Article

Research on Stock Market Risk Contagion of Major Debt Crises Based on Complex Network Models—The Case of Evergrande in China

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Abstract: After a major debt crisis occurs in a listed company, the stock prices of related enterprises may also fluctuate sharply, resulting in the spread of debt risk to more enterprises. Taking the stocks of listed companies as network nodes, we constructed a complex stock market network over three periods of time through the logarithmic return rate of stocks for the three periods of prophase, metaphase, and anaphase of the debt crisis. We studied the topological characteristics of the network and destructiveness over the three periods. Finally, the minimum spanning tree was used to construct a network and the community structure of the network. The empirical analysis took the debt crisis of the China Evergrande Company as an example to analyze the impact of its major debt crisis on the Chinese stock market. The research findings were as follows: First, the debt crisis increased the inter-industry connections within the network, that is, the correlations between enterprises in different industries was enhanced. Second, the closeness of the cross-industry connections increased the connectivity efficiency of the network, but compared with the other two periods, the debt crisis in the metaphase was less stable. Third, community research showed that in the metaphase of the debt crisis, the enterprises became the core nodes of the network.

Keywords: destruction resistance; complex network; organization structure; minimum spanning tree

MSC: 91-10; 91G00

1. Introduction

Major debt crises inevitably impact related enterprises and make the debt risks spread among a wide range of related enterprises. The debt crisis of China Evergrande occurred in July 2021, which had a certain negative impact on China’s financial markets and caused fluctuations in the prices of related stocks. Therefore, how to prevent and control the spread of infectious risks caused by major debt crisis events has become a major point of focus for the financial industry. The complex network theory offers an effective method to study the spread of enterprise risk, and to prevent and control the spread of infectious risk in complex networks, we need to analyze the topological characteristics of the network and the resistance of the network itself.

There are many research works in the extant literature on network topological characteristics, destructiveness, and community structure, the main purpose of which was to analyze the impact of major emergencies or policies on the financial industry. Zhang and Zhuang (2019) [1] constructed the Chinese stock market network and studied the relationship between the topological characteristics of the network and the international stock market index. Shahzad (2019) [2] adopted the bivariate cross-quantitative graph method to analyze the spillover network structure of the stock market from the perspectives of a
bear market, normal market, and bull market, and determined the direction of the spillover risk effect. Memon (2019), Kazemliari (2019) and Cao (2018) [3–5] built a correlation network for shares based on the threshold method, adopted the stochastic matrix theory to remove market trends, and studied the difference between the network topology structure and the traditional network topology structure during financial crises and Chinese stock market turbulence. These studies simply analyzed the changes in the stock market network topology caused by emergencies from the perspective of network topology. In addition to network topology characteristics, some scholars analyzed the impact of emergencies on complex stock market networks from the perspective of network destructiveness. Varkey (2016), Yang (2019) and Gu (2016) [6–8] used minimum absolute contraction and quantile regression of the selection operator to construct a tail risk spillover network of bank stocks listed in China and studied the relationship between network cascading failures and attacked nodes. In addition, some scholars studied crises from the perspective of community structure. Hu (2019) [9] used the minimum spanning tree algorithm to build the complex network of Shanghai and Shenzhen stock markets, and analyzed its community structure to study the stock market fluctuations caused by fluctuations in an enterprise’s stock. Zhang (2015) [10] compared the complex network constructed by the Asia-Pacific stock index during a financial crisis and stability, and studied the effect of a financial crisis on the complex network community structure. Li (2018) [11] analyzed the impact of the 2008 financial crisis on the world’s major stock indexes and observed the dynamic changes of the network community structure.

Some studies used network methods to research financial markets. Liang et al. (2023) [12] delved into the intricacies of the Chinese stock market, examining the impact of the COVID-19 pandemic on the topological structure dynamics of stock correlations. By analyzing the correlation matrix between enterprises and constructing complex networks, they uncovered notable shifts in inter-industry correlations, indicating a strengthening of correlations within industries and a weakening of correlations between industries. Another facet of financial networks explored by Liang et al. (2023) [13] involved the reconstruction of enterprise debt networks using compressed sensing techniques. Their study introduced an innovative approach to reconstructing unknown links in debt networks between enterprises, leveraging time-series data of accounts receivable and payable. Expanding the scope to global stock markets, Ouyang et al. (2023) [14] offered a comprehensive analysis of risk contagion mechanisms using multilayer connectedness networks in the frequency domain. By examining interconnectedness between global stock markets over a substantial time frame, they uncovered nuanced behaviors in risk contagion across short-, medium-, and long-term frequencies. Shifting focus to China’s financial sub-markets, Xu et al. (2022) [15] investigated the path of risk contagion before and after the COVID-19 outbreak. Employing complex network theory and the DCC-GARCH model, they analyzed the dynamic correlation coefficients between financial sub-markets in China, identifying the key pathways of risk contagion. These studies significantly contributed to our understanding of the complexities inherent in financial networks, offering insights into the evolution of network structures, mechanisms of risk contagion, and implications for risk management strategies.

