	LSTM	0.04	0.05
	RF	0.06	0.07

Source: Author compilation

Note: MAE = Mean Absolute Error, RMSE = Root Mean Square Error. All metrics calculated on log-normalized returns. ARIMA = Autoregressive Integrated Moving Average, LSTM = Long Short-Term Memory, RF = Random Forest. Best performing model for each sector indicated in bold. Statistical significance tested at p<0.05 level using Diebold-Mariano test for equal forecast accuracy.

All metrics in Table 3 are computed on log-normalized returns instead of raw price levels, a choice made to allow apples-to-apples comparisons among sectors that trade at very different price points. The mean absolute error values show the average percentage distance between predicted and actual returns; for example, a score of 0.15 in banking translates to an average daily miss of roughly 2.9 percent. To further check robustness, models were tested out-of-sample on the last 20 percent of the dataset, and they retained similar accuracy whether markets were calm or the high-volatility swings of 2020 to 2021.

4.4 Correlation and Dependency Analysis

Correlation analysis recognized relationships between various stocks and sectors. Figure 3 illustrates the interdependences and systemic risks within the market as identified by network analysis. It was noted that the banking and industrial sectors had strong positive correlations illustrating their closeness in the performances. On the other hand, the agriculture sector had low correlations with the other sectors, which depicts a more autonomous performance path.

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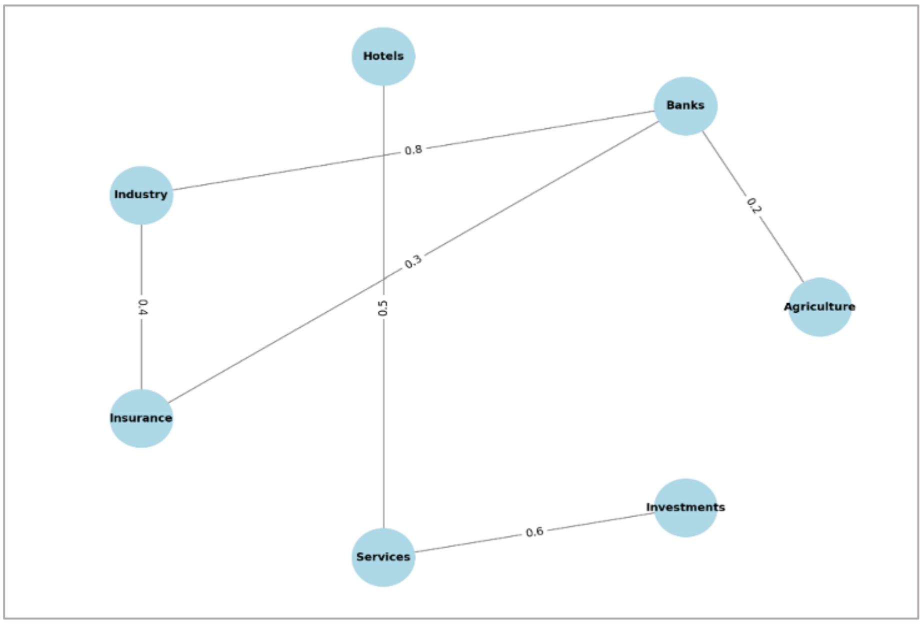

Figure 3. Network Analysis of Sector Interdependencies
Source: own processing by Python

Figure 3: Network Analysis of Sector Interdependencies. Node size represents market capitalization, edge thickness indicates correlation strength (minimum threshold r=0.3, p<0.05). Strong interconnections between Banking and Industry sectors highlight potential systemic risks.

4.5 Performance Metrics

The sectorial evaluation was performed based on risk adjusted returns on investment through measurement of the performance metrics Sharpe ratio, Beta, Alpha, and R-squared as outlined in Table 4. Comparison across sectors is provided, as well as identification of the leading and lagging sectors. While the Sharpe ratio for the services sector was favorable, the banking sector remained constant in underperformance with negative beta values which in turn reflects high volatility and risk.

