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DATA ANALYSIS AND COMMUNITY DETECTION OF JUMP RISKS IN THE IRAQ STOCK EXCHANGE: A STUDY IN COMPLEX NETWORK PROPERTIES

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Abstract. Real-world financial systems exhibit non-random topological structures, making the identification of their network structures a fundamental step toward understanding market dynamics. This study addresses the limitations of traditional sector-based models by proposing a network-oriented framework for assessing the risk of systemic shocks in emerging markets. The methodology is based on network partitioning using community detection techniques. Firstly, the data were pre-processed by applying cleaning and standardization procedures to improve data quality before constructing the financial network. The network is constructed from the correlation matrix of the analyzed data by applying an appropriate threshold value to determine links between companies and identify the resulting network connections. Afterward, a community detection algorithm, specifically the Louvain method, is applied to identify clusters of companies. This method, which is based on modularity optimization to detect groups of strongly interconnected assets, is applied to a network of 88 actively traded companies. The experimental results show that this approach successfully identifies five financial communities comprising a mix of diverse sectors that differ radically from the official market segmentation through the analysis of the participation coefficient and the correlation Z-score. Also, 11 companies were classified as "bridges" that strengthen market cohesion, compared to 77 companies classified as "pillars of stability." Two economic realities appeared accordingly: First, the absence of a dominant sector that consistently drives prices; second, the market's structural flexibility and resilience, meaning that a collapse of a specific sector does not necessarily lead to the collapse of the entire market.

2020 Mathematics Subject Classification. 62H20; 62P20.

Key words and phrases. community detection; Louvain algorithm; modularity; jump risks; Iraq stock exchange (ISX).

1. Introduction

Given the increasing complexity of networks within the global financial system, traditional methods such as the arithmetic mean and simple standard deviation are no longer sufficient to understand the

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links between entities [1], in their previous studies, researchers analyzed macroeconomic variables and financial risks in Arab markets, including the Iraq Stock Exchange(ISX) [2], the Amman Stock Exchange (ASE) [3], the Egyptian Stock Exchange (EGX) [4], and the UAE Financial Market [5,6]. Basic research has also shown that financial markets function as complex systems, and modeling them as networks provides a deeper and more accurate understanding of their internal structure [7]. Therefore, these simple, traditional methods are no longer sufficient to understand the increasing complexity of systems over time [8].

With this in mind, we conducted a more advanced study of financial market data modeling, which helped us build an accurate financial network using modern tools and the Louvin algorithm, which is highly effective at detecting communities and handling redundant data in large network structures. On the other hand, some previous studies have relied on graphs filtered using the (PMFG) technique to understand topological structures [9,10].

On the other hand, we find that investment diversification—particularly in financial markets—is considered one of the alternatives for building long-term wealth without relying on oil. However, many individuals and investors in various countries remain hesitant to invest in stocks [11], largely because they believe the market is fraught with risks and they cannot afford to risk their money [12]. This is the main motivation behind this research, which addresses a research gap that involves meeting the actual need for more advanced analytical tools such as graph theory in modeling financial market networks and subsequently analyzing them using clustering techniques that segment the market based on similarity, Use of a standardized metric to measure the quality of the resulting communities' partitioning monitors systemic risk channels, which ultimately protects the market from the possibility of financial contagion or market shocks.

2. Literature Review

Recent research has demonstrated the effectiveness of computational models in tracking fluctuations in the Iraqi stock market, confirming their superiority over traditional linear models [13]. On the other hand, models based on graph theory have significantly improved the accuracy and efficiency of network analysis and data distribution [14]. Many studies emphasizing that previous studies have not explored the possibility of using these techniques to identify relationships between companies in the Iraqi stock market [2,15], which explains our need to apply different algorithms in this field, as confirmed by [16], which concluded that there is no single algorithm that can be considered ideal for all cases, highlighting the importance of selecting the algorithm most suitable for the nature of the data. On the other hand, in our current study, we take network analysis a step further by employing a topological metric that incorporates z-score and the participation coefficient to identify jump points [17], in contrast to previous studies that used price volatility to detect jumps [18]. In this study, we applied the community detection technique to demonstrate that entities within the financial network function as interconnected communities rather than isolated units, thereby revealing the deep structural patterns that drive the market network and identifying how financial contagion spreads.

