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RESEARCH PAPER

Financial Complexity: Evidence from Iran

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Abstract

In recent years, technological advances have increased complexity across many domains of human life, including the economy and its subsectors such as finance. These developments have posed challenges for many economies, including Iran. This study investigates financial complexity in the Iranian economy over the period 2005–2021. To this end, an adjacency matrix for Iran's financial sector is constructed using World Bank data in order to depict the interconnectedness and complexity of the country's financial system. The resulting financial graph indicates that the capital market exerts a weaker influence than the money and insurance markets, whereas among financial institutions, banks and other depository institutions play a central role in the country's financial system. The government and state-owned banks, channeling funds obtained from the banking sector, also play a significant role in Iran's financial system. Using McCabe's method, the complexity number for the financial graph of Iran was calculated to be 79, which indicates a very high level of complexity and also high systemic risk in the financial system of Iran.

Keywords: capital market, finance, financial networks, Iran's economy, McCabe complexity.

JEL Classification: C45, C58, C63.

Introduction

Financial markets exert a significant influence on the economy and may therefore be regarded as a key driver of a country's growth and development. By reducing market frictions, financial markets and institutions can promote a more efficient allocation of resources and thereby foster long-term economic growth (Diamond, 1984; Boyd and Prescott, 1986; King and Levine, 1993; Durusu-Ciftci et al., 2017). The financial sector comprises many heterogeneous institutions and can become highly interconnected. Many financial crises are rooted in problems of interconnectedness within financial markets. Such interconnectedness can render economies more vulnerable to systemic financial crises (Kannan et al., 2009).

Failure of the financial sector—the core of the economic system—can undermine the wider economy and is a key source of systemic risk.

In the financial literature, systemic risk is often defined as the possibility of a sudden collapse of the financial system that can lead to economic instability and crisis. High interconnectedness and complexity in the financial sector can therefore expose economies to elevated systemic risk and financial crisis. Recent financial crises have underscored the importance of financial institutions and their interconnections (Rizan et al., 2022). Given the importance of the financial sector, governments seek to prevent the failure of financial institutions in order to protect the broader economy and reduce the likelihood of crisis. It is important to determine how much each component of the financial system contributes to overall systemic risk (Brunnermeier and Cheridito, 2019).

Over the last few decades, problems related to the spread of crises and economic shocks have become the main subject of many scientific works in the field of economics and especially financial economics. The literature on systemic risk has grown rapidly (Giglio, 2016; Brownlees and Engle, 2017; Benoit et al., 2017; Brunnermeier and Cheridito, 2019), yet few studies have treated financial complexity as a primary driver of financial crises.

A clearer understanding of systemic risk, financial-market complexity, and the degree of interdependence among markets can support the design of policies to mitigate potential damage. Measuring the complexity of the financial system can therefore contribute to a better allocation of resources—the financial system's primary function—and to improved efficiency of the financial and economic system. It may also improve the prediction of financial-market behavior, one of the most important systems in the economy. Several studies have examined complexity in the economic and financial domains (Balland et al., 2021; Botta et al., 2020; Salim et al., 2023), but they do not measure the level of financial complexity. We address this gap by examining two questions: (i) how can the level of financial complexity in Iran's financial sector be measured; and (ii) which part of the financial sector exerts the greatest influence on Iran's economy as a whole?

This paper develops a framework for measuring financial complexity by using network analysis to represent Iran's financial system. Network analysis is an established approach to data mining and knowledge discovery in financial data (Tang et al., 2018) and provides an intuitive way to examine relationships among system components. In finance, networks help describe the system's structure and potential contagion effects. This method can yield important insights into system-level dynamics and help uncover changes in market microstructure, bubble formation, and business models (Raddant and Kenett, 2016). To quantify complexity, we apply McCabe’s cyclomatic complexity, a widely accepted measure in computer science (Gong and Schmidt, 1985).

This paper is presented in the following sections. In the second part, some of the studies in the field of financial complexity are introduced. In the third part, the research literature related to complexity and financial complexity is presented. In the fourth part, the results of the research related to the network analysis method and complexity calculation according to McCabe's method are given. The summary and conclusion are given in the fifth part of the research.