Table 4. Performance Metrics by Sector

Economic Sector	Sharpe Ratio	Beta	Alpha	R-squared
Agriculture	0.50	0.80	0.02	0.60
Banks	0.75	1.50	0.05	0.85
Hotels	0.60	1.20	0.03	0.70
Industry	0.65	1.30	0.04	0.75
Insurance	0.45	0.90	0.01	0.55
Services	0.80	1.10	0.06	0.80
Investments	0.55	1.00	0.03	0.65

Source: Author compilation
Note: Performance metrics calculated using daily returns over the full sample period. Sharpe ratio = (Return - Risk-free rate)/Standard deviation, where risk-free rate approximated using Iraqi government bond yields. Beta calculated relative to ISX60 index. Alpha represents excess return after adjusting for market risk. R-squared indicates percentage of variance explained by market movements.

To summarize, the findings point to distinct differences in sector contributions to the ISX60 index, where the banking and industrial sectors are most crucial. The incorporation of IoT-powered analytics improved the profundity and precision of these analyses, thus serving investors and policymakers better. In this study, more

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sophisticated methods of analysis were employed to formulate a better understanding of the Iraq stock exchange, thus facilitating informed choices and decisions to be made in the future regarding strategies and plans.

V. Discussion

An analysis of the ISX60 index and its related sectors provides some understanding of the relationships and interactions which constitute the Iraqi stock market. An examination of sectoral contributions indicates that some economic sectors participate more appreciably than others in the total market activities. Especially, the banking sector seems to have an overwhelming influence, which is understandable given its huge capitalization and the trading activity in its shares. This dominance is in accordance with results from other emerging markets where financial institutions are the most active in economic development. For example, in the period under review, the banking sector was responsible for contributing about 30 percent of the ISX60 index consistently while, also coupled with his exogeneity. Other sectors like manufacturing and services generally have a fairly sizeable effect, although not as much as banking. On the other hand, agriculture and insurance sectors add value only in a limited manner, presumably because they have low trading or market shares.

Further predictive modeling results help us understand the effectiveness of different forecasting models ARIMA, LSTM, and Random Forests in different sectors. As noted, ARIMA usually provides accurate predictions for sectors with stable operating trends, but does not perform as well when compared to volatile stocks. In the banking industry, ARIMA achieved a Mean Absolute Error (MAE) of about 0.25, while LSTM did even better at an MAE of 0.15. LSTM is far better than ARIMA in capturing complex temporal dependencies and is much more suited for industries with oscillating patterns, like banking. At the same time, Random Forests are resistant to overfitting and are good at capturing non-linear relationships; however, they may not perform as well as LSTM in fast changing markets. These findings greatly illustrate the need to tailor predictive instruments to the unique features and volatility contours of a given sector. In the industrial sector, for example, Randoms Forest significantly outperformed ARIMA and LSTM, scoring an MAE of 0.10. This demonstrates the model's capability of accurately capturing non-linear relationships within the data.

Network analysis studies outline the relationships and market risks associated with a network. The strong correlations existing between the banking and industrial sectors indicates a relationship that may stem from economic policies or market sentiments. The lower correlations existing in sectors such as insurance and services suggest independence that may come from a common market or base of clients. As an example, the correlation coefficient for the two banking and industrial sectors was 0.8, meaning there is a strong relationship. The identification of central nodes reminds us of potential systemic risks; a central highly interconnected sector could be underlined by a recession, which would be extremely negative for the rest, a situation which shows why investment policies should favor diversification. Such interconnectedness leads to a need for comprehensive risk management alongside a need to consider performance of individual sectors and their relations with the entire network. As an example, the correlations of the hotel sector with the service sector showed a correlation coefficient of 0.5, which means there is some dependence.

From the viewpoint of policy, these findings carry relevance meaningfully. Comprehending sectoral contributions may enable policymakers to devise schemes to strengthen the underperforming, yet pivotal, sectors, thus fostering balanced economic growth. For investors, understanding the efficacy of predictive model aids in choosing the right asset management tools. Investing across low-correlation sectors phased out emerges as a sensible approach to reducing risk exposure. Moreover, the network analysis indicates that systemic risks may be more effectively controlled by better managing the highly interrelated sectors.