3. Empirical Case Study

We used information from the Iraq Stock Exchange for this investigation [19]. This was obtained officially through a letter of cooperation from the Department of Mathematics at the College of Applied Sciences, Baghdad University of Technology, written to the Securities Commission, in order to carry out an empirical and analytical investigation. The data we obtained included 91 companies listed on the stock market. After reviewing and examining the data, we retained a sample of 88 active companies for the study and excluded companies with incomplete trading records. To be precise in describing the annual data, we clarify that it consists of an Excel file with columns representing opening price, high, low, current price, closing price, previous closing price, change%, number of shares, trading value, and number of trading days. The rows consist of companies representing the market's actual sectors, such as the banking sector, the industrial sector, the agricultural sector, and others.

4. Methodology

To address the challenge of identifying hidden patterns in the structure of the Iraqi Stock Exchange, we adopted a network-based approach [18], which consists of four main steps that we implemented in MATLAB.In the first step, we imported the data from the Excel file to process it by removing missing values to clean up the table fully. We then extracted the net numerical data by expanding the columns from 3 to 13, and to ensure data consistency, we applied a standardization process [20]. In the second step, we calculated the correlation matrix from the standardized data [7]. Next, we move on to the third step, in which we transform the relationships into a clear, well-defined network by setting the threshold at 0.7. We then convert the correlation matrix into a network of binary connections (0 or 1) to represent the adjacency matrix. If the correlation value is less than the threshold, we assign a value of 0, which means excluding weak links; if the correlation value is greater than the threshold, we assign a value of 1 [21]. In the fourth and final step, we converted the binary adjacency matrix into a graph representing the financial network of the Iraqi market, for which we had been using raw data from the outset. After following these carefully considered steps, we applied the "Louvain algorithm " to extract the deep structure of the network [22], preparing22 it for network analysis, as explained in the Results section.

4.1. **Network Construction.**

Let $\mathbf{v}_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,m}]$ be a feature vector representing the m normalized trading characteristics of company i. The similarity matrix $\mathbf{M}$ is constructed where each element M_{jk} represents the Pearson correlation coefficient between the trading characteristics of company j

and company k, calculated as:

$$M_{jk} = \rho_{jk} = \frac{\sum_{p=1}^{m}(x_{j,p} - \bar{x}_j)(x_{k,p} - \bar{x}_k)}{\sqrt{\sum_{p=1}^{m}(x_{j,p} - \bar{x}_j)^2 \sum_{p=1}^{m}(x_{k,p} - \bar{x}_k)^2}} \tag{1}$$

where:

- m: The total number of trading characteristics.
- $p = 1, \ldots, m$: The index representing each specific trading characteristic.
- $x_{j,p}$ and $x_{k,p}$: The normalized values of the p-th characteristic for companies j and k.
- $\bar{x}_j = \frac{1}{m}\sum_{p=1}^{m} x_{j,p}$: The mean of all trading characteristics for company j.

We begin by calculating the similarity matrix ($\mathbf{M}$) based on Pearson's correlation coefficient. Next, we apply a thresholding process to convert it into an adjacency matrix, which in turn serves as input to the Louvain algorithm, which functions as a greedy optimization technique for detecting communities within complex financial networks [23].

4.2. **Community Detection.** Community detection is a useful tool for understanding complex networks, as it can identify groups of nodes or clusters and reveal hidden patterns in network structures. In recent years, The importance of community detection has become increasingly evident, particularly in the field of network analysis [21]. Various methodologies based on the concept of modularity have been developed to process and analyze large-scale networks [24]. Since the problem of achieving optimal modularity is statistically classified as NP-hard—a problem that is difficult to solve algorithmically in large networks— studies have shifted toward adopting approximate solutions based on greedy search strategies, leading to more modern algorithms that employ semi-deterministic programming techniques to ensure higher accuracy in the results. As outlined in our network Construction steps The threshold of 0.7 was determined based on a comparative analysis of the values that accurately filter the network. This threshold was chosen because it yields a more robust structure for the communities, with a high modularity value relative to its counterparts. A detailed explanation of the methodology used to select this threshold, along with a comparison of modularity values across different levels in Table 1 under the Results section. This process transforms the correlation matrix from mere raw numbers into an interconnected network. By running the Louvain algorithm, the algorithm improves local modularity by moving individual nodes to neighboring communities to maximize the increase in modularity (Q). The algorithm then aggregates the network by merging communities into "super-nodes," creating a new, smaller network. This process is repeated using MATLAB until the optimal partition is reached and the modularity (Q) is maximized at 0.3787 [25], ensuring the most accurate final partition of communities within the Iraq Stock Exchange network. The value of Modularity is calculated according to the following formula [26]:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \tag{2}$$