Background

Salim et al. (2023) examine relationships among financial data in the capital market using a network model. They use U.S. stock-market data for 2002–2019 and apply principal component analysis (PCA) and Granger causality. Their findings show a significant correlation between stock returns and crisis periods, indicating co-movement and a highly connected financial market during crises. The results also show that correlations among stock returns increase during crises. Using Granger causality, they identify banking and insurance institutions as sources of systemic risk.

Li et al. (2022) investigate the effect of financial-network complexity on financial stability. Because modeling real financial networks is difficult, they use random matrices to represent the financial network. Their results indicate that financial stability is closely related to network complexity: the larger the network or the denser its connections, the lower financial stability tends to be. They also find that imbalance in network connections arising from rapid growth reduces financial stability.

Espinosa-Vega and Russell (2020) develop a theoretical model of the relationship among the interconnectedness of financial institutions, systemic financial crises, and long-term recessions. The institutions considered are banks, and linkages among banks are examined solely through assets. They conclude that greater mutual interaction among banks increases opacity and asymmetric information, which can lead to loan defaults, deepen crises, and generate systemic risk. Interlinkages among financial institutions (here, banks) can therefore play a major role in aggravating systemic financial crises.

Using the Lorenz model, Liao et al. (2020) introduced a system of differential equations to simulate a financial system. Results indicated that the behavior of this system was unpredictable and sensitive to initial conditions. An examination of the dynamics of this system showed pseudo-random behavior. In other words, the financial model has chaotic behavior according to the assumption made in the research; therefore, the financial system is complex.

Botta et al. (2020) presented an agent-based model that integrates an increasingly complex financial sector with the real economy. In this study, the impact of the increasing complexity of both the financial system and its financial products on economic growth, macroeconomic stability, and inequality was tested. The results of this research showed that although higher financial complexity may lead to faster economic growth, it leads to financial fragility in an economic system prone to crisis and increases the level of income and wealth inequality.

Tang et al. (2018) studied two major markets of China and the United States of America from the point of view of network analysis. According to the results, the characteristics of the network and hierarchical structures were different for the two stock 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 the efficiency of transactions decreases with the limitation in interaction and the shrinking of the banking network, because the intermediary chains become longer, while limiting the linking of banks to each other leads to an increase in financial stability.

Raddant and Kenett (2016) examine the network of financial markets by analyzing about 4,000 stocks from 15 countries and estimating pairwise relationships across markets using 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. Moreover, the energy, materials, and financial sectors play an important role in connecting markets, and this role has increased over time for the energy and materials sectors. They also calculated interconnectedness using network theory to depict the relationship between sectors and capital markets.

This study analyses the financial sector in Iran as a system and covers all of its components, including financial markets and institutions (such as banks, capital markets, and insurance companies), while in other studies one or part of the financial system has been investigated. This is the first time that the financial complexity of the Iranian financial system has been calculated. This is also the first study in the field of complexity to calculate financial complexity using McCabe's Cyclomatic Complexity method.

Literature Review

Financial Complexity

The concept of economic complexity has been applied to a range of issues, including economic growth (Laverde-Rojas et al., 2023), technological change (Antonelli, 2016), and inequality (Chiang Lee and Wang, 2021). This study takes a step toward applying this concept to the financial side of the economy, and in particular to the macroeconomic effects of rising financial complexity.

Complexity refers to the quality or state of being complicated and difficult to understand, perform, or construct. The term is often used synonymously with uncertainty, lack of control, or lack of transparency. Chan (2001) notes that the degree of complexity relates to the potential behavior of complex and unpredictable phenomena. In the structural description of complex systems, a large number of components and their complex and extensive interactions are mentioned.

