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Financial Complexity: A Comparison Study of Türkiye, Iran, Saudi Arabia and the UAE

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Finansal Karmaşıklık: Türkiye, İran, Suudi Arabistan ve BAE Üzerine Karşılaştırmalı Bir Çalışma

Abstract

Over the last few decades, the global financial network has become increasingly complex due to the rapid growth in science and technology, as well as the expanding number of financial instruments worldwide. In this setting, several issues and problems arose, including the rising systemic risk in the financial sector, which in turn increased the sector's vulnerability. In emerging markets, such as Türkiye, Iran, Saudi Arabia, and the UAE, the potential risk may arise due to the financial complexity of these markets. Therefore, the probability of crises will increase. This study investigated the complexity of financial systems in these countries using McCabe’s network approach from 2005 to 2020. Measuring complexity indicates that Türkiye, with a score of 95, Iran (77), Saudi Arabia (49), and the UAE (36) have been graded in terms of financial complexity. As a result, Türkiye has the highest, and the UAE has the lowest systemic risk among these countries. Additionally, the results suggest that capital markets do not play a significant role in these economies.

Keywords : Financial Complexity, McCabe’s Complexity, Türkiye, Iran, Saudi Arabia, United Arab Emirates.

JEL Classification Codes : C58, C63, C45.

Öz

Son yıllarda, bilim ve teknolojideki hızlı büyüme ve artan sayıdaki finansal araçlar nedeniyle küresel finansal ağ daha karmaşık bir hale gelmiştir. Bu durum finans sektöründe sistemik riskin artması ve dolayısıyla bu sektörün daha fazla kırılgan hale gelmesi gibi bazı sorunları beraberinde getirmiştir. Türkiye, İran, Suudi Arabistan ve BAE gibi gelişmekte olan piyasalarda, bu tür piyasaların finansal karmaşıklığı nedeniyle olası riskler ortaya çıkabilir. Bu bağlamda kriz olasılığı artabilir. Bu çalışmada, 2005-2020 yılları arasında McCabe’nin karmaşıklık ölçütü kullanılarak bu 4 ülkedeki finansal sistemlerin karmaşıklığı araştırılmıştır. Araştırma sonucuna göre, 95 ile Türkiye, 77 ile İran, 49 ile Suudi Arabistan ve 36 ile BAE finansal karmaşıklık açısından derecelendirilmiştir. Türkiye en yüksek, BAE ise en düşük sistemsel riske sahiptir; sermaye piyasasının incelenen ekonomilerde etkili bir rolü olmadığı görülmüştür.

Anahtar Sözcükler : Finansal Karmaşıklık, McCabe Karmaşıklık Ölçütü, Türkiye, İran, Suudi Arabistan, Birleşik Arap Emirlikleri.

1. Introduction

The economic efficiency and stability of the country's financial sector are essential for achieving a healthy economy. The financial market has a significant capacity to drive a country's growth and development. This market is the core of the economic system, and if this fails, the performance of the economic system as a whole will suffer. In other words, the ability of markets and financial institutions to reduce market friction can lead to a more efficient allocation of resources, thereby accelerating long-term economic growth (Diamond, 1984; Boyd & Prescott, 1986; King & Levine, 2010).

Nearly all opinions suggest that financial markets may sometimes be too interconnected, thereby creating systemic risk. The risk in these markets could cause significant damage and losses to the global economy. Previously, it was discussed that some companies or institutions are so large that their failure may have worse consequences for the economic system (ECB, 2010).

Systemic risk in financial markets refers to the potential for a sudden collapse of a financial system, resulting in instability within the financial markets. Since this risk has a pervasive effect on the entire system and is quickly transmitted to the entire capital market or the country's economy, it is referred to as systemic risk. The simultaneous movement between different market segments causes this risk. In other words, systemic risk occurs when there is a high correlation between the risks and crises of various market segments (Acharya et al., 2009). The systemic risk in a country's economy may depend on the degree of complexity and interconnection between the country's economy and its financial sector. One way to assess a country's systemic risk is to examine its financial system using network theory.

In network science, the structure of networks plays an essential role in directing micro-events to macro-phenomena. This issue will worsen when there is a high correlation between different market parts. In other words, the behaviour of networks is influenced by their structure. It is necessary to model these systems to investigate the structure of complex and real networks such as economic systems. In the financial sector, the strong potential of network analysis has recently been highlighted as a tool to understand better financial markets and models, as well as assess systemic risk. In other words, the global financial system can be shown as a large, complex network (Caccioli et al., 2018). Financial networks, like stock markets, are complex systems that can be modelled and analysed using network science techniques.

Market structure studies conducted from a network perspective can significantly enrich the traditional perspective adopted in economics. Network analysis, which considers the overall structure of the network, contributes to existing theoretical results on systemic risk in the interbank market and provides a stronger basis for assessing contagion risk through simulations. In general, there are three stages to control systemic risk as a scientific research field; the first step is to understand and model the mechanisms and phenomena of the real world, the second is to predict the future state of the system, and the third and last step is to regulate the system to prevent the occurrence of undesirable happenings. For this purpose, this paper aims to calculate systemic risk by measuring the complexity of a financial system.