where Q is the modularity value that measures the network in terms of communities,m represents the total number of links in the network A_{ij} is an adjacency matrix where the value is 1 if there is an edge between node i and node j based on a threshold of 0.7, and 0 otherwise. k_i, k_j represent the degrees of the two nodes i, j respectively, $\delta(c_i, c_j)$ is the Kronecker delta function, which equals 1 if nodes i and j belong to the same set $(c_i = c_j)$, and equals 0 if they belong to different sets. The results consist of two stages: first, community detection and the calculation of modularity; second, the use of cartographic maps to classify the topological roles of companies and identify the market's systemic jump points. The methodology is systematically applied and implemented from the initial data collection stage through network analysis and economic interpretation, as illustrated in Figure 1.

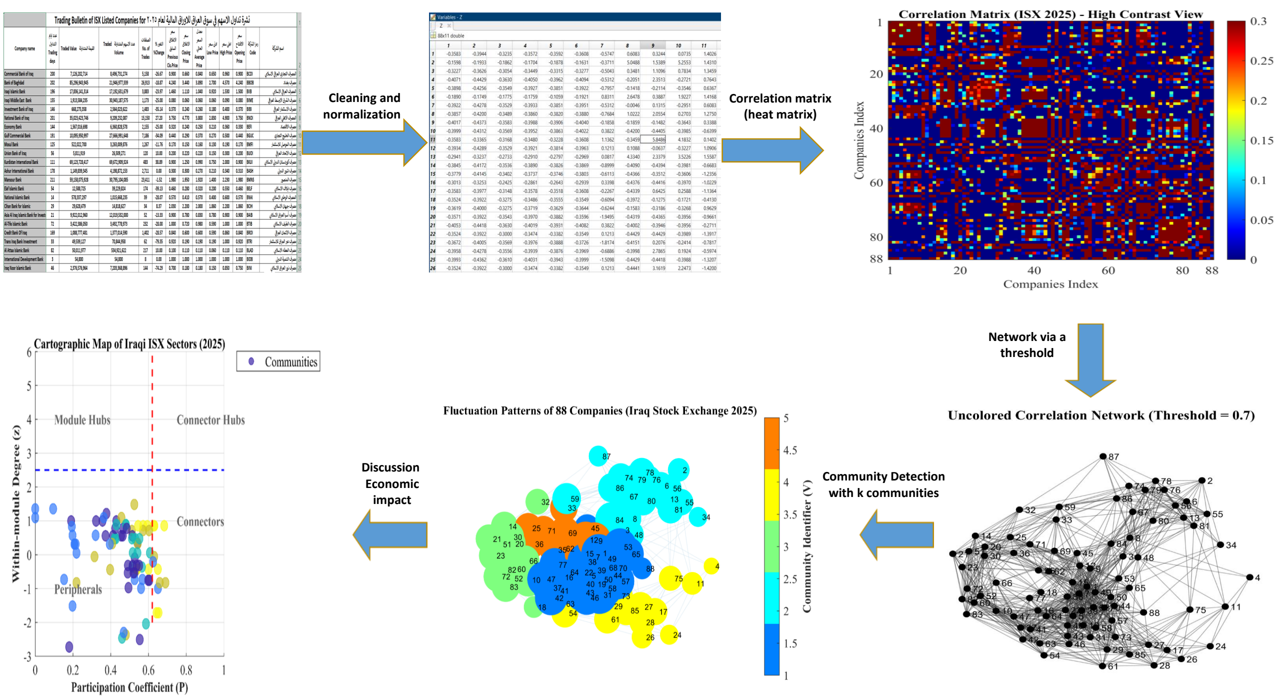


FIGURE 1. A workflow that includes data standardization, network construction, community detection using the Louvain method, and topological analysis of systematic jump points.

4.3. **Louvain algorithm.** Given the structural framework of the Iraq Stock Exchange (ISX), functionally, we applied this algorithm [22] to construct the network through two iterative steps: first, we treat each company as a separate community; then, we test the algorithm to see if moving a company to a neighboring community increases the network's modularity. If the result improves, the move is accepted, and this optimization continues until we reach a stage where modularity cannot be further increased. Afterward, these discovered communities are merged into larger super-nodes, and the process begins again with the two-step procedure on this new, smaller network. When the network reaches its highest level of stability, the process stops, and the best modularity value and partition quality are recorded.