Some studies examined the implications of financial crises on regional and global financial networks. Ralf and John (2013) [16] conducted a comparative study on the impact of the Asian and global financial crises on East Asian regionalism. They argued that the divergent impacts of these crises on regional institutions stemmed from their origins—internal versus external—and the varying degrees of severity. Chowdhury et al. (2019) [17] investigated the evolving integration of Asian financial markets within the global financial network from 1995 to 2016. Their analysis revealed an overall deepening of connections, particularly during periods of financial stress, with a subsequent reduction in links post-crisis. Lee et al. (2018) [18] investigated the effects of the 2008 global financial crisis on global stock markets using complex network analysis. They utilized threshold networks (TNs) and minimal spanning trees (MSTs) to illustrate the structural changes in financial networks.
Their findings indicate that during the crisis, Asian countries exhibited weak connectivity compared with the tightly linked European and American zones. The study highlighted the robustness and clustering effects in TNs and the central hub role of France in the MSTs, providing a comprehensive view of the network structure’s topological changes during the crisis. Garcia et al. (2023) [19] focused on the transmission of volatility in European sovereign debt markets using a two-step approach for statistical inference in financial networks. These studies collectively highlighted the complexity and evolving nature of financial networks in response to crises, emphasizing the importance of regional and global linkages and the role of key nodes. These references are inspiring and informative for this research.

However, most of these studies analyzed the impacts of unexpected events on the complex network of the stock market with a single method using network topological characteristics, destructiveness, or community structure. Moreover, there were few studies on the impact of the Evergrande debt crisis on the stock market. This study combined these three methods to study and analyze the stock network during three periods of this major debt crisis, that is, prophase, metaphase, and anaphase, and observed the dynamic changes of the network structure during different periods through the network topology characteristics. The change in connectivity efficiency of the network was studied through destructiveness. Using the minimum spanning tree and the network community structure, this study investigated the influence of this major debt crisis on other related industries.

The motivation of this study was that complex network theory offers a robust framework for modeling intricate interconnections and dependencies within financial systems, revealing hidden patterns and vulnerabilities that traditional methods may fail to detect. Analyzing network topological characteristics enables the assessment of structural properties during crises. Measures such as node connectivity, centrality, and clustering coefficients offer insights into how disruptions spread through networks, identifying critical nodes and pathways of contagion. Moreover, studying network resistance and resilience is crucial for effective risk management. Quantifying a network’s ability to withstand shocks and disruptions enables the development of strategies to enhance robustness and mitigate future crisis impacts. In summary, complex network theory and network topological analysis are essential for comprehensively understanding the dynamics of stock market networks during debt crises. These methodologies provide a sophisticated approach to analyzing risk propagation, assessing vulnerabilities, and developing strategies to ensure financial stability and resilience.

2. Complex Network Modeling of Stock Market

The coefficient of correlation of the logarithm rate of return can be used to construct a complex network of correlations between stocks of different enterprises [20], which can be represented by the graph $G(V, R, W)$, where $V$ denotes the set of corporate stocks, $R$ denotes the set of corporate stock relations, and $W$ denotes the weight set of the correlations between the stocks of enterprises in the correlation network. The weights of stocks of two enterprises can be expressed by the Pearson correlation coefficient. To construct the correlation network structure, first, we need to calculate the similarity between the evolution of the time series of stocks. We build a complex network of $N$ stock nodes. Suppose that the closing price of the $i$th stock on day $t$ is $P_i(t)$, then the logarithmic return rate of the stock is

$$Y_i = \ln P_i(t) - \ln P_i(t - 1).$$

Then, the Pearson coefficient of correlation between stocks $i$ and $j$ is calculated according to the time series of the return rate:

$$\rho_{ij} = \frac{\langle Y_i Y_j \rangle - \langle Y_i \rangle \langle Y_j \rangle}{\sqrt{(\langle Y_i^2 \rangle \langle Y_i \rangle^2)(\langle Y_j^2 \rangle \langle Y_j \rangle^2)}}, -1 \leq \rho_{ij} \leq 1.$$
According to (2), the correlation matrix has symmetry, that is, \( \rho_{ij} = \rho_{ji} \). The coefficient \( \rho_{ij} \) of the correlation between the stock nodes is calculated, and an \( N \times N \) correlation coefficient matrix is obtained. The distance between stocks \( i \) and \( j \) can be obtained by the correlation coefficient:

\[
d_{ij} = \sqrt{2(1 - \rho_{ij})},
\]

where \( d_{ij} \in [0, 2] \) and satisfies three properties: (1) if and only if \( i = j, d_{ij} = 0 \); (2) \( d_{ij} = d_{ji} \); and (3) \( d_{ij} \leq d_{ik} + d_{kj}, i \neq j \neq k \) and \( i, j, k \in [N] \).