2. Background Literature

Raddant & Kennett (2016) examined the network of financial markets in an article. For this purpose, they analysed 4000 stocks from 15 countries and estimated the statistical relationships between pairs of stocks from different markets using the regression and GARCH methods. The results showed that countries such as the United States and Germany are at the core of the global stock market. Additionally, the energy, materials, and financial sectors play a crucial role in connecting markets, a role that has intensified over time for the energy and materials sectors. They also calculated interconnectedness using network theory to depict the relationship between sectors and capital markets.

Gofman (2017) estimated a network-based model of the over-the-counter interbank loan market in the United States to investigate the effectiveness and stability of the bank size restriction policy proposed to reduce financial network entanglement and improve financial stability. Results showed that transaction efficiency decreases with limitations in interaction and the shrinking of the banking network as intermediary chains become more extended and limit the linking of banks to each other, leading to increased financial stability.

Using network analysis, Tang et al. (2018) studied two major markets, China and the United States of America. The research found that the characteristics of the networks and hierarchical structures differ between the two stock markets.

Chowdhury et al. (2018), in a study titled The Changing Network of Financial Linkage: the Asian Experience, which the Asian Development Bank publishes, investigated the changing network of financial markets for six periods from 1995 to 2016, constructing a network that captures the concepts of the direction of links between markets, the significance of these links, and their strength. Emphasis is placed on the transition of the networks before and after the Asian financial crisis of 1997-1998 and the global financial crisis of 2008-2009. The analysis encompasses 19 European countries, including Türkiye, 15 countries from Asia and the Pacific, two from Africa, two from North America, and four from Latin America. The analysis reveals an increase in interconnectedness during periods of stress and a decline in links following crisis periods. Results indicate a general deepening of connections between the Asian market and the rest of the world over the past two decades. They suggest that many of these markets have transitioned from being primarily linked to developed non-Asian markets through key bridge markets, such as Hong Kong and China, to creating stronger direct links with these external markets, highlighting the importance of key geographical nodes in market development.

Espinosa-Vega and Russel (2020) developed a theoretical model to investigate the relationship between the entanglement of financial institutions, systemic financial crises, and long-term recessions. The financial institutions examined in this research are banks, and the relationship between banks is defined only through the transfer of assets.

Using the Lorenz model, Liao et al. (2020) introduced a system of differential equations to simulate a financial system. Results indicated that the behaviour of this system was unpredictable and sensitive to initial conditions. Examining the dynamics of this system showed pseudo-random behaviour. In other words, the financial model exhibits chaotic behaviour, according to the assumptions made in the research. Therefore, the financial system is complex.

Botta et al. (2022) presented an agent-based model that integrates an increasingly complex financial sector with a real aspect of the economy. This study examined the impact of the increasing complexity of the financial system and its associated financial products on economic growth, macroeconomic stability, and income inequality. The simulation results of this research indicate that although higher financial complexity may lead to faster economic growth, it also contributes to financial fragility in an economic system prone to crisis and exacerbates income inequality.

Li et al. (2022) investigated the effect of financial network complexity on financial stability. Due to the difficulty of modelling the real financial network, random matrices were used as a substitute for the financial network matrix.

Salim et al. (2023) employed a network model to examine the interrelationship between financial data in the capital market. For this purpose, they utilised the United States stock market statistics for the period 2002-2019, the principal component analysis (PCA) method, and the Granger causality test. According to their research, the correlation coefficient for the studied stock returns is statistically significant, indicating a strong initial relationship and daily movement in the market under study.

Most studies have examined only a part of the financial market and have been done in one or two countries. The present study aims to investigate and compare four countries (Türkiye, Iran, Saudi Arabia, and the United Arab Emirates) from the perspective of financial institutions and their relationship and influence on the entire economy because in emerging economies in recent years, the flow of capital entering the country has increased, which has brought high returns and exposed the financial system to potential risks, including systemic risk. The ability to manage these flows largely depends on the level of complexity of the domestic financial network; therefore, it is necessary to examine the financial networks of these countries and their corresponding levels of complexity. In the upcoming research, the financial systems of Türkiye, Iran, Saudi Arabia, and the UAE will be examined from the perspective of financial development variables. For this purpose, using the financial development variables provided by the World Bank, all aspects of the financial sector in these countries have been considered, and the financial network for each country has been calculated and analysed.

3. The Importance of Research

The necessity of achieving a healthy economy in any country lies in the efficiency and capability of the country's financial sector. In general, the task of the financial sector in the economy is to transfer credit funds and capital from savers, financial institutions, and capital owners to investors, producers of goods and services, and the government. One of the other tasks of this sector is to move with the real sector of the economy, which provides the flow of goods and services from producers to consumers and human power from households to producers. These processes require financial exchanges, which, alongside technological advancements, lead to an increase in complexity and entanglement within countries' financial systems. On the one hand, increasing complexity in the financial system leads to higher efficiency, faster economic growth, and ease and speed of financial transactions. On the other hand, it has created challenges and increased costs, making the financial system more vulnerable and ultimately rendering the financial markets more fragile. For this reason, examining the financial systems of countries from the perspective of network analysis, measuring their complexity, and exploring ways to reduce it in economic and financial systems, as well as the decision-making processes, is critical.