4.4. **Cartographic Mapping and Jump Points.** After defining the network structure of the market sample, we move beyond that by employing the cartographic mapping technique in this study to classify the distinctive topological role of each company and then assess the interaction and dynamics among the company's internal links (i.e., within a single community) and their external extensions (i.e., across different communities). Following the community screening process and the identification of the five communities, our methodology classifies the roles of the contract within the market framework using two key metrics. The participation coefficient (PC) and the Z-score (correlation coefficient) within the unit reflect the strength of the connections between a specific node (i) and the rest of its local communities. The mathematical relationship for these metrics, established by Guimera and Amaral [27], can be defined as follows:

$$z_i = \frac{\kappa_i - \bar{\kappa}_{s_i}}{\sigma_{\kappa_{s_i}}} \tag{3}$$

where z_i represents the standard score of a node (company); that is, this metric measures the strength of a node's connections to other nodes within its community and statistically indicates how far the number of a node's connections deviates from the community's average. The number κ_i represents the number of actual connections this company has with other companies within its community. Specifically, $\bar{\kappa}_{s_i}$ is the average of all companies' connections within this community, and $\sigma_{\kappa_{s_i}}$ is the standard deviation of corporate linkages in this community. The participation coefficient P_i quantifies the distribution of a node's links across different communities and can be defined as:

$$P_i = 1 - \sum_{s=1}^{N_M} \left(\frac{\kappa_{is}}{k_i} \right)^2 \tag{4}$$

In this context, k_i represents the overall degree of node i, while κ_{is} denotes the specific number of edges connecting the node i to other nodes within community s. Consequently, we classify nodes exhibiting simultaneously high values of both P_i and z_i as "Systemic Jump Points." These particular companies serve as the main conduits for the dissemination of market liquidity and the transmission of systemic hazards inside our structural framework [28]. Practically speaking, we separate the companies in the top percentile of participation coefficient scores. Then, these particular nodes are identified as important systemic leap points, necessitating the more in-depth economic analysis that we provide in Section 5.

5. Results and Discussion

In this area, we will concentrate on the useful outcomes of the network analysis for our study, building on the mathematical foundation we developed in the preceding section. We will thoroughly study how these organizations form coherent networks and track the transmission of systemic hazards among them, rather than merely giving statistical results.

5.1. **Topological Architecture and Community Detection.** A visual depiction of this topological structure is shown in Figure 2, which is based on the community recognition algorithm's findings, which revealed 5 significant communities at the correlation threshold of $T = 0.7$. In order to make market dynamics and inter-sectoral interconnections easier to understand, the statistically inferred communities are shown as discrete colored clusters.

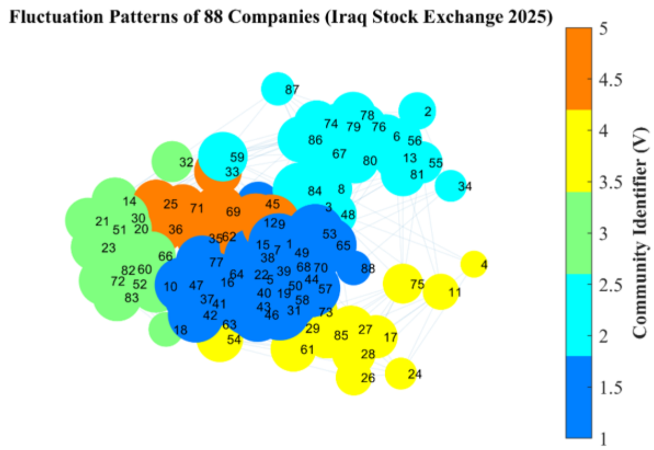


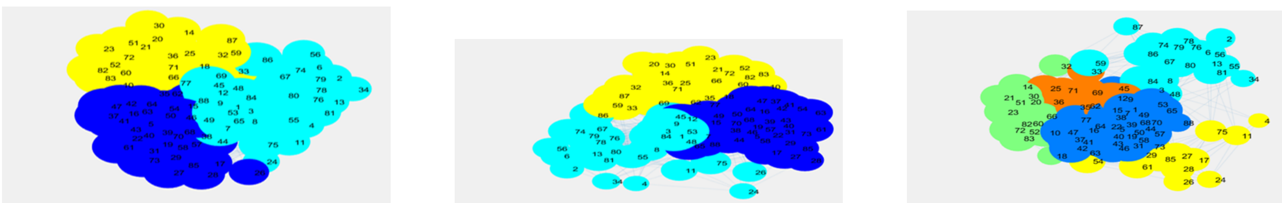
Figure 2. The ISX community detection network shows 5 communities at threshold $T = 0.7$..

