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# CONTAGION DYNAMICS IN THE IRANIAN STOCK MARKET

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## ABSTRACT

Contagion in financial markets takes place both because of fundamental or non-fundamental reasons like herd behaviors that can increase market risk levels and even end in inefficient allocation of financial resources. Thus, understanding the contagion and its dynamics will be critical for the participants of financial market. Hence, using network-based epidemic modeling, the study examined the dynamics of contagion in the Iranian stock market from 2011 to 2019 and short-term and long-term scales. To this end, first the correlation network of 46 Iranian stock market groups was developed and then analyzed using short-term and long-term contagion dynamics simulations. The results showed that the extent and speed of contagion is much higher in the short-term than in long-term and in long-term a significant number of groups can be immune to the contagion. However, in long-term the rate of return to pre-contagion status is shorter than in short-term.

## INTRODUCTION

Financial markets are complex with many actors interacting with each other showing chaotic and / or collective behavior. Thus, the ability to describe and understand the relationships of complex financial market systems can help market participants and regulators to properly understand market information and use the vast amount of financial data to reach their specific goals. One of the advantages of this knowledge is its helping market participants to understand the mechanism of financial asset price formation, fluctuations and their dynamics and use it to manage financial assets risk.

Nonetheless, understanding and modeling such complexities calls for a theoretical tool, and complex networks analyses have attracted the attention of many financial researchers to this end in recent years. For instance, Allen and Babus (2008) and Billio et al. (2012) have considered network analysis as a significant part of financial market analysis critical in better understanding financial markets, especially in times of crisis. Studies by scholars like Allen and Gale (2000), Elliott et al. (2014), Gabrieli (2011), Rogers and Veraart (2014), Acemoglu et al. (2015), and Berndsen et al. (2018), Berndsen et al. (2018), and Rokni et al. (2018) have shown that in a financial network, network dynamics over time, topological properties, number and intensity of communication between network members are critical in cascade reactions, contagion and dissemination of different risks in financial networks.

Indeed, in the analyses generally based on traditional time series data, the most important defaults can probably be considered the neglect of cross-correlations and implicit and hidden information in the high volume of time series. The presence of heterogeneous members in stock markets has led to complex behaviors in this financial market and it is improbable that all the necessary information, especially for risk management, portfolio management, regulation and policymaking be obtained with individual analysis of firms and industries in the stock market. Moreover, traditional analyses cannot consider the network and domino effects existing in a financial system that are decisive in the financial stability and risk of the system. These phenomena make the complexity of transactions, the entanglement of dependencies, and the spread of the stock market even more, and inattention to them could diminish the ability to manage asset risk. Thus, the lack of a network analysis to understand the dynamics of contagion in the Iranian stock market is felt.

According to the points stated, as many networking incidents happen dynamically and lack a static process (like cascade effects or herd behaviors common in financial markets), the study will examine contagion phenomenon in the Iranian stock market using Network-Based Epidemic Modeling in the framework of a complex network analysis. Moreover, it will examine how other market members will be involved in case of an event for one stock market member, what will be its dynamics, when the most contagion will happen in the market and how long it takes for the market to return to its previous state. The results of such cognition help market participants better understand the collective behavior of the market and use it to implement their investment strategies and regulation.

The paper will is organized as follows: In the second part, the theoretical foundations and literature are presented. In the third chapter, the methodology is introduced and then in chapter four, the results obtained are presented. Ultimately, the last chapter is related to the conclusions and suggestions.

## THEORETICAL FOUNDATIONS AND LITERATURE

It is first better to know contagion. Kaminsky and Reinhart (2000) define contagion as shock transmission, and Masson (1999) defines contagion as shock transmission beyond fundamental linkages. According to Forbes and Rigobon (2001), contagion is the changes in risk transfer mechanisms in crisis times.

Contagion is clearly a policy-based phenomenon. Firstly, as some contagions have external effects and lead to inefficient risk allocation in the economy, since brokers not considering the effects of their actions on others increase the level of economic risk. Here, ex ante policies like market regulation can be used to restore efficiency. Moreover, ex post intervention can be done if necessary to neutralize the contagion or reduce its effects in other markets in case they are unsuccessful. Secondly, if the contagion is so extensive, such publications can contribute to the general instability of the financial system and negatively affect economic growth. In a scenario like this, macroeconomic stabilization policies can help combat the consequences of extensive contagion for the whole economy (ECB, 2005).