4. Financial System Network Methodology

The financial market comprises various components, including commercial banks, insurance companies, hedge funds, individual investors, and central banks. These components interact through the buying and selling of financial assets, creating complex networks of financial liabilities, mutual assets, and correlations in asset returns (Caccioli et al., 2018). The advantage of modelling the financial system as a complex network is that it is possible to directly analyse the complex feedback between micro and macro phenomena without simplifying the structure of financial links. The network approach to financial systems is essential for assessing systemic risk and financial stability. It can help reduce or increase the external effects that the risk associated with a single institution may cause to the entire system.

Modelling a financial network with numerous connections is crucial because each connection can potentially amplify the spread of contagion within the financial network. Additionally, any connection between system components in the financial system increases systemic risk in a non-linear manner (Tabak et al., 2018). Kumar (2018) states that systemic risk refers to the risk of the entire financial system collapsing, which is caused by the weakness of the structure or correlation within the financial system as a whole. Systemic risk occurs when there is a high correlation between different market segments. In other words, the basis of systemic risk is the correlation between losses (Ostad et al., 2021). The systemic risk depends on the collective behaviour of financial network components and their degree of interconnection.

The complex structure of links between financial institutions and infrastructures, as well as among sectors of the economy or entire financial systems, can be represented using a network representation or graph. By understanding the financial system as a complex and dynamic network, empirically analysing its characteristics, and developing contagion and behavioural models, one can gain a deeper understanding of systemic risk and identify better variables, institutions, and financial markets that have systemic importance.

Therefore, to model the financial system, it is necessary to specify its components separately and then calculate the relationship between these components using the correlation coefficient. Since any country's financial system aims to achieve financial development, the World Bank's Global Financial Development Database has developed a comprehensive and relatively simple conceptual framework for measuring financial development worldwide. This framework identifies four key variables that indicate the good performance of a financial system: financial depth, accessibility, efficiency, and stability. These four dimensions are then measured for two primary components in the financial sector: financial institutions and financial markets.

The selected variables for examining the financial system in the selected countries of the region (Türkiye, Iran, Saudi Arabia, and the UAE), according to the statistics available in the World Bank reports, are described in Table 1. There are 22 variables; 12 variables fall into the financial depth category, two variables are categorised as efficiency, one variable is related to instability, and the rest are classified as 'others'. These variables are primarily located in the financial institutions group, with three specifically related to financial markets. Financial institutions, including banks, other depository financial institutions, and insurance institutions. Financial markets encompass the stock market and the OTC (over-the-counter) market.

Table: 1
Details of Variables

Row	Variable	Index Name	Description	Symbol
1	**Financial Depth**	Private credit by deposit money banks to GDP(%)	Domestic money banks provide the private sector with financial resources as a share of GDP. They comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits.	**DI.01**
2	**Financial Depth**	Deposit money banks' assets to GDP(%)	Total assets held by deposit money banks as a share of GDP. Assets include claims on the domestic real nonfinancial sector, which comprises central, state, and local governments, nonfinancial public enterprises, and the private sector. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits.	**DI.02**
3	**Financial Depth**	Deposit money bank assets to deposit money bank assets and central bank assets(%)	Total assets held by deposit money banks as a share of the sum of deposit money bank and Central Bank claims on the domestic nonfinancial real sector. Assets include claims on the domestic real nonfinancial sector, which comprises central, state, and local governments, nonfinancial public enterprises, and the private sector. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits.	**DI.04**
4	**Financial Depth**	Liquid liabilities to GDP (%)	The ratio of liquid liabilities to GDP. Liquid liabilities are also known as broad money or M3. They are the sum of currency and deposits in the central bank (M0), plus five transferable deposits and electronic currency (M1), plus time and savings deposits, foreign currency transferable deposits, certificates of deposit, and securities repurchase agreements (M2), plus travellers' checks, foreign currency, time deposits, commercial paper, and shares of mutual funds held by residents.	**DI.05**
5	**Financial Depth**	Central bank assets to GDP(%)	The ratio of central bank assets to GDP. Central bank assets are claims on the domestic real non-financial sector by the central bank.	**DI.06**