The network architecture can be examined to reveal the following structural features:

- **Node Identification and Topology:** A single listed corporation is represented by each node. Precise structural tracking within the larger market network is made possible by the inscribed sequence number, which matches the company's identifier in the original dataset.
- **Synchronization and Cluster Formation:** The color scale shows how the market is clearly divided into five main communities. Businesses with comparable price volatility and synchronized performance are put together in the same color-coded cluster, Highlighting Strong Connections [29].
- **Hub Intersections and Structural Proximity:** The significant association between these enterprises is directly reflected in the structural proximity of the communities and the obvious spatial clustering of the company nodes. Additionally, the presence of pivotal (hub) companies

that simultaneously influence and are influenced by multiple sectors—like Modern Sewing ($P_i = 0.6900$) and The Light Industries ($P_i = 0.6834$), which have the highest participation coefficients—is what drives the dense overlap at the network's core [**?**].

The results indicated that lower thresholds, $T = 0.5$, $T = 0.6$, retained weak correlations—which could be termed "market noise"—leading to low standardization values. In contrast, applying the $T = 0.7$ threshold filtered out those weak correlations, yielding the highest typicality value and dividing the market into 5 communities; see figure 3. The figure visually confirms this topological development, demonstrating that $T = 0.7$ is the optimal threshold for the analysis in this study. It should be noted that when the value T becomes greater than 0.7, there will be more isolated nodes, which, unfortunately, will reduce the number of companies being analyzed.



(A) $T = 0.5$ (B) $T = 0.6$ (C) $T = 0.7$

FIGURE 3. Topological evolution of the ISX financial network and community detection results at different thresholds.

As indicated in Table 1, the standardization coefficient Q was assessed using different correlation criteria to support the selected network design.

TABLE 1. Comparison of Modularity values (Q) across different thresholds.

Threshold	**Number of communities**	**Modularity (Q)**
0.5	3	0.2527
0.6	3	0.3142
0.7	**5**	**0.3787**

5.2. **Strategic Role Analysis of Connector Companies.** Based on the results presented in Table 2, the 11 companies identified using the participation coefficient are grouped into a central structural role. This selection is consistent with the methodology established by Guimerà and Amaral (2005) whereby companies with a participation coefficient exceeding 0.62 are classified as connecting companies that act as bridges linking different communities, rather than local companies. These results indicate that these companies contribute significantly to strengthening market cohesion and reducing the risk of isolation between communities. Our findings regarding firms that act as bridges are consistent with the arguments put forward by [31] regarding the role of inter-linkages in maintaining the cohesion of the financial network and reducing fragmentation across communities. The structural relationships between various communities are also highlighted by locating these related enterprises on the Iraqi stock exchange. As a result, certain agreements like those with Kharkh Tour Amusement City, Iraqi Engineering Works, and United Bank for Investment Regardless of the sectors to which these contracts belong—sectors that do not seem to be visibly associated in the XIS index—the channels described in Table 2 are important means of disseminating financial shocks and market information.

5.3. **Identification of Systemic Jump Points.** Several businesses are situated at the core of the Iraqi market network, where they serve as "systemic jump points," according to an analysis of the structural features shown in Table 2. We were able to discover five main hubs through our data research, which we have highlighted in light blue in the table to underline their outstanding position in the market. These five businesses are significant since they have the greatest "participation coefficients" (P_i). To put it another way, they function as essential, direct links between different financial communities and clusters that would otherwise be isolated from one another rather than as isolated entities [27]. They are given the status of "connec27tors" in this capacity, serving as the pillars that guarantee the seamless operation of the Iraqi securities market. We can see how these entities stand out as high-traffic nodes by looking at the topological map in Figure 4. This tactical placement shows that the market network's overall resilience depends solely on these five nodes. [32].This interpretation is entirely in line with contemporary applications of complex network analysis, particularly "modularity optimization" techniques, which highlight a crucial idea: the presence of these strategic nodes serves as the market's first line of defense against the possibility of fragmentation and serious structural disintegration. [33].