According to the financial literature, contagion channels can be divided into two categories. The first channel is real links like business, financial and political connections. However, the second channel is in the behavior of investors and is considered a non-fundamental factor. This change can have different reasons. The first is the herding behavior of investors after reviewing new information, exacerbated by information asymmetry. Kodres and Pritsker (2002) revealed that the contagion of idiosyncratic shocks between markets happens via portfolio change and is reinforced by information asymmetry. The second one is the simultaneous withdrawal of money by investors to cash in on investments. Moreover, Longstaff (2002) indicated that investors prefer cash assets in times of uncertainty. Thirdly, it has to do with to institutional investors and their collective behaviors, especially in response to changing rules and regulations (Glick and Rose, 1999; Dornbusch et al., 2000; Nneji et al., 2016).

In the empirical studies in financial markets, using the information network modeling of market participants, Kelly and Grada (2000) modeled the contagion of New York Bank Irish depositors' behavior and found that their social network was the main determinant of behavior in the crisis time. Rösch and Kaserer (2013) indicated that market liquidity risk transmits illiquidity in markets and thus liquidity commonality can be the driving force behind financial contagion.

Cipriani and Guarino (2008) revealed that when personal values are heterogeneous among informed traders, an information cascade (like complete blockage of information) happens and prices cannot collect scattered information among traders. In a cascade of information, all the traders that have the same preferences follow the same course, either follow the market (herd) or go against it (contrarianism). Furthermore, they examined financial contagion in two assets, showing that information cascades in one market can be generated by information spillovers from another market. Such spillovers have pathological consequences and lead to long-term mismatch between prices and fundamental factors.

Gai and Kapadia (2010) examined how the probability and potential effect of contagion are affected by aggregate and idiosyncratic shocks, changes in network structure, and asset market liquidity. In a highly connected system, the losses of the other party to a failing institution can be more widely disseminated and absorbed in other institutions. Hence, increasing connections and sharing risk may reduce the likelihood of contagious default. Furthermore, several financial communications increases the likelihood of contagion spread. Thus, the effects of any crisis that happens can differ drastically.

Glasserman and Young (2015) estimated how much connections reduce expected losses and projected default under a wide range of shock distributions in a financial network. Their findings showed that the network structure is significant in its contagion and magnification. Additionally, the effects of spillover become more evident when the size of the network nodes is heterogeneous.

Chang and Cheng (2016) examined the contagion in the US financial markets (currency, bonds, stocks and money) using the Granger causality test. Their results showed varying degrees of contagion in the US financial markets, and they admitted that these results provide good advice on capital allocation strategies and can be useful for portfolio management in crisis times.

Zhang et al. (2020) modeled and studied the spillover effects of risk and contagion on the G20 stock market based on the fluctuation network and space econometrics. They found that significant effects of spillover and contagion between markets, and that its structure was hierarchical, with features that included dynamic changes.

In some studies on epidemic models in the financial markets, Shive (2010) developed an epidemic model for investor behavior in the Finnish stock market. He found that socially motivated transactions predict stock returns and the effects are not reversed - it shows that people share useful information. Zhou et al. (2019) used an epidemic model to examine capital flows in the Chinese stock market, finding herd or contagious behavior prevailing in the Chinese stock market.

To the knowledge of scholars at the time of writing this paper, no studied had been done in Iran to model Iran's financial markets according to the phenomenon of contagion and network-based epidemic modeling. Thus, the study is innovative in this regard.

## DATA AND METHODOLOGY

The analysis method was Graph Theory and analysis of complex networks. To this end, first, the correlation coefficient of return of 46 Iranian stock market groups was calculated in two time scales, daily and annual. Table 1 presents the list of these groups. After calculating the correlations and refining the statistically significant correlations, the Iranian stock market correlation network will be built in the two mentioned time scales and epidemic modeling will be based on the network. The rest of this chapter, first a brief introduction of Graph Theory is introduced, and then construction of a graph (network) is reviewed. The last section introduces network-based epidemic modeling.