6	**Financial Depth**	Financial system deposits to GDP(%)	Demand, time and saving deposits in deposit banks and other financial institutions as a share of GDP.	**DI.08**
7	**Financial Depth**	Life insurance premium volume to GDP(%)	The ratio of life insurance premium volume to GDP. Premium volume refers to the insurer’s direct premiums earned or received during the preceding calendar year.	**DI.09**
8	**Financial Depth**	Nonlife insurance premium volume to GDP (%)	The ratio of non-life insurance premium volume to GDP. Premium volume refers to the insurer’s direct premiums earned (for Property/Casualty) or received (for Life/Health) during the preceding calendar year.	**DI.10**
9	**Financial Depth**	Private credit by deposit banks and financial institutions to GDP(%)	Private credit by deposit money banks and other financial institutions as a percentage of GDP.	**DI.12**
10	**Financial Depth**	Domestic credit to private sector (% of GDP)	Domestic credit to the private sector refers to financial resources provided to the private sector, such as loans, purchases of non-equity securities, trade credits, and other accounts receivable that establish a claim for repayment. For some countries, these claims include credit to public enterprises.	**DI.14**
11	**Financial Depth**	Stock market capitalisation to GDP(%)	The total value of all listed shares in a stock market is a percentage of the country's GDP.	**DM.01**
12	**Financial Depth**	Stock market total value traded to GDP(%)	The total value of all traded shares in a stock market exchange is a percentage of the country's GDP.	**DM.02**
13	**Efficiency**	Stock market (%)turnover ratio	The total value of shares traded during the period is divided by the average market capitalisation.	**EM.01**
14	**Efficiency**	Credit to government and enterprises to GDP(%)	The ratio of credit extended by domestic banks to the government and state-owned enterprises to GDP.	**EI.08**
15	**Stability**	Bank credit to bank (%)deposits	Domestic money banks provide financial resources to the private sector as a share of total deposits. Domestic money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. Total deposits include demand, time, and savings deposits in banks.	**SI.04**
16	**Other**	Bank deposits to (%) GDP	The total value of demand, time and saving deposits at domestic deposit money banks as a share of GDP. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits.	**OI.02**
17	**Other**	External loans and deposits of reporting banks vis-à-vis the banking sector (% of domestic bank deposits)	Percentage of loans and deposits of reporting banks to the domestic bank deposits in the banking sector.	**OI.10**
18	**Other**	External loans and deposits of reporting banks vis-à-vis the nonbanking sectors (% of bank deposits)	Percentage of loans and deposits of reporting banks compared to those of the non-banking sector in domestic bank deposits.	**OI.11**
19	**Other**	External loans and deposits of reporting banks vis-à-vis all sectors (% of bank deposits)	Percentage of loans and deposits of reporting banks compared to all sectors in domestic bank deposits.	**OI.12**
20	**Other**	Remittance inflows (%)to GDP	Workers’ remittances and compensation of employees comprise current transfers by migrant workers, as well as wages and salaries earned by non-resident workers. Data comprise three items defined in the fifth edition of the IMF’s Balance of Payments: workers’ remittances, compensation of employees, and migrants’ transfers.	**OI.13**
21	**Other**	Consolidated foreign claims of BIS reporting banks to (%) GDP	The ratio of consolidated foreign claims to GDP among banks reporting to the BIS. In the consolidated banking statistics, claims granted to nonresidents are referred to as cross-border claims. Local claims refer to the foreign affiliates (branches or subsidiaries) of domestic banks in the host country, which are resident in the country of the host country's residents.	**OI.14**
22	**Other**	The ratio of global leasing volume to (%) GNP	Ratios calculated by White Clarke Global Leasing Report.	**OI.17**

Reference: World Bank Report.

The first step is to identify the variables. If the correlation between pairs of variables is calculated, their relationship with each other is determined. Considering that the financial sector is a dynamic system, the investigated variables are examined during the investigated period to capture the dynamics within this system. For this purpose, the required data for the countries of Türkiye, Iran, Saudi Arabia, and the United Arab Emirates were examined from 2005 to 2020, the last year of available data.

After defining the variables, the next step is to calculate the correlation matrix between pairs of variables. The interaction network, based on the correlation matrix, is used to analyse the type and level of connection between components in the financial network of these countries. To do this, the Pearson correlation (equation no. 1) is used to obtain the correlation matrix of the indicators of the financial system for the examined variables for each country:

$$\rho_{i,j}(\Delta t) = \frac{(r_i r_j) - (r_i)(r_j)}{\sqrt{(r_i^2 - (r_i)^2)(r_j^2 - (r_j)^2)}} \tag{1}$$

The correlation matrix between the inspected variables, calculated at a 1% significance level, is generated using SPSS software to input the adjacency matrix. The third step is to estimate the adjacency matrix, which is defined by Equation 2. If the correlation between two variables is significant, a value of 1 is placed in the matrix; otherwise, a value of 0 is placed in the matrix.

$$A_{N\times N}\left[i, j\right] = \left\{ \begin{matrix} 1 & if\,(V_i, V_j) \in E \\ 0 & otherwise \end{matrix} \right\} \tag{2}$$

For analysing the financial system, using network analysis, the graph of the financial system should be drawn, which is step four, known as drawing a network for a financial system. The use of graphs in social network research has clarified many complex phenomena (Morzy et al., 2017). These simple extensions or refinements of binary simple graphs offer powerful tools for understanding complex interrelations across multiple settings. In a multilayered network, when networks are observed over time, pairs of nodes can become connected (Koskinen et al., 2023).

A given network can be represented in several ways, for example, using an adjacency matrix defined as Equation 2. Each of the network's components is related to each other (Pearson’s correlation coefficient is significant at the 1% level), as indicated by the number 1. Conversely, variables and components that are unrelated to each other are assigned a value of 0. The calculation of the adjacency matrix is used as input for the graph, and the resulting graph is examined in terms of its structure and performance. Additionally, for complexity calculations, the adjacency matrix will serve as the input for the financial network. We used Python software to create a network or graph of the financial systems of the countries under investigation, where the inputs were the adjacency matrices calculated for each country.