Table 2. ISX Network Analysis: Strategic Roles of Companies (Connectors)

Community	**Company Name**	**Participation** (P_i)	(z_i) **score**
5	United Bank For Investment	0.6531	-1.7127
5	Al-Khatem Telecoms	0.6314	-0.42817
5	Kharkh Tour Amusement City	0.6429	-0.82495
5	Al-Ameen Estate Investment	0.6496	-0.99129
4	Modern Sewing	0.6900	0.85635
2	Iraqi Engineering Works	0.6503	-0.82495
5	Iraqi Carton Manufacturies	0.6276	0.85635
4	Ready Made Clothes	0.6598	-0.82495
5	The Light Industries	0.6834	0.85635
4	Ishtar Hotels	0.6302	-0.054997
2	Middle East for Production-Fish	0.6244	-0.20869

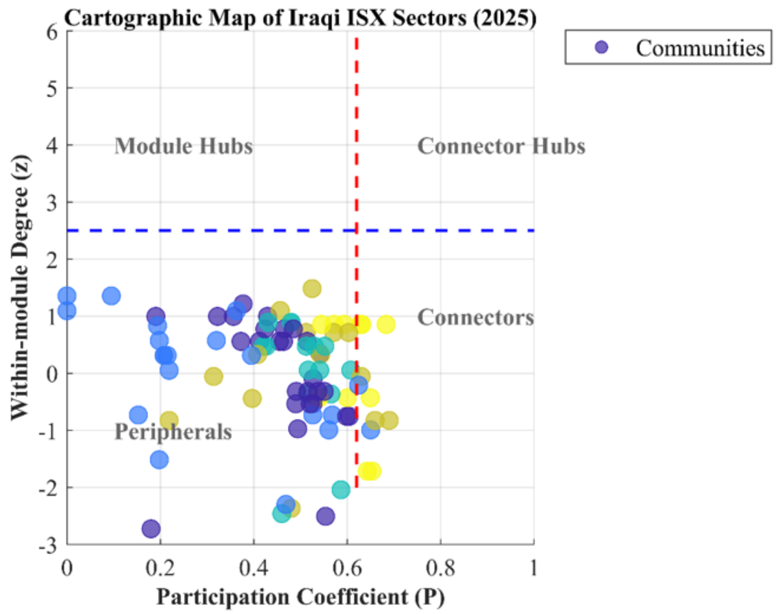


FIGURE 4. Cartographic Map of Iraqi ISX Sectors (2025)

5.4. **Economic Implications of Network Topology.** We consult Table 2 once more to analyze the node metrics in conjunction with the overall image depicted in Figure 4 in order to fully comprehend and elucidate the economic consequences of the ISX network structure. Given their comparatively low ratings inside the unit (z_i), the 11 strategic enterprises that were identified do not necessarily reflect typical "whales" or industry leaders. Instead, they become market-wide financial sensors and liquidity intermediates due to their extraordinarily large participation coefficients (P_i). Because these businesses operate in a variety of industries, such as banking, telecommunications, and manufacturing, they avoid capital stagnation, which is the buildup of money within a single industry, and they guarantee that money flows freely throughout the whole stock market (for instance, if a particular company files for bankruptcy, a rumor spreads, or a stock crashes, the contagion of losses will spread across all sectors). This dynamic, which includes all five identified groups, is clearly confirmed by the cartographic map. The remaining 77 enterprises, however, are concentrated in the "peripheral" zone, which means that their financial shocks or local crises will not disrupt the broader market—the identified strategic companies occupy the critical "linkages" zone. They act as crucial entry points for the flow of money. More significantly, the map shows that businesses are conspicuously absent from the higher "connection hubs" zone. This is a very favorable structural feature from an economic standpoint since it shows that there isn't just one monopolistic company controlling the Iraqi stock market. Additionally, from the standpoint of behavioral finance, these pivot points are essential for reducing herd behavior and improving the long-term stability of the structure of the Iraqi stock exchange. Recent complex network analyses in emerging markets, which show that structural topology is essential for measuring market stability and managing the spread of herd behavior, are highly consistent with this empirical conclusion. [34,35].

6. Conclusion

In summary, this work demonstrates that five interconnected communities may be identified by applying community detection approaches to data from the Iraq Stock Exchange (ISX), particularly by measuring partition quality using the Louvain algorithm. The ISX official sectoral classification is very different from that of the Community. Additionally, 11 important hub enterprises were successfully founded by merging this algorithm with cartographic mapping. These businesses are structurally important even though they aren't often market titans.

The five with the greatest participation coefficients serve as crucial "gateways," channeling liquidity, preventing market fragmentation, and absorbing cross-sectoral financial shocks. This study adds value by proving that the ISX has structural immunity to monopolies. The significant lack of strong "Connector Hubs" inherently discourages investors from participating in homogeneous "herd behavior," reducing the possibility of a complete market collapse in times of crisis. In practice, this topological analysis provides investors with a data-driven roadmap for building structurally balanced portfolios and acts as an "early warning system" for regulatory bodies to prevent systemic bottlenecks.