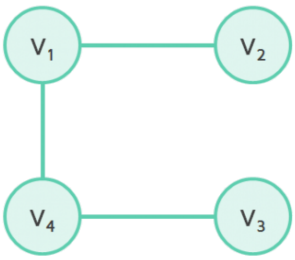
**Table 1: List of groups in the Iranian stock market**

| Industry name | Industry name | Industry name |
|---|---|---|
| Investment | Sugar | Production of fertilizers and nitrogen compounds |
| Leasing | Industrial contracting | Vehicle |
| Software and services | Cement, lime and gypsum | Auto Parts |
| Telecommunication equipment | Engineering activity | Cleaning products |
| Excavation | Other non-metallic mineral products | Printing and publishing |
| Oil products | Transportation by rail | Beverages |
| Telecommunications | Ports and shipping | Sweets |

| | | |
|---|---|---|
| Medicinal | Ground freight transport | Dairy products |
| Mass construction, real estate | Banks and credit institutions | Crops |
| Rubber and plastic | Insurance | Retail, except of motor vehicles |
| Metal ores | Coal | Other food products |
| Paper products | Metal products | Diverse chemicals |
| Iron and steel | Ceramic and tile | Textile |
| Wood | Hardware and equipment | Electric machines |
| Home appliances | Production of non-iron precious metals | Industrial equipment |
| | | Machinery |

**Introducing the concept of graph**

In mathematics terminology, Graph Theory is the study of graphs: pair relationships between components of a set modeled with some mathematical structures. A simple graph is shown with $G = (V, E)$ where v is the vertex or nodes and E is a set of edges. A graph is formed of edges that connect the nodes. It is said that two nodes are connected if they have a common edge. We describe the connection properties of a graph using the adjacency matrix A. An adjacency matrix is an n×n matrix where n is the number of nodes in a graph. If a pair of nodes is connected by an edge, they are called adjacent, and in the row i and column j, the graph adjacent to the matrix we denote by takes 1, otherwise zero. If the adjacency matrix is symmetric, $a_{ij} = a_{ji}$ , then it shows a undirected graph. Figure 1 shows a simple graph consisting of (4 nodes and 3 edges) and its adjacent matrix that was symmetrical.