Economic systems, and specifically financial systems as social systems, are examples of complex systems created by humans. Not only are asset portfolios interrelated, but banks and other institutions in modern finance are also interconnected. The financial sector consists of many heterogeneous institutions. For example, banks will react differently than insurance companies, which in turn will have a different response from pension funds, sovereign wealth funds, and hedge funds (Brunnermeier and Cheridito, 2019). Banks can address liquidity imbalances by borrowing and lending in the interbank market, but in doing so they expose themselves to contagion risk (Babus, 2016). Fluctuations in financial markets—both an indicator of complexity and a key factor in systemic risk—can also play an important role in investors' decisions (Spierdijk et al., 2012). Given the distinctive complexities of social systems, economic crises and collapses may not be fully modeled, analyzed, and predicted with mathematical equations alone.

A country's financial system, as a social system, comprises many components and linkages, which generate a high level of complexity. Its components include all active agents in financial markets. In financial markets, firms do not act independently; their activities affect one another directly or indirectly, and these effects are not constant over time. As a result, entanglement and interconnectedness arise among these institutions' activities, which are commonly associated with systemic risk. For this reason, the financial system is regarded as a complex system, and this complexity can elevate systemic risk and the likelihood of crisis.

On the one hand, rising complexity in the financial system can raise efficiency, speed economic growth, and facilitate faster financial transactions. On the other hand, it makes the system more vulnerable and fragile and increases the likelihood of systemic risk. This creates challenges and raises the cost of identifying and assessing risks, which may ultimately reduce domestic and foreign investment. Measuring—and, where appropriate, reducing—complexity in economic and financial systems and in decision-making processes is therefore important. It is therefore necessary to study financial complexity in order to assess the current state of the financial sector and to help reduce complexity and systemic risk.

Calculate Financial Complexity

Measuring complexity allows different systems to be compared on a common scale. This is especially important for systems that are structurally or functionally related. In order to investigate and calculate the level of complexity in the financial system of an economy, first, the variables under investigation should be specified, and then the relationships between them should be calculated and depicted. Accordingly, the steps for measuring the level of financial complexity in an economy are as follows:

Step One – Defining the Variables

In the first step of measuring complexity, the relevant variables must be defined. The main variables are those that determine the structure and performance of a financial system for achieving the main goal of financial markets, namely financial development. To this end, the financial development indicators introduced by the World Bank—namely financial depth, access, efficiency, and stability—which are available for Iran, are used. These indicators have been calculated across different dimensions of financial development and are available for all countries.

Step Two – Correlation Matrix between Pairs of Data

To analyze the type and strength of linkages among components of Iran's financial network, an interaction network based on a correlation matrix is employed. For this purpose, the Pearson correlation coefficient (Equation 1) is used to construct the correlation matrix of the indicators of Iran's financial system:

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

Step Three - Adjacency Matrix

An adjacency matrix is defined in Equation 2. If the correlation between two variables is significant, the number 1 is placed in the matrix; otherwise, 0 is placed.

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

Step Four – Drawing a Network for the Financial System

The use of figures in social network research has provided analytical clarity for a vast range of complex phenomena (Morzy et al., 2017). Figures have been used to make sense of relationships among entities in one-mode, two-mode, and multilayer networks. Multilayer networks may also be linked in pairs through ties between nodes in different layers or slices (Kivelä et al., 2014). These extensions and refinements of simple binary figures provide a powerful set of tools for interpreting complex interrelations across multiple settings. In a multilayer network observed over time, pairs of nodes that represent the same entities in consecutive periods can be linked (Koskinen et al., 2023).

Finding useful visual representations of the adjacency matrices of a complex process is equivalent to finding a good dimensionality reduction of an N-dimensional system, where N is the number of nodes. A figure or network is one of the most complete methods that can be used 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 figure is the best way to represent complex networks because it provides a comprehensive model for representing many real-world phenomena. A system with a greater number of components and a higher relationship between them is more complex.