Finding useful visual representations of the graphs of a complex process is equivalent to finding a good dimensional reduction of an N-dimensional system, where N is the number of nodes. A graph or network is one of the most comprehensive methods for calculation and forecasting in a system. Networks are becoming increasingly important in contemporary information science because they provide a holistic model for representing many real-world phenomena (Morzy et al., 2017). A graph is the best way to convey complex networks because it allows for a comprehensive model representing many real-world phenomena. A system with a more significant number of components and a higher degree of interconnection is more complex.

In general, a network (or graph) is a visual representation of a set of interconnected components. Each of these components is referred to as a “vertex” or “node”. Vertices are also connected through “edges”. A graph is defined as (V, E), where V is the set of vertices and E is the set of edges. A network is an ordered pair $G = \langle 0 \rangle$, where $V = \{\mathrm{V}1, \ldots, \mathrm{V}N\}$ is the set of vertices (nodes) of this network and $E = \{(\mathrm{V}i, \mathrm{V}j) \in V \times V\}$ is the set of edges.

5. Internal Financial Network Analysis

5.1 Central Criteria

A key concept in network analysis that also applies to the financial system is centrality. In a broad sense, centrality refers to the importance of a node in the network. Traditional centrality measures the number of links ending at a node (degree) or leaving a given node or the distance from other vertices via the shortest paths. In other words, the variable with the most significant number of links to other variables is at the core or centre of the network, and changes in this variable affect most of the variables in the network, also transferring the behaviour of other variables to the entire network. Therefore, it is very important to identify the core variable in the network.

5.2 Network Structure

In a network, a variable may not be related to any of the variables in the network; however, when it is related to other variables, the properties and behaviour of a node (component) cannot be analysed based solely on the properties and behaviours of that node. This node may be influenced by nodes linked to it and nodes with no direct link but are connected and affected. Therefore, to understand the behaviour of a node, the behaviour of many nodes must be analysed, including nodes that may be several nodes away from each other in the network. Additionally, the number of loops formed in a network impacts the overall performance of the entire network.

5.3 Network Complexity Measuring

One method of analysing a network is to examine it from the perspective of complexity or interconnectedness. Complexity refers to the quality or state of being complicated to understand, perform, or create. Complexity is often associated with uncertainty, a lack of control, or a lack of transparency (Cambridge Dictionary). One of the most widely accepted indicators of network complexity is McCabe’s cyclomatic number, calculated according to Equation 3, which involves five steps or a final step.

$$V(G) = E - N + 2 \tag{3}$$

In this equation, E is the number of edges, and N is the number of nodes in the network or graph. V(G) represents the maximum number of independent paths that can be represented through the network. Table 2 provides an overview of the complexity number and the corresponding meaning of V(G).

Table: 2
Concept of Graph Complexity Number

Complexity	Concept	Systemic Risk
10-1	Structured graph, high testability	Low
20-10	Complex graph, medium testability	Medium
40-20	Complex graph, low testability	High
40>	Graph too complex, untestable	Too high

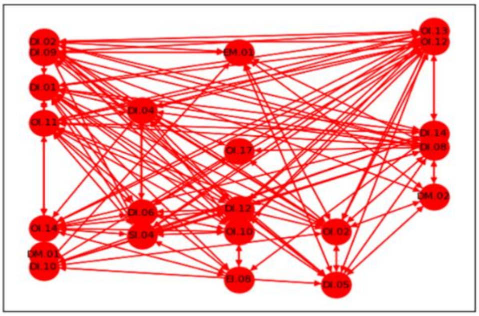
Sources: <http://www.mccabe.com/>.

6. Experimental Results of the Research

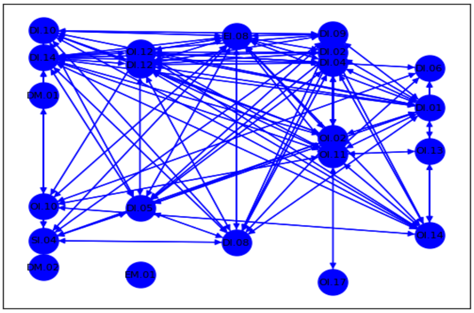
The limitation of this study was accessing data for all investigated countries. Since this research aims to examine the financial network of Türkiye, Iran, Saudi Arabia, and the UAE, for the results to be comparable, the selected variables must have sufficient overlap for comparison. For this, 22 financial development variables provided by the World Bank have been selected. In Türkiye and Iran, data were available for 22 financial development variables covering the entire study period from 2005 to 2020, the last year of data availability. For Saudi Arabia and the United Arab Emirates, data were available for 18 and 19 variables, respectively.