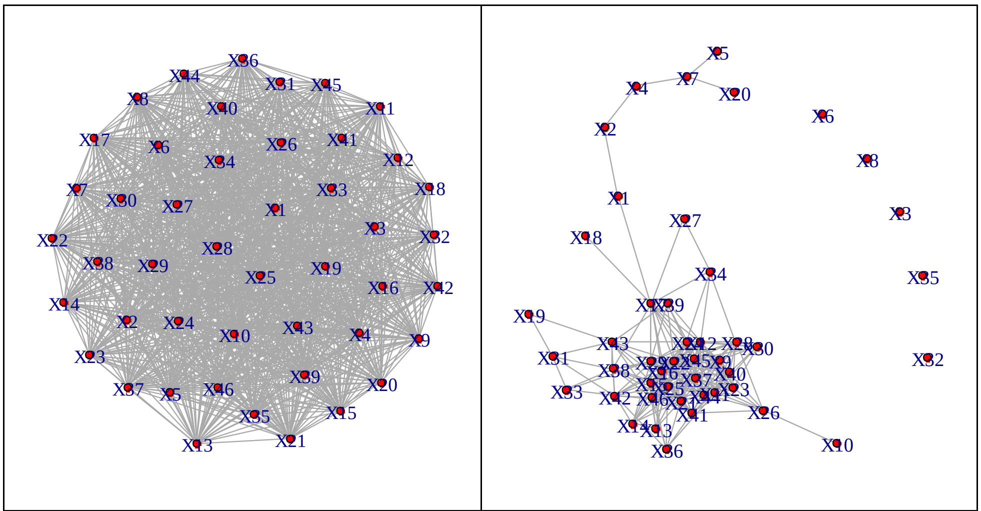

$$A_G = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix}$$

**Figure 1: An undirected graph and its adjacent matrix**

**Constructing graph (network) of Iranian stock market**

In the first step, the adjacency matrix must be built, obtained by calculating the correlation between the two groups' returns. We calculate this adjacency matrix for both daily and annual periods and then we have 2 graphs daily and annually. To this end, first the time series data of the price index of 46 stock markets of Iran with daily and annual frequency from the first trading day of 2011 to the March 20 of 2020 were extracted, and then its return is calculated. Then correlation coefficient returns of each of the 46 stock market groups are then calculated for each daily and annual frequency. Thus, two matrices with 46 rows and columns of correlation coefficients were generated for both daily and annual time scales. Then $2.58 \times \frac{1}{\sqrt{T}}$ critical value was used to determine whether or not the correlation coefficient is significant at the 99% confidence level, where T is the sample size (Krehbiel, 2004). The sample size was observed in daily data 1780 and 7 annually. Thus, for the daily scale, the critical value is 0.0611 and the critical value for the annual scale is 0.9121. Then if the correlation coefficient obtained for both groups i and j is greater than these values, the correlation is statistically significant at the 99% confidence level.

Then the adjacency matrix for daily and annual graphs was constructed based on the correlation coefficient of returns of the main groups of the Iranian stock market. If the correlation coefficient between groups i and j is significant, a value of 1 is given to the adjacency matrix, and the value of zero is inserted if the correlation coefficient is not significant. This type of matrix construction is called the winner-takes-all approach. This is done in pairs for all 46 stock market groups to create a daily and annual proximity matrix. After making the adjacency matrix, the graphs are formed and can be analyzed. Figure 2 shows the graphs of the constructed networks.



Short-term network | Long-term network

**Figure 2: Graph of long-term and short-term networks of the Iranian stock market**

**Network-based epidemic modeling**

The term epidemic refers to a phenomenon that is more prevalent than expected. The term is most commonly used to refer to diseases and their spread throughout the population - like malaria, plague and AIDS - but is sometimes widely used in other contexts like describing the prevalence of problems in a system or market.

One of the most widely used classes of epidemic models are susceptible-infected-removed (SIR) models. Assume a population with N + 1 members at any point in time with a random number, say NS(t), of members of a community susceptible, a random number of NI (t) members are infected, and an NR (t) member at any point in time have recovered from the contagion (say, they recover) and are not infected again (thus being eliminated from the epidemic process).

Assume that we have an infected limb and N susceptible limbs, NI (0) = 1 and NS (0) = N and let s and i show the number of susceptible limbs and the number of infected limbs. In SIR model, the number of susceptible, infected, and excluded varies according to the following instantaneous contagion probabilities (Kolaczyk & Csárdi, 2014):

$$\mathbb{P}(N_S(t+\delta t) = s-1, N_I(t+\delta t) = i+1 \,|N_S(t) = s, N_I(t) = i) \approx \beta s i \delta t \tag{1}$$

$$\mathbb{P}(N_S(t+\delta t) = s, N_I(t+\delta t) = i-1 \,|N_S(t) = s, N_I(t) = i) \approx \gamma i \delta t \tag{2}$$

$$\mathbb{P}(N_S(t+\delta t) = s, N_I(t+\delta t) = i-1 \,|N_S(t) = s, N_I(t) = i) \approx (1-(\beta s+\gamma) i \delta t \tag{3}$$

Here, δt is the infinitesimal value and NR (t) is obtained with respect to NS (t) + NI (t) + NR (t) = N + 1.

The model above shows that at any time t, a new disease occurs among the susceptible (because of the contact with one of the infected) and its instantaneous probability is a ratio of the product of the number of susceptible s and the number of patients i. Similarly, patients recover with a proportion of the immediate probability i. These probabilities are scaled with β and γ parameters showing the initial rate and the recovery rate. Moreover, parameters β and γ are rate parameter of an exponential distribution.

The model states that with the number of susceptible s and the assumed infected i in the period t, the process remains in the state (s, i) for a given time, distributed as an exponential random variable, at the rate (βs + γ) i. Then a transition to the state (s-1, i + 1) occurs with probability βs / (βs + γ) i, or a transition to the state (s, i-1) with probability γi / (βs + γ) i. Epidemic modeling is a favorite subject of the scholars working on network-based dynamic process models.