Future research must overcome these constraints because this analysis is limited to a static structural picture of 88 listed businesses for the fiscal year 2025. We strongly advise switching to the analysis of "dynamic networks" employing longitudinal data collected over a number of years. In the end, a better understanding of overall market stability will be obtained by monitoring these structural changes during several economic cycles and applying this comparison model to other developing regional financial markets.

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References

[1] L. Enriques, A. Romano, T. Wetzer, Network-Sensitive Financial Regulation, European Corporate Governance Institute (ECGI) - Law Working Paper No. 451/2019, https://ssrn.com/abstract=3387708.

[2] B.S. Mahdi, A. Almahdwi, J. Hattem, Iraqi Stock Market Structure Analysis Based on Minimum Spanning Tree, in: AIP Conference Proceedings, AIP Publishing, 2023, pp. 040083. https://doi.org/10.1063/5.0114925.

[3] H.A. Abdoh, Correlation Based Clustering of the Amman Stock Exchange, Int. J. Econ. Financ. Issues 7 (2017), 259–265.

[4] S.M.M.M. Saleh, The Impact of Applying Machine Learning Algorithms on Predicting Stock Price Trends: An Empirical Study of Companies Listed on the Egyptian Stock Exchange, J. Adm. Financ. Quant. Res. 5 (2025), 3–46.

[5] J.M. Dempere, The Impact of the United Arab Emirates' Macroeconomic Variables on Emirati Stock Market Indexes, Int. J. Bus. Perform. Manag. 20 (2019), 330–355. https://doi.org/10.1504/ijbpm.2019.105249.

[6] M.S. Oudat, B.J. Ali, S. Abdelhay, H.M. Hazaimeh, M.S.R. Altalay, A. Marie, M. El-Bannany, The Effect of Financial Risks on the Performance of Islamic and Commercial Banks in UAE, Front. Appl. Math. Stat. 9 (2024), 1250227. https://doi.org/10.3389/fams.2023.1250227.

[7] R.N. Mantegna, Hierarchical Structure in Financial Markets, Eur. Phys. J. B 11 (1999), 193–197. https://doi.org/10.1007/s100510050929.

[8] F.X. Diebold, K. Yılmaz, On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms, J. Econom. 182 (2014), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012.

[9] M. Tumminello, T. Aste, T. Di Matteo, R.N. Mantegna, A Tool for Filtering Information in Complex Systems, in: Proceedings of the National Academy of Sciences, National Academy of Sciences, 2005, pp. 10421–10426. https://doi.org/10.1073/pnas.0500298102.

[10] M. Tumminello, T. Di Matteo, T. Aste, R.N. Mantegna, Correlation Based Networks of Equity Returns Sampled at Different Time Horizons, Eur. Phys. J. B 55 (2007), 209–217. https://doi.org/10.1140/epjb/e2006-00414-4.

[11] B.A. Jasim, H. Chaibi, Market Risk Disclosure and Investor Behavior in the Iraq Stock Exchange, J. Account. Sci. 10 (2026), 1–15. https://doi.org/10.21070/jas.v10i1.2045.

[12] M. Billio, M. Getmansky, A.W. Lo, L. Pelizzon, Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors, J. Financ. Econ. 104 (2012), 535–559. https://doi.org/10.1016/j.jfineco.2011.12.010.

[13] Q.A.A.T.G. Al-Jubouri, Comparison of ARIMA, ANN, and PMRS Forecasting for the Iraq Stock Exchange, University of Mosul, College of Computer Sciences and Mathematics, 2012.

[14] S.S. Samaan, H.A. Jeiad, A Survey of Graph Techniques Applied in Software Defined Networking, Iraqi J. Comput. Commun. Control Syst. Eng. 23 (2023), 115–124. https://doi.org/10.33103/uot.ijccce.23.3.10.

[15] J. Kaehler, C.S. Weber, H.S.-D. Aref, The Iraqi Stock Market: Development and Determinants, Rev. Middle East Econ. Financ. 10 (2014), 151–175. https://doi.org/10.1515/rmeef-2013-0053.

[16] K.A. Salman, H.K. Khafaji, Arabic Document Clustering: A Survey, in: 2022 4th International Conference on Current Research in Engineering and Science Applications (ICCRESA), IEEE, 2022, pp. 59–64. https://doi.org/10.1109/iccresa57091.2022.10352511.