Step Five – Calculation of Complexity

The complexity of a network or graph is usually calculated based on various characteristics such as the number of nodes, the number of edges, node degree, and the distance between nodes. One of the most widely accepted indicators of graph complexity is McCabe's cyclomatic number, which is appropriate for directed graphs (Gong and Schmidt, 1985). In a strongly connected graph, the cyclomatic number equals the maximum number of linearly independent paths (McCabe, 1976) and is calculated as shown in Equation 3:

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

where E is the number of edges, N is the number of nodes in the figure, and P is the number of subgraphs. V(G) represents the maximum number of independent paths in the graph. An alternative formulation is to use a graph in which each exit point is connected back to the entry point. In this case, the graph is strongly connected, and the cyclomatic complexity of the program is equal to the cyclomatic number of its graph, which is defined as:

$$V(G) = E - N + P \tag{4}$$

This may be seen as calculating the number of linearly independent cycles that exist in the graph, i.e., those cycles that do not contain any other cycles within themselves. Because each exit point loops back to the entry point, there is at least one such cycle. For a single cycle, P is always equal to 1. Therefore, a simpler formula for a single cycle is:

$$V(G) = E - N + 2 \tag{5}$$

McCabe (2008) in his presentation "Software Quality Criteria for Risk Identification" introduces a taxonomy to interpret cyclic complexity. Table 1 provides an overview of the complexity number and the corresponding meaning of V(G).

Table 1. The Concept of Graph Complexity Number

Concept	Complexity
Structured graph, high testability - low risk	10-1
Complex graph, medium testability - medium risk	20-10
Complex graph, low testability - high risk	40-20
Graph too complex, untestable - too high risk	40 >

Source: http://www.mccabe.com/.

Experimental Results

Definition of the Examined Variables

The World Bank's Global Financial Development Database (GFDD) provides a comprehensive yet relatively simple conceptual framework for measuring financial development worldwide. This framework identifies four sets of variables that characterize the performance of a financial system: financial depth, access, efficiency, and stability. These four dimensions are measured for the two main components of the financial sector, namely financial institutions and financial markets. Given that the focus of this study is Iran's financial system, the variables selected to examine financial complexity—based on statistics available in World Bank reports—are presented in Table 2. This study examines 22 variables: 12 related to financial depth, two to efficiency, one to stability, and the remainder classified as Others. The investigated variables are mainly in the group of financial institutions and three variables are related to financial markets. Institutions include banks and other depository financial institutions as well as insurance companies and financial markets consisting of the stock market and OTC (over-the-counter).

Table 2. Details of Variables

Row	Variable	Index Name	Description	Symbol
1	Financial Depth	Private credit by deposit money banks to GDP(%)	The financial resources provided to the private sector by domestic money banks as a share of GDP. Domestic money banks 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 domestic real nonfinancial sector which includes central, state and local governments, nonfinancial public enterprises and 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 sum of deposit money bank and Central Bank claims on domestic nonfinancial real sector. Assets include claims on domestic real nonfinancial sector which includes central, state and local governments, nonfinancial public enterprises and private sector.	**DI.04**
4	Financial Depth	Liquid liabilities to GDP(%)	Ratio of liquid liabilities to GDP. Liquid liabilities are also known M3. They are the sum of currency and deposits (M0), plus 5transferable deposits and electronic currency (M1), plus time deposits, foreign currency transferable deposits, certificates of deposit, and securities repurchase agreements (M2), plus travelers' checks, foreign currency time deposits, commercial paper, and shares of mutual funds.	**DI.05**
5	Financial Depth	Central bank assets to GDP(%)	Ratio of central bank assets to GDP. Central bank assets are claims on domestic real nonfinancial 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 (%)	Ratio of life insurance premium volume to GDP. Premium volume is the insurer's direct premiums earned (if Property/Casualty) or received (if Life/Health) during the previous calendar year.	**DI.09**
8	Financial Depth	Nonlife insurance premium volume to GDP(%)	Ratio of nonlife insurance premium volume to GDP. Premium volume is the insurer's direct premiums earned (if Property/Casualty) or received (if Life/Health) during the previous calendar year.	**DI.10**
9	Financial Depth	Private credit by deposit money banks and other financial institutions to GDP(%)	Private credit by deposit money banks and other financial institutions to GDP.	**DI.12**
10	Financial Depth	Domestic credit to private sector (% of GDP)	Domestic credit to private sector refers to financial resources provided to the private sector, such as through loans, purchases of non-equity securities, and 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 capitalization to GDP(%)	Total value of all listed shares in a stock market as a percentage of GDP.	**DM.01**