We consider G as a network graph describing the structure of the relationship between Nv members of the network. Suppose a member (node) gets involved at time t = 0 (e.g., there is a crisis in the stock market of an industry or a symbol). The involved node is involved for a certain time that has an exponential distribution at the gamma rate and then recovers. At the involvement times, the member interacts with other members of the network by an exponential distribution at the beta rate, ending in the contagion of the phenomenon to other members of the network. We define Xi (t) = 0,1,2, according to which a node is susceptible, involved, or recovered at time t.

Assume that $X(t) = (X_i(t))_{i \in V}$ is the resulting time process for the G network graph. We show the process mode at time t with x states. Every change from x to x' involves one change in one and only one member at a time. Assume that that x and x' differ in member i. then one can show that the model process can be described by the following criterion.

$$P(X(t+\delta t)=x'|X(t)=x)\approx\begin{cases}\beta M_i(x)\delta t, & \text{if } x_i=0 \text{ and } x_i'=1\\ \gamma\delta t, & \text{if } x_i=1 \text{ and } x_i'=2\\ 1-[\beta M_i(x)+\gamma]\delta t, & \text{if } x_i=2 \text{ and } x_i'=2\end{cases} \quad (4)$$

Here, Mi (x) is the number of neighbors of member i involved in time t, NS (t) members of the network susceptible to involvement, NI (t) members involved, NR (t) the members recovered or immune. The properties of NS (t), NI (t), and NR (t) processes will be affected by the properties and topology of G-network graph, which can be determined by simulation and show how the contagion dynamics occur in the network.

## RESULTS

As SIR models introduced are simulation-based, it is necessary to use simulation with the production of random numbers to study the dynamics of contagion in the Iranian stock market network. The number of times random numbers are generated is called the simulation iteration, and the higher the number, the higher the convergence of the results. Nonetheless, the higher the number of iterations, the more computing power will be required. Moreover, the exponential distribution rate parameter of the network edges is used to value the β and γ parameters. Ultimately, the results of producing these random numbers in line with the rule described will show the dynamics of contagion according to the characteristics and topology of the market network.

Hence, prior to simulation, one has to estimate their exponential distribution rate parameter by plotting the density function of the daily and annual graph edges. The rate parameter in the daily graph is 1.04 and 0.10 in the annual graph (Figures 3 and 4)1. Hence, the parameters β and γ in the model are equal to these parameters of the estimated rate.

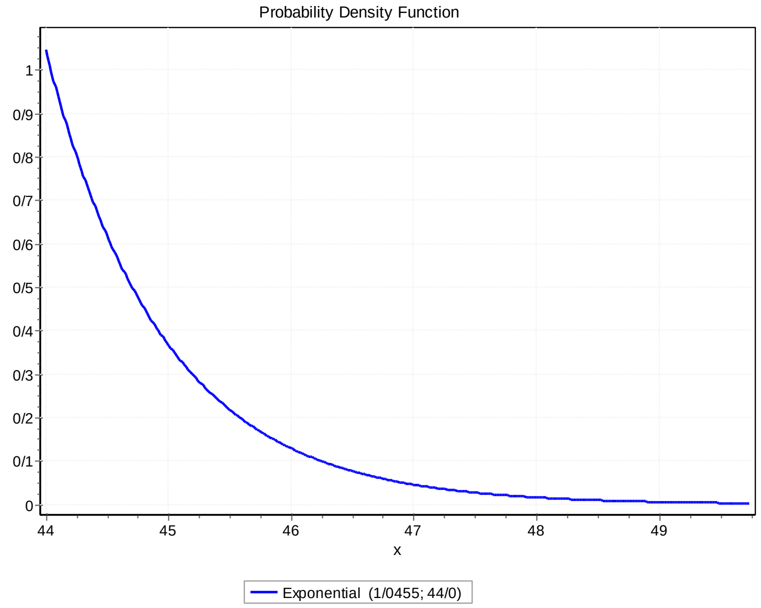



**Figure 3: Exponential distribution of edges in the daily graph**

[1] In the diagrams, the parameters β and γ are reported in parentheses.