To examine the financial network, it is necessary to re-examine the steps of the network analysis. In brief, the correlation matrix was calculated for pairs of variables across these countries. Then, the Adjacency matrix is obtained using the correlation matrix. For the pair of variables with a significant correlation at the 1% level, the value is 1; otherwise, it is 0. The adjacency matrix was calculated for all four countries; the results are in the appendix. Using the Adjacency matrix, the financial network of each country is drawn separately using Python software. The results are shown in the set of figures below.

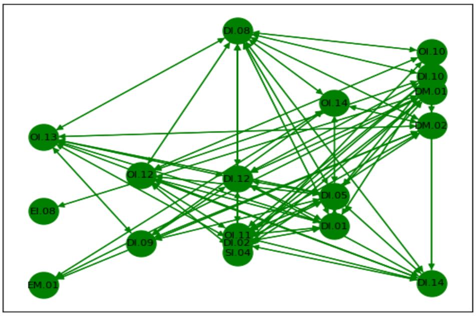
Türkiye's Financial Network



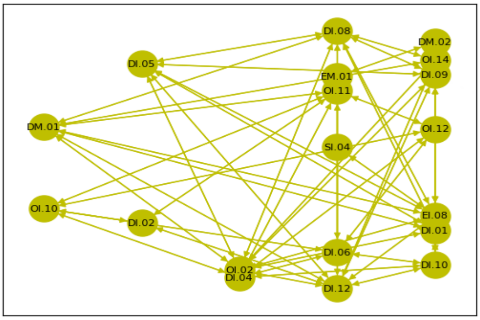
Iran's Financial Network



Saudi Arabia’s Financial Network



UAE’s Financial Network



In Türkiye's financial graph, private credit by deposit money banks and other financial institutions to GDP (DI.12) and private credit by deposit money banks to GDP (DI.01) have 16 connections with different variables in the network, representing the highest number of edges in Türkiye's financial network. In general, it can be concluded that in Türkiye, credits paid to the private sector are the most important part of the financial network. In other words, it forms the core of this network. Stock market capitalisation to GDP (DM.01) in the financial graph of Türkiye is not related to any variable and is considered a neutral variable. The amount of complexity calculated using the McCabe number for Türkiye’s financial network, using equation 3, has been obtained at 95, which is the highest in all the countries in this study and indicates a very high complexity in this country, which creates a too high systemic risk as a result of this high complexity.

In the graph drawn for Iran's financial system, Credit to the government and state-owned enterprises as a percentage of GDP (EI.08) and domestic credit to the private sector (DI.14) have 15 edges, with the highest number of edges in the financial graph. After these two variables, credit by deposit money banks to GDP (DI.01) and private credit by deposit money banks and other financial institutions to GDP (DI.12) have the highest number of edges, i.e. 12. In other words, the variables related to government, domestic, and private credits are at the core of Iran’s financial network, so banks and credits in the financial graph play a central role in Iran's financial system. Moreover, the stock market turnover ratio (EM.01) is unrelated to any other variable in the existing financial system. Additionally, stock market capitalisation to GDP (DM.01) and Stock market total value traded to GDP (DM.02), the only capital market variables examined in this study, are related and not associated with other variables. The calculated complexity number for Iran’s financial graph is 77, indicating that the system's complexity and systemic risk in this network is too high. In other words, considering that the model's components exhibit a high degree of correlation, there is a possibility of system collapse, particularly in the banking and credit sectors, which could lead to a crisis.

In the case of Saudi Arabia, the ratio of financial system deposits to GDP (DI.08) has a significant relationship with 13 variables in the network. Therefore, this variable is the core of Saudi Arabia's financial network. Liquid liabilities to GDP (DI.05) are related to 12 variables in the network and are placed after the core variable. In the Saudi financial network, the neutral variable with little or no significant relationship with another part of the financial system is a credit to the government. State-owned enterprises to GDP (EI.08): According to the calculations, the complexity number obtained for Saudi Arabia is 49, which is lower than that of Türkiye and Iran. Still, according to the interpretation presented in Table 2, this graph is also classified as having a high complexity and too systemic risk.

In the UAE's financial network, similar to Türkiye, private credit by deposit money banks and other financial institutions as a percentage of GDP (DI.12) is the network's core. In the financial network of this country, the variables DM.02 and EM.01, i.e., the stock market's total value as a percentage of GDP and the stock market turnover ratio, are closely related and do not exhibit a significant correlation with other variables. This issue can lead to the conclusion that in the financial network of the UAE, bank and private sector credits are among the most critical components of this network, while financial markets have a partial effect on this network and operate independently of it. The calculated complexity number for the UAE is 36, indicating high complexity. However, this amount is lower compared to Türkiye, Iran, and Saudi Arabia, suggesting the lowest systemic risk among the four countries under review.

Table 3 summarises the results of the analysis of the drawn financial networks in terms of the number of financial complexities using equation 3.