12	Financial Depth	Stock market total value traded to GDP (%)	Total value of all traded shares in a stock market exchange as a percentage of GDP.	**DM.02**
13	Efficiency	(%) Stock market turnover ratio to GDP	Total value of shares traded during the period divided by the average market capitalization for the period.	**EM.01**
14	Efficiency	Credit to government & state-owned (%) enterprises to GDP	Ratio between credit by domestic banks to the government and state-owned enterprises and GDP	**EI.08**
15	Stability	(%) Bank credit to bank deposits	The financial resources provided to the private sector by domestic money banks 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 saving deposits.	**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.	**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 vis-à-vis the banking sector to the domestic bank deposits.	**OI.10**
18	Other	External loans and deposits of reporting banks vis-à-vis the nonbanking sectors (% of domestic bank deposits)	Percentage of loans and deposits of reporting banks vis-à-vis the nonbanking sectors to the domestic bank deposits.	**OI.11**
19	Other	External loans and deposits of reporting banks vis-à-vis all sectors (% of domestic bank deposits)	Percentage of loans and deposits of reporting banks vis-à-vis all sectors to the domestic bank deposits.	**OI.12**
20	Other	(%) Remittance inflows to GDP	Workers' remittances and compensation of employees comprise current transfers by migrant workers and wages and salaries earned by nonresident workers. Data are the sum of three items defined in the fifth edition of the IMF's Balance of Payments Manual: 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 of the banks that are reporting to BIS. Foreign claims are defined as the sum of cross-border claims plus foreign offices' local claims in all currencies. In the consolidated banking statistics claims that are granted or extended to nonresidents are referred to as cross-border claims.	**OI.14**
22	Other	Ratio of global leasing volume to GNP	Ratios calculated by White Clarke Global Leasing Report.	**OI.17**

Source: World Bank Report.

Forming the Adjacency Matrix for the Financial System of Iran's Economy

After identifying the study variables for Iran, the next step in determining the level of complexity is to calculate pairwise correlations and construct the correlation matrix. Because the financial sector is a dynamic system, the variables are examined over a defined time period to capture this dynamism. Accordingly, data for Iran covering 2005–2021 were analyzed. The data are available at https://databank.worldbank.org/source/global-financial-development and cover the period through 2021. The correlation matrix was computed in SPSS; results at the 5% and 1% significance levels are reported in Table 3. The outcomes of forming the adjacency matrix are shown in Table 4. Because edge weights (correlation magnitudes) are not required in the present method, an adjacency matrix is needed to construct the financial network. In this matrix, each pair of variables is coded 1 if a significant correlation exists and 0 otherwise. The resulting adjacency matrix is presented in Table 4.