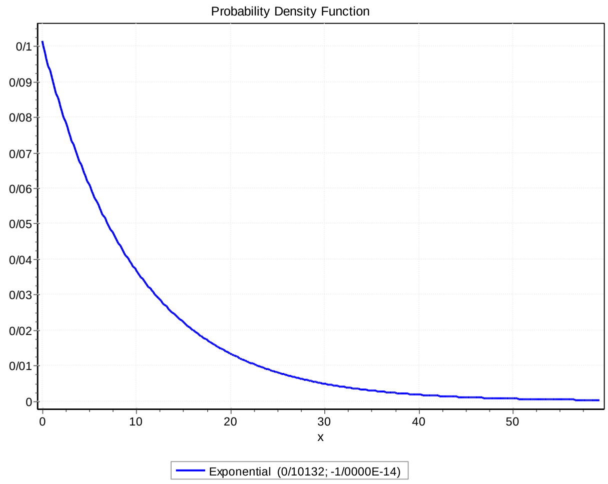



**Figure 4: Exponential distribution of edges in the annual graph**

Figures 5 and 6 indicate simulation of contagion dynamics results in the Iranian stock market network at daily and annual levels using epidemic modeling with 1000 iterations. In the graphs, the full color lines are the middle value and the dotted lines are the value of the first and ninth deciles obtained from the simulation.2 The results are interpreted according to simulations median values .

As the results in Figure 5 show, in the daily period, in less than one period the information shock will spread to more than 30 other groups in the stock market if we assume that the release of information (or an information shock) occurs for one group in the Iranian stock market. After this period, the number of involved groups is reduced and finally, after 4 periods, the effect of information shock on stock market groups disappears. The results of simulation indicated that the number of groups recovered from the shock after two periods is more than 40 groups, i.e. the effect of the shock has been discharged from them. The number of contagion susceptible groups also indicates that changes spread very quickly to all market groups in less than a period of time.

Ultimately, Figure 6 shows the epidemic simulation results for the annual graph. As is seen, the difference between the topological properties of the annual graph and the daily graph in the results of contagion simulation is quite clear. In this graph, a shock in one of the market groups involves (affects) about 20 stock market groups and this shock is transmitted to them about a period later. Finally, after about 5 periods, contagion to other groups in the market ends. The number of groups recovered from contagion indicates that in the annual graph, the speed of recovery is much slower and finally reaches a fixed number of 35 groups after 5 periods. The significant difference of the annual graph is the number of susceptible groups, where the number of vulnerable groups decreases at a slower rate due to the heterogeneous relationships of the groups with each other, and eventually stabilizes in approximately 10 groups. One of the important themes of the results of this simulation is that it shows that the contagion of shocks in short periods of time occurs more rapidly and becomes more rapid. On the other

[2] R environment and the igraph pack have been used to perform the simulation.

hand, as we move towards the long-term, the information shocks inflicted on groups become less intense and persist over more periods in the market.