Table: 3
Results of Network Graphs: 2005-2020

Country	Number of variables	Number of edges	Central Variable(s) in the graph	McCabe's Complexity Number	Systemic Risk
Türkiye	22	115	DI.01-DI.12	(115-22)+2=95	Too high
Iran	22	97	DI.14 - EI.08	(97-22)+2=77	Too high
Saudi Arabia	18	65	DI.08	(65-18)+2=49	Too high
UAE	19	53	DI.12	(53-19)+2=36	High

According to the surveys, the core of the financial network in each of the four countries is comprised of variables related to financial depth, i.e., banks and other financial institutions. In Türkiye, Iran, and the UAE, credits play an effective role, while in Saudi Arabia, deposits are more important than credits. Additionally, in all four countries, the capital market is relatively unimportant in the financial network and functions as a distinct part of the economy. Moreover, in Iran, the government plays a significant role in the financial sector, whereas in other countries, the role of the private sector in the financial economy is more prominent.

7. Conclusion and Policy Recommendation

In this article, the level of financial complexity in Türkiye, Iran, Saudi Arabia, and the UAE is calculated and analysed using McCabe's complexity method and the financial development variables provided by the World Bank from 2005 to 2020. The results of the investigations show that the calculated complexity numbers for Türkiye, Iran, and Saudi

Arabia are 95, 77 and 49, respectively. According to the results, i.e. the financial complexity numbers, Türkiye, Iran and Saudi Arabia have very high complexity and consequently high systemic risk. Compared to these three countries, the UAE has the lowest complexity score of 36 and exhibits the lowest systemic risk among the three mentioned countries.

Additionally, the financial graph (network) investigation reveals that, during the period under investigation, the primary and core sectors in the financial systems of the four countries are banks and credit institutions, specifically the money market. This means the capital market does not play a decisive role in their economy. Moreover, in Iran, the government plays a more significant role than the private sector, whereas the private sector is more influential in Türkiye, Saudi Arabia, and the UAE. In Türkiye, Iran and the United Arab Emirates, credits are significant, but deposits are more critical in Saudi Arabia.

McCabe's high complexity number, and thus, high systemic risk in all of these countries, indicates that the financial systems in these countries are fragile in the event of a sudden change in their financial sector, which can significantly impact the entire system. So policymakers can improve and track the results of the policies they adopt in the financial system. Therefore, they should be more cautious in their financial system strategies. Additionally, the core of financial systems prioritises policymakers for appropriate reform in the financial system. According to the results, based on the importance of the banking sector in all investigated countries, the money market is more effective than the capital market. This suggests that debt-based financing is more prevalent in the money markets of these countries than asset-based funding in their capital markets.

To reduce the financial complexity and systemic risk in these countries, it is necessary to decentralise the financial system. According to the results obtained for the countries investigated governments must focus on developing the capital market in the financial market rather than the money market. For this purpose, governments can facilitate the process of companies entering the capital market, thereby reducing the influence of the money market while also developing capital markets. Therefore, the financial system will be diversified similarly.

To reduce financial complexity, we suggest that company financing should be through the capital market rather than banks and the money market, especially in Iran, Türkiye, and Saudi Arabia, which have high McCabe complexity numbers, identifying high systemic risk.

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Appendix: Research Findings

Adjacency Matrix of Pairs Variable (Türkiye)

	DI.06	DI.04	DI.02	DI.14	DI.08	DI.09	DI.05	DI.10	DI.12	DI.01	DM.01	DM.02	EM.01	EI.08	SI.04	OI.02	OI.14	OI.12	OI.10	OI.11	OI.17	OI.13
DI.06	0	1	0	0	0	0	0	0	1	1	0	0	0	0	1	0	1	1	1	1	1	0
DI.04	1	0	1	0	1	0	0	0	1	1	0	0	0	0	1	1	1	1	1	1	1	1
DI.02	0	1	0	1	1	0	1	1	1	1	0	0	1	0	1	1	1	1	1	1	0	1
DI.14	0	0	1	0	0	0	0	1	1	1	0	0	0	1	1	0	1	1	0	1	0	1
DI.08	0	1	1	0	0	1	1	1	1	1	0	1	1	0	0	1	0	0	0	1	1	1
DI.09	0	0	0	0	1	0	1	0	0	0	0	1	1	0	0	1	0	0	0	0	0	1
DI.05	0	0	1	0	1	1	0	1	1	1	0	1	1	0	0	1	0	0	0	0	0	1
DI.10	0	0	1	1	1	0	1	0	1	1	0	0	1	0	0	1	0	0	0	0	0	1
DI.12	1	1	1	1	1	0	1	1	0	1	0	0	0	1	1	1	1	1	1	1	0	1
DI.01	1	1	1	1	1	0	1	1	1	0	0	0	0	1	1	1	1	1	1	1	0	1
DM.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DM.02	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
EM.01	0	0	1	0	1	1	1	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0
EI.08	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	0	1	0	1	1	0	0
SI.04	1	1	1	1	0	0	0	0	1	1	0	0	0	1	0	0	1	1	1	1	0	1
OI.02	0	1	1	0	1	1	1	1	1	1	0	1	1	0	0	0	0	1	0	1	1	1
OI.14	1	1	1	1	0	0	0	0	1	1	0	0	0	1	1	0	0	1	1	1	0	1
OI.12	1	1	1	1	0	0	0	0	1	1	0	0	0	0	1	1	1	0	1	1	0	1
OI.10	1	1	1	0	0	0	0	0	1	1	0	0	0	1	1	0	1	1	0	1	0	1
OI.11	1	1	1	1	1	0	0	0	1	1	0	0	0	1	1	1	1	1	1	0	0	1
OI.17	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
OI.13	0	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	0	0