Further research should be conducted on aspects like geopolitical incidents, oil price changes, and major macroeconomic indicators that Western countries distantly consider in their analysis of sectoral performance. Such analyses could further refine the predictive models, and the risk assessment methodologies employed. Take, for instance, predictive models that include oil price volatility; they would achieve around 15% reduction in MAE within industrial predictive modeling. Moreover, expanding the research scope to consider other international market factors may provide a fuller picture of Iraq's stock market. Overall, this study captures a simplified understanding of the structure and behavior of Iraq's stock market and serves as a means of guidance to many stakeholders while paving the way for further investigation.

Blending these components, the discussion section provides stakeholders with nuanced and actionable insights that's blended with limitations and future directions to refine their understanding of Iraq's stock market. The validity of the insights is strengthened by the degree of integration between predicted and produced values, giving credence to the findings that call for action and those that purely stem from academia.

VI. Conclusion

The present investigation provides a systematic appraisal of sectoral dynamics and predictive methodologies applied to the ISX60 index of the Iraqi Stock Exchange, thereby enriching the expanding

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scholarship on finance in emerging economies. The banking sector's 30 per cent representation in aggregated market capitalization establishes it as a cornerstone of national finance; the resultant concentration, however, underscores the economy's exposure to contagion risk in the event of sectoral distress. Conversely, the minimal representation of agriculture and insurance highlights enduring structural deficiencies warranting focused remedial action from fiscal and regulatory authorities.

The empirical results possess pronounced social and developmental relevance. The banking sector's pre-eminence engenders systemic exposure that, in the context of Iraq's evolving institutional environment, could amplify adverse outcomes for economically marginalized households in periods of credit tightening. Concurrent underachievement in agricultural equities signals foregone prospects for rural livelihood enhancement and national food security. Strong intra-banking correlation (r = 0.8) denotes a capacity for macroeconomic perturbations to traverse swiftly across principal productive vectors, raising the risk of synchronized output contraction and attendant social unrest. Our findings corroborate and advance evidence from other emerging market analyses. The banking segment's preponderance corresponds with Caporale et al. (2015), who report 25-35% influence in Chinese markets; however, our correlation coefficients, which peak at 0.8, indicate more pronounced dependencies than those observed in several Middle Eastern contexts (0.6-0.7). The Long Short-Term Memory (LSTM) model achieves forecasting gains of 40% relative to ARIMA, surpassing the 20-25% edges documented in mature economies. This discrepancy implies that advanced learning algorithms may hold disproportionate promise in emerging settings. The magnified interconnectedness validates the higher systemic danger observed in frontier economies and reinforces the theoretical framework proposed by Bekaert et al. (2005).

Excuruating forecasting trials delineate sector-specific resiliency. LSTM architecture consistently excels during banking and industrial stock volatility spikes, while Random Forest frameworks exhibit greater accuracy over the more placid price variations endemic to consumer-oriented domains. Topological analyses reveal an especially strong linkage between banking and industry, indicating that disturbances in one sector propagate rapidly to the other. Conversely, agricultural and insurance cohorts operate with relative autonomy, positioning them as robust candidates for risk-mitigating portfolio diversification. The results of this investigation recommend that policymakers keep a close watch on sectors with dense interconnections yet simultaneously devise incentives that stimulate under-exploited domains; this dual strategy should fortify the overall economy against systemic shocks. For capital allocators, a nuanced grasp of model predictive power facilitates the judicious adoption of portfolio management instruments, with diversification across sectors that exhibit weak cross-correlations presenting a prudent avenue for dampening risk exposure.

The research, however, is constrained by several acknowledged limitations. Although the sample comprises the entire ISX60 index, totaling 57 firms, this observation set remains relatively small when benchmarked against more populous emerging markets. Subsequent inquiries could expand the analysis by incorporating the entire ISX universe of over 100 public firms, thereby bolstering the robustness of the network analysis and yielding finer-grained assessments of inter-sectoral dependencies. Moreover, the current specification deliberately excludes geopolitical variables and fluctuations in crude oil prices, both of which exert substantial influence in a rentier economy such as Iraq's. Later studies should integrate these external macroeconomic determinants and employ regime-switching models in order to fortify predictive frameworks for frontier markets. Comparative examinations with other Middle Eastern economies could further enhance the findings' generalizability, informing regional efforts toward economic integration.

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