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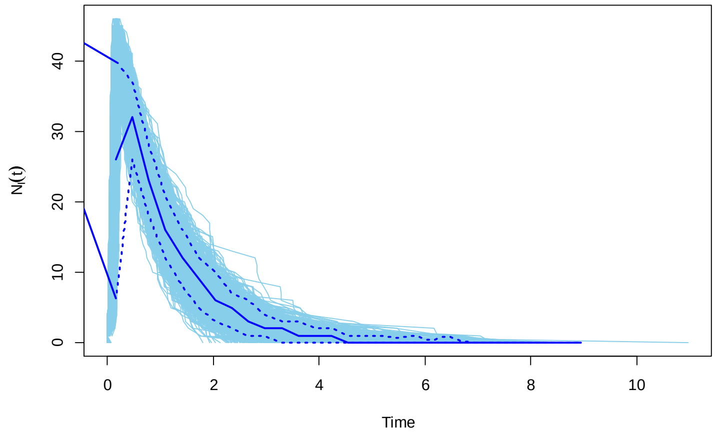
<tr><td>The number of groups involved</td><td>
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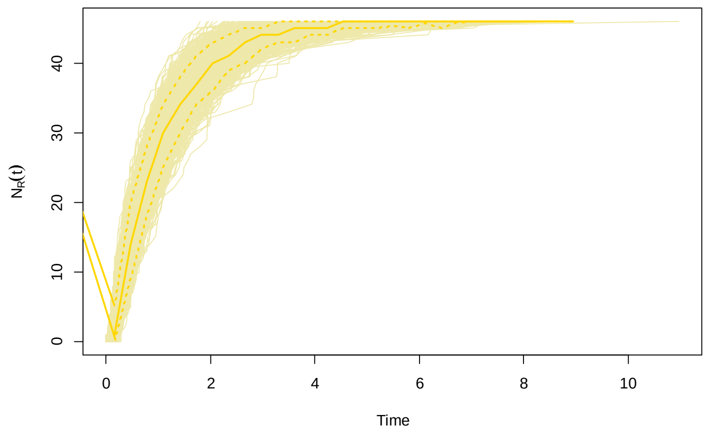
<tr><td>The number of groups recovered</td><td>
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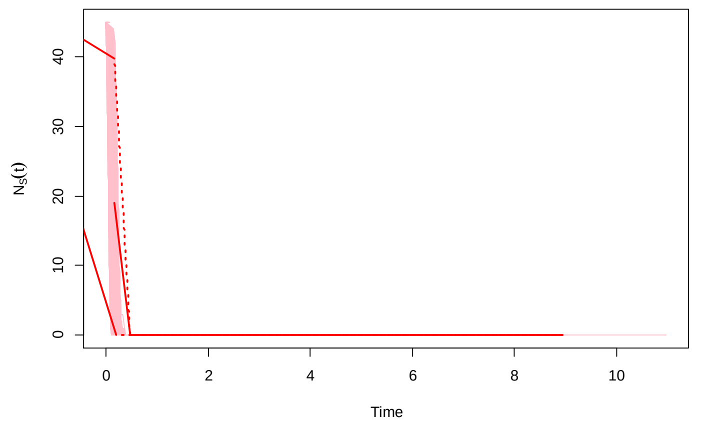
<tr><td>The number of susceptible groups</td><td>
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**Figure 5: Contagion dynamics in the daily stock market graph**