Table 3. Correlation between Pairs Variables

	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	1	-0.48	-0.56	-0.48	-0.41	-0.46	-0.43	-0.56	-0.5	-0.5	-0.43	-0.47	0	-0.63*	0.29	-0.41	0.91**	0.76**	0.73**	0.76**	-0.71*	0.76**
DI.04	-0.48	1	0.95**	1**	0.87**	0.76**	0.89**	0.65*	0.98**	0.98**	-0.08	-0.13	-0.19	0.8**	-0.58	0.87**	-0.72**	-0.71**	-0.66*	-0.85**	0.58	-0.45
DI.14	-0.56	0.95**	1	0.95**	0.94**	0.87**	0.95**	0.81**	0.99**	0.99**	0.13	0.06	-0.27	0.93**	-0.71**	0.94**	0.8**	0.8**	-0.77**	-0.82**	0.45	-0.44
DI.02	-0.48	1**	0.95**	1	0.87**	0.76**	0.87**	0.65*	0.98**	0.98**	-0.08	-0.13	-0.19	0.8**	-0.58	0.87**	-0.72**	-0.72**	-0.66*	-0.86**	0.58	-0.45
DI.08	-0.41	0.87**	0.94**	0.87**	1	0.95**	1**	0.87**	0.91**	0.91**	0.16	0.08	-0.31	0.92**	-0.89**	1**	-.66*	-0.66*	-0.64*	-0.62*	0.29	-0.14
DI.09	-0.46	0.76**	0.87**	0.76**	0.95**	1	0.94**	0.94**	0.8**	0.8**	0.23	0.15	-0.36	0.95**	-0.91**	0.95**	-0.66*	-0.67*	-0.66*	-0.57	0.3	-0.08
DI.05	-0.43	0.89**	0.95**	0.87**	1**	0.94**	1	0.87**	0.92**	0.92**	0.15	0.08	-0.29	0.92**	-0.87**	1**	-0.67*	-0.68*	-0.65*	-0.65*	0.3	-0.17
DI.10	-0.56	0.65*	0.81**	0.65*	0.87**	0.94**	0.87**	1	0.72**	0.72**	0.29	0.21	-0.36	0.94**	-0.87**	0.87**	-0.71**	-0.7*	-0.71**	-0.53	0.25	-0.19
DI.12	-0.5	0.98**	0.99**	0.98**	0.91**	0.8**	0.92**	0.72**	1	1**	0.02	-0.03	-0.21	0.86**	-0.63*	0.91**	-0.75**	-0.7**	-0.7*	-0.83**	0.47	-0.46
DI.01	-0.5	0.98**	0.99**	0.98**	0.91**	0.8**	0.92**	0.72**	1**	1	0.02	-0.03	-0.21	0.86**	-0.63*	0.91**	-0.75**	-0.75**	-0.7*	-0.83**	0.47	-0.46
DM.01	-0.43	-0.08	0.13	-0.08	0.16	0.23	0.15	0.29	0.02	0.02	1	0.89**	-0.36	0.35	-0.34	0.16	-0.37	-0.38	-0.42	-0.06	-0.15	-0.11
DM.02	-0.47	-0.13	0.06	-0.13	0.08	0.15	0.08	0.21	-0.03	-0.03	0.89**	1	0.06	0.25	-0.25	0.08	-0.34	-0.28	-0.31	-0.06	-0.23	-0.16
EM.01	0	-0.19	-0.27	-0.19	-0.31	-0.36	-0.29	-0.36	-0.21	-0.21	-0.36	0.06	1	-0.39	0.39	-0.31	0.16	0.38	0.43	0.04	-0.12	-0.12
EI.08	-0.63*	0.8**	0.93**	0.8**	0.92**	0.95**	0.92**	0.94**	0.86**	0.86**	0.35	0.25	-0.39	1	-0.82**	0.92**	-0.84**	-0.85**	-0.84**	-0.72**	0.36	-0.35
SI.04	0.29	-0.58	-0.71**	-0.58	-0.89**	-0.91**	-0.87**	-0.87**	-0.63*	-0.63*	-0.34	-0.25	0.39	-0.82**	1	-0.89**	0.46	0.5	0.52	0.29	-0.04	-0.17
OI.02	-0.41	0.87**	0.94**	0.87**	1**	0.95**	1**	0.87**	0.91**	0.91**	0.16	0.08	-0.31	0.92**	-0.89**	1	-0.65*	-0.65*	-0.64*	-0.62*	0.29	-0.14
OI.14	0.91**	-0.72**	0.8**	-0.72**	-.66*	-0.66*	-0.67*	-0.71**	-0.75**	-0.75**	-0.37	-0.34	0.16	-0.84**	0.46	-0.65*	1	0.92**	0.89**	0.9**	-0.67*	0.77**
OI.12	0.76**	-0.71**	0.8**	-0.72**	-0.66*	-0.67*	-0.68*	-0.7*	-0.7**	-0.75**	-0.38	-0.28	0.38	-0.85**	0.5	-0.65*	0.92**	1	0.99**	0.83**	-0.57	0.69*
OI.10	0.73**	-0.66*	-0.77**	-0.66*	-0.64*	-0.66*	-0.65*	-0.71**	-0.7*	-0.7*	-0.42	-0.31	0.43	-0.84**	0.52	-0.64*	0.89**	0.99**	1	0.76**	-0.49	0.64*
OI.11	0.76**	-0.85**	-0.82**	-0.86**	-0.62*	-0.57	-0.65*	-0.53	-0.83**	-0.83**	-0.06	-0.06	0.04	-0.72**	0.29	-0.62*	0.9**	0.83**	0.76**	1	-0.79**	0.79**
OI.17	-0.71*	0.58	0.45	0.58	0.29	0.3	0.3	0.25	0.47	0.47	-0.15	-0.23	-0.12	0.36	-0.04	0.29	-0.67*	-0.57	-0.49	-0.79**	1	-0.6
OI.13	0.76**	-0.45	0.44	-0.45	-0.14	-0.08	-0.17	-0.19	-0.46	-0.46	-0.11	-0.16	-0.12	-0.35	-0.17	-0.14	0.77**	0.69*	0.64*	0.79**	-0.6	1