[17] S. Saha, J. Gao, R. Gerlach, A Survey of the Application of Graph-Based Approaches in Stock Market Analysis and Prediction, Int. J. Data Sci. Anal. 14 (2022), 1–15. https://doi.org/10.1007/s41060-021-00306-9.

[18] D. Kitanovski, I. Mishkovski, V. Stojkoski, M. Mirchev, Network-Based Diversification of Stock and Cryptocurrency Portfolios, Appl. Netw. Sci. 10 (2025), 20. https://doi.org/10.1007/s41109-025-00708-9.

[19] Iraq Stock Exchange, Annual Trading Data and Market Reports for Listed Companies 2025, Iraq Stock Exchange, 2026. https://www.isx-iq.net.

[20] J. Han, M. Kamber, Data Mining: Concepts and Techniques, Morgan Kaufmann, San Francisco, 2006.

[21] M. Newman, Networks, Oxford University Press, Oxford, 2018. https://doi.org/10.1093/oso/9780198805090.001.0001.

[22] V.D. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, Fast Unfolding of Communities in Large Networks, J. Stat. Mech. 2008 (2008), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008.

[23] G.S. Konstantinov, A. Sadeghi, Unsupervised Learning II: Network Theory, in: AI in Asset Management: Tools, Applications, and Frontiers, CFA Institute, pp. 15–39, (2025). https://doi.org/10.56227/25.1.37.

[24] S.F. Ibraheem, B. Al-Sarray, A Review of Community Detection Based on Modularity Optimization in Complex Networks, Iraqi J. Sci. 65 (2024), 2775–2793. https://doi.org/10.24996/ijs.2024.65.5.34.

[25] M. Chen, K. Kuzmin, B.K. Szymanski, Community Detection via Maximization of Modularity and Its Variants, IEEE Trans. Comput. Soc. Syst. 1 (2014), 46–65. https://doi.org/10.1109/tcss.2014.2307458.

[26] M.E.J. Newman, Modularity and Community Structure in Networks, in: Proceedings of the National Academy of Sciences, National Academy of Sciences, 2006, pp. 8577–8582. https://doi.org/10.1073/pnas.0601602103.

[27] R. Guimerà, L.A.N. Amaral, Cartography of Complex Networks: Modules and Universal Roles, J. Stat. Mech. 2005 (2005), P02001. https://doi.org/10.1088/1742-5468/2005/02/p02001.

[28] A.K.C. Rusli, F.F. Said, Z.A. Karim, M.R. Yaakub, Federal Reserve Policy and Systemic Risk Spillovers: A Minimum Spanning Tree (MST) Analysis of Bank Credit Default Swap (CDS), with a Focus on United States of America Banks within the Global Network, J. Ekon. Malays. 59 (2025), 137–149. https://doi.org/10.17576/jem-2025-5903-10.

[29] B. Bhattacharjee, M. Maiti, A Study on the Topological Insights and Network Visualization Mapping of the Indian Equity Market, Risks 13 (2025), 76. https://doi.org/10.3390/risks13040076.

[30] D. Siudak, The Dependency Structure of the Financial Multiplex Network Model: New Evidence from the Cross-Correlation of Idiosyncratic Returns, Volatility, and Trading Volume, PLOS ONE 20 (2025), e0320799. https://doi.org/10.1371/journal.pone.0320799.

[31] R. Casarin, M. Costola, E. Yenerdag, Financial Bridges and Network Communities, SSRN (2018). https://doi.org/10.2139/ssrn.3178053.

[32] S. Battiston, M. Puliga, R. Kaushik, P. Tasca, G. Caldarelli, DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk, Sci. Rep. 2 (2012), 541. https://doi.org/10.1038/srep00541.

[33] J.-P. Onnela, D.J. Fenn, S. Reid, M.A. Porter, P.J. Mucha, M.D. Fricker, N.S. Jones, Taxonomies of Networks from Community Structure, Phys. Rev. E 86 (2012), 036104. https://doi.org/10.1103/PhysRevE.86.036104.

[34] Y. Shi, Y. Zheng, K. Guo, X. Ren, Relationship between Herd Behavior and Chinese Stock Market Fluctuations during a Bullish Period Based on Complex Networks, Int. J. Inf. Technol. Decis. Mak. 21 (2022), 405–421. https://doi.org/10.1142/s0219622021400010.

[35] Z. Wang, G. Zhang, X. Ma, R. Wang, Study on the Stability of Complex Networks in the Stock Markets of Key Industries in China, Entropy 26 (2024), 569. https://doi.org/10.3390/e26070569.