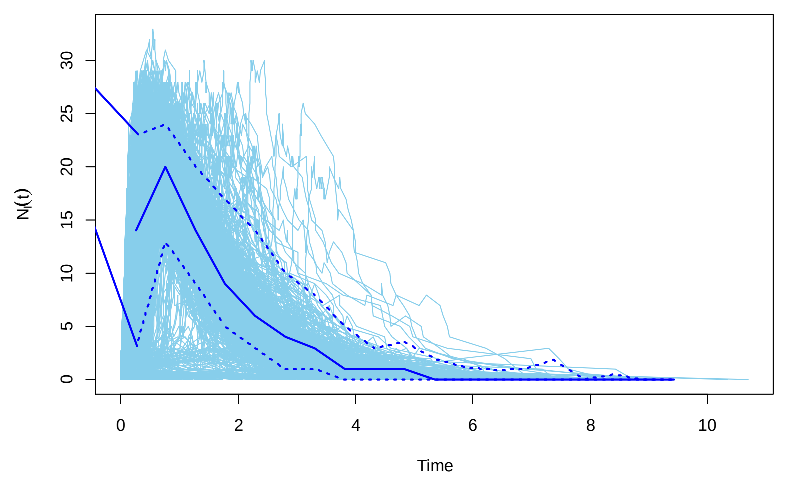
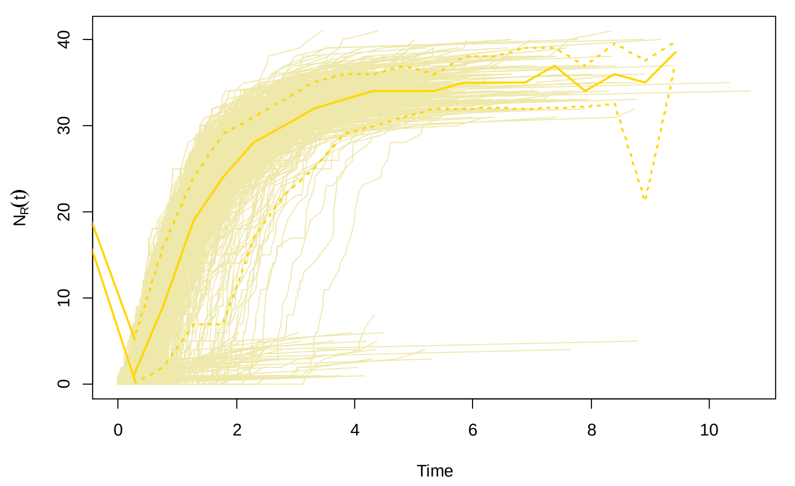
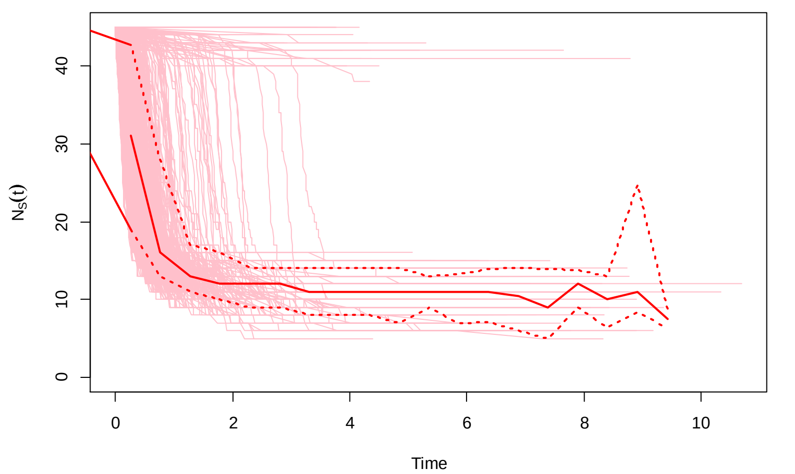
| | |
|---|---|
| The number of groups involved |  |
| The number of groups recovered |  |
| The number of susceptible groups |  |







**Figure 6: Contagion dynamics in the annual stock market graph**

## CONCLUSION

In traditional risk analysis, the idiosyncratic complications of a market participant are exogenous data. Nonetheless, in a systemic environment, negative outcomes for one participant can affect the whole system. For instance, cascades or spillovers can affect other members of the system, which is an exogenous phenomenon known as contagion. Contagion is usually connected to and arises from a network structure, and the structural mechanisms of the network aggregate the complications throughout the system.

Regarding this, the study tried to answer the question “What are the dynamics of contagion in the Iranian stock market?" Because of the complexity and interactions that members of a financial market have, contagion dynamics in 46 groups of Iranian stock market was analyzed for daily and annual bases in the framework of Graph Theory and complex network analysis using a network-based epidemic simulation.

The findings showed that in the short-term, the Iranian stock market network is very complex and intertwined, and any incident for any of the network members (stock market groups) affects a large number of other group members. In other words, the contagion of information and shocks happen fast and in less than one period, and almost all members of the network are affected, with most of the groups involved returning to their original state about 2 periods later. On the contrary, in long-term, the interactions and interdependencies of stock market groups significantly reduce, and the speed of information dissemination and contagion is slower in long-term than in the short-term. However, the severity and contagion is higher than the groups in long-term, and contagion evacuation happens at a slower rate and lasts up to 5 periods. Moreover, contagion does not occur to about a quarter of groups in long-term. Thus, the dynamics of contagion are quite different from the short-term in long-term.

Among the significant results of such a conclusion is that fundamental analysis of groups is critical not only for themselves but also for their affiliated groups, especially in long-term. However, this is less important in the short-term, as each event extends to most groups with the large correlation of groups. Moreover, the more a group of a stock market is connected with other groups, the more likely it is to become contagious. Not only groups that are directly connected to each other, but also groups that are not directly connected to each other are affected by each other. Thus, it is necessary to consider more the degrees of connections and correlations between groups and contagion dynamics at various time scales in portfolio risk management, so that the black swan - unpredictable or unforeseen events - of the Iranian stock market are determined with higher probability.

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