Source: Research Finding.

Note: * Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed). DI: Stands for Depth of Financial Institutions. DM: Stands for Depth of Financial Markets. EI: Stands for Efficiency of Financial Institutions. EM: Efficiency for Depth of Financial Markets. SI: Stands for Stability of Financial Institutions. SM: Stability of Financial Institutions.
OI: Other Variables of Financial Institutions. OM: Other Variables of Financial Markets.

Table 4. Correlation Matrix of Pairs Variable

	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

Source: Research finding.

Drawing Graphs for the Financial System of Iranian Economy

To draw the graph of Iran's financial system, according to the created adjacency matrix, the nodes that have a correlation of one are connected by edges. Thus, the variable EM.01 is deleted because it is not related to any other variable. Furthermore, variables DM.01 and DM.02, which are the only market variables examined in this study, are related only to each other and not to other variables; therefore, they are removed.

The financial graph for the remaining variables was drawn using the adjacency matrix with Python software. The output for the entire financial system is shown in Figure 1, and the outputs for the variables of financial depth and others are presented in Figures 2 and 3. In Figure 1, it can be seen that variables EI.08 and DI.14 have 15 edges (cores of the graph), which is the highest number of edges in the financial graph. Next, variables DI.01 and DI.12 have the next highest number of edges, i.e., 12. According to the definitions of variables in Table 2, the variables with the highest number of edges are related to government, domestic, and private credits. In other words, banks and credits in the financial graph play a key role in the financial system of Iran's economy.

Among the 22 variables under investigation, 9 variables are in the financial depth category. Figure 2, drawn for financial depth variables, shows that all variables are strongly correlated and the level of complexity for this group of variables is obviously high (see the cores of Figure 2, which are similar in terms of edges). The "Other" variable category contains 7 variables, as shown in Figure 3. In this figure, variable OI.14 is the center or core of the figure.

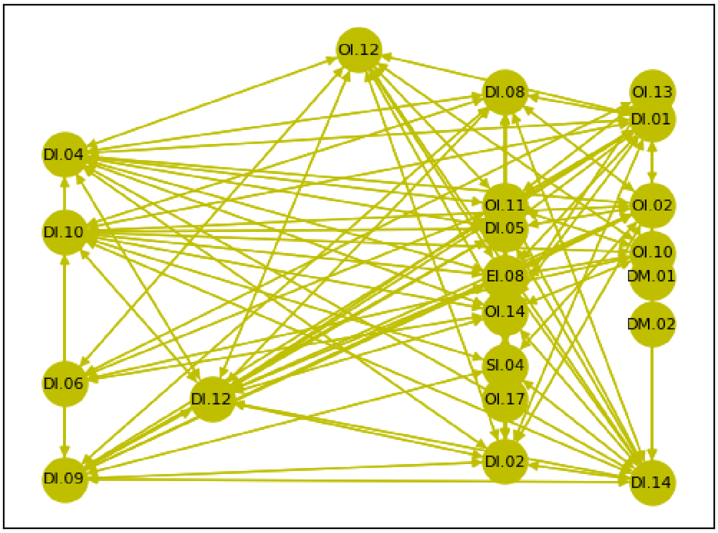

Figure 1. The Overall Figure of the Financial System (Including Financial Institutions and Markets)
Source: Research finding.