Adjacency Matrix of Pairs Variable (Iran)

	DI.06	DI.04	DI.14	DI.02	DI.08	DI.09	DI.05	DI.10	DI.12	DI.01	DM.01	DM.02	EM.01	EI.08	SI.04	OI.02	OI.14	OI.12	OI.10	OI.11	OI.17	OI.13
DI.06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1
DI.04	0	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	0	0
DI.14	0	1	0	1	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	0	0
DI.02	0	1	1	0	1	1	1	0	1	1	0	0	0	1	0	1	1	1	0	1	0	0
DI.08	0	1	1	1	0	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0
DI.09	0	1	1	1	1	0	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0
DI.05	0	1	1	1	1	1	0	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0
DI.10	0	0	1	0	1	1	1	0	1	1	0	0	0	1	1	1	1	0	1	0	0	0
DI.12	0	1	1	1	1	1	1	1	0	1	0	0	0	1	0	1	1	1	0	1	0	0
DI.01	0	1	1	1	1	1	1	1	1	0	0	0	0	1	0	1	1	1	0	1	0	0
DM.01	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
DM.02	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
EM.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EI.08	0	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	0	0
SI.04	0	0	1	0	1	1	1	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0
OI.02	0	1	1	1	1	1	1	1	1	1	0	0	0	1	1	0	0	0	0	0	0	0
OI.14	1	1	1	1	0	0	0	1	1	1	0	0	0	1	0	0	0	1	1	1	0	1
OI.12	1	1	1	1	0	0	0	0	1	1	0	0	0	1	0	0	1	0	1	1	0	0
OI.10	1	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	1	1	0	1	0	0
OI.11	1	1	1	1	0	0	0	0	1	1	0	0	0	1	0	0	1	1	1	0	1	1
OI.17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
OI.13	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0

Adjacency Matrix of Pairs Variable (Saudi Arabia)

	DI.02	DI.14	DI.08	DI.09	DI.05	DI.10	DI.12	DI.01	DM.01	DM.02	EM.01	EI.08	SI.04	OI.14	OI.12	OI.10	OI.11	OI.13
DI.02	0	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	1
DI.14	1	0	1	0	1	1	1	1	0	0	0	0	0	0	1	0	1	1
DI.08	1	1	0	0	1	1	1	1	0	1	0	0	1	1	1	1	1	1
DI.09	0	0	0	0	1	0	1	0	0	1	0	0	0	1	0	0	0	1
DI.05	1	1	1	1	0	1	1	1	1	0	0	0	0	1	1	0	1	1
DI.10	1	1	1	0	1	0	1	1	0	0	0	0	0	0	1	0	1	0
DI.12	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	1
DI.01	1	1	1	0	1	1	1	0	0	0	0	0	0	0	1	0	1	1
DM.01	1	0	0	0	1	0	1	0	0	0	1	1	1	0	0	0	0	0
DM.02	0	0	1	1	0	0	0	0	0	0	1	0	1	1	0	1	1	1
EM.01	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0
EI.08	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
SI.04	0	0	1	0	0	0	0	0	1	1	0	0	0	0	1	1	1	0
OI.14	0	0	1	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0
OI.12	0	1	1	0	1	1	0	1	0	0	0	0	1	0	0	1	1	0
OI.10	0	0	1	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0
OI.11	0	1	1	0	1	1	0	1	0	1	0	0	1	0	1	0	0	0
OI.13	1	1	1	1	1	0	1	1	0	1	0	0	0	0	0	0	0	0

Adjacency Matrix of Pairs Variable (UAE)

	DI.06	DI.04	DI.02	DI.08	DI.09	DI.05	DI.10	DI.12	DI.01	DM.01	DM.02	EM.01	EI.08	SI.04	OI.02	OI.14	OI.12	OI.10	OI.11
DI.06	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1
DI.04	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1
DI.02	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
DI.08	0	0	0	0	1	1	0	1	1	1	0	0	1	0	1	1	0	0	0
DI.09	0	0	0	1	0	1	0	1	1	0	0	0	1	0	1	0	0	0	0
DI.05	0	0	0	1	1	0	0	1	1	0	0	0	1	0	1	0	0	0	0
DI.10	1	1	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0
DI.12	0	0	1	1	1	1	1	0	1	1	0	0	1	0	1	1	0	0	0
DI.01	0	0	0	1	1	1	1	1	0	1	0	0	1	0	1	1	0	0	0
DM.01	0	0	0	1	0	0	0	1	1	0	0	0	1	0	1	1	0	0	1
DM.02	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
EM.01	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
EI.08	0	0	0	1	1	1	0	1	1	1	0	0	0	1	1	1	0	0	0
SI.04	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
OI.02	0	0	0	1	1	1	0	1	1	1	0	0	1	0	0	1	0	0	0
OI.14	0	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0	0	0
OI.12	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
OI.10	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
OI.11	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0