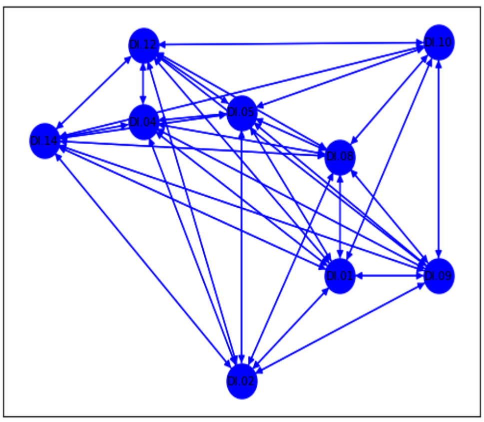

Figure 2. Financial Network of Depth Variables
Source: Research finding.

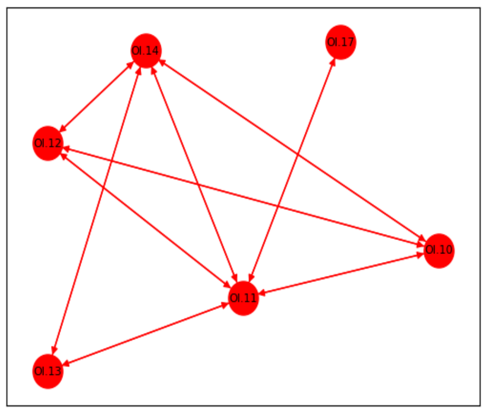

Figure 3. Financial Network of Other Variables
Source: Research finding.

Complexity Calculation

For calculating the complexity using McCabe's cyclomatic method, after drawing the figures, the number of nodes and edges of the figure must be determined. Because Figure 1 does not have an independent subgraph, the complexity calculation is done using Equation 5. After removing some variables with zero or limited effect in the financial graph, the number of variables that form nodes (N) in the financial graph is 19; as mentioned in the previous section, EM.01, DM.01, and DM.02 are omitted. The total number of edges (E) in the figure is 96. However, considering that the relationship between pairs of variables is two-way, in order to avoid double calculation of the number of edges for the upper triangular or lower triangular matrix, the adjacency matrix is considered; thus, the number will be equal to 79 (E). The complexity number is calculated according to the following equation:

$$V(G) = E - N + 2 \qquad \text{Duplicate (5)}$$

$$E = 96$$

$$N = 19$$

$$\Rightarrow V(G) = 79$$

According to the data and the above equation, the complexity number for the financial system of Iran's economy is calculated as V(G) = 79. This number shows the very high complexity of Iran's financial system and indicates that the financial sector of Iran's economy has a very high risk.

Conclusion

In this research, the financial complexity in Iran's economy during the years 2005–2021 was investigated and calculated with the aim of analyzing the financial system. According to Iran's financial network and level of complexity, the following results are obtained:

First, the capital market in Iran's economy does not have a crucial role in the financial system of the country. Secondly, the government plays a central role in the financial system, which shows the significant role of the government in the financial structure of Iran. Thirdly, banks and depository financial institutions are more influential compared to the capital market and insurance companies. Also, comparing Figures 2 and 3, financial depth variables have a more complicated graph than other variables.

According to the calculations done for the graph complexity, the number 79 was obtained, which indicates very high complexity and high risk. The findings show that the financial system in Iran runs a high level of risk which, although it may have advantages for policy makers, is certainly not beneficial for the economy. In order to reduce financial complexity, we suggest more corporate financing through the capital market; and in order to reduce the role of the government in the financial system, banks and other financial institutions should allocate fewer credits to government sectors.

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