In graph theory, a connected and loopless graph is called a tree. The minimum spanning tree is the tree with the smallest sum of weights of the combined edges in the graph. Some scholars used the minimum spanning tree (MST) method to build a stock network, and then performed cluster analysis; they found that the minimum spanning tree algorithm can reveal the hierarchy of the network. Currently, the Kruskal and Prim algorithms are common algorithms for constructing the minimum spanning tree. The Prim algorithm is adopted in this paper, and the specific steps are as follows:

Step 1: First select two nodes with the shortest distance from the distance matrix obtained by formula (3) to connect them.

Step 2: Select the minimum distance from the remaining data, find the corresponding two nodes, and connect them.

Step 3: In the remaining data, the node with the shortest distance is selected for connection, and the connection process cannot be looped.

Step 4: Repeat the third step above, and we will obtain a connected graph with \( N \) nodes and \( N - 1 \) edges.

3. Topology Properties of Complex Network

3.1. Network Degree Distribution

After the network is constructed, the degree of node \( i \) is assumed to be \( k_i \), and the greater the degree value of the node, the higher is its importance. The average degree of the network can be obtained by taking the average degree of each node, denoted as \( \bar{k} \), i.e.,

\[
\bar{k} = \frac{1}{N} \sum k_i.
\]

3.2. Clustering Coefficient

The value of the clustering coefficient is in the range \([0, 1]\), and is mainly used to measure the local clustering between the nodes of the network, that is, the degree of interconnection of the network [21]. In the network, we consider node \( i \), which is connected to \( k_i \) other nodes through \( k_i \) edges; then, there are at most \( k_i(k_i - 1)/2 \) edge connections between these network nodes, but the actual number of links of \( k_i \) nodes is \( E_i \), and thus, the clustering coefficient \( C_i \) of node \( i \) is

\[
C_i = \frac{2E_i}{k_i(k_i - 1)}.
\]

And the average clustering coefficient \( \bar{C} \) of the network is

\[
\bar{C} = \frac{1}{N} \sum C_i.
\]
3.3. Average Path Length

The path \( L_{ij} \) between two nodes \( i \) and \( j \) is defined as the number of edges contained in the shortest path connecting these two nodes; then, the average path length \( \bar{L} \) of the network is defined as the average path length between any two nodes, i.e.,

\[
\bar{L} = \frac{1}{N(N+1)} \sum_{i \geq j} L_{ij},
\]

(7)

3.4. Network Destructibility

Network destructibility refers to the ability of the network to continue to function when a network node (or edge) randomly fails or is subjected to malicious attacks. It is defined as the decline in value of the overall connectivity efficiency performance of the network after the failure occurs. The average path length is a commonly used index to measure the network connectivity efficiency. Therefore, the measurement of the network connectivity efficiency \( E \) can be expressed as

\[
\bar{L} = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{L_{ij}}, \quad \forall i, j \in [N].
\]

(8)

Formula (8) shows that the stronger the connectivity of the network, the higher the efficiency between the node pairs, and the efficiency is 0 when the network is disconnected.

3.5. Small-World Networks and Scale-Free Networks

The two most important models that describe the topology of real system networks are small-world networks and scale-free networks [22]. Small-world networks usually have large clustering coefficients and a short node path length, while scale-free networks refer to complex networks in which nodes obey the power-law distribution, that is, most nodes in the network have fewer degrees, and the degree distribution \( P(k) \) is

\[
P(k) = ak^{-\gamma}.
\]

(9)

The parameter \( \gamma \) is the power-law exponent, and by taking the logarithm of both sides, we obtain

\[
\ln P(k) = \ln a - \gamma \ln k.
\]

(10)

3.6. Betweenness Centrality

The betweenness centrality of a node refers to the proportion of the number of shortest paths passing through the node to the total number of shortest paths in the network [23–25]. Nodes with high betweenness centrality play an important role in network connection and information flow in the network, that is, when the node with high betweenness centrality is eliminated in the network, some node relationships in the network are affected. The betweenness centrality of node \( v \) is defined as

\[
BC(v) = \frac{2}{(N-1)(N-2)} \sum_{s \neq v \neq t} \frac{\delta_{st}(v)}{\delta_{st}},
\]

(11)

where \( BC(v) \) denotes the betweenness centrality of node \( v \), and \( \delta_{st}(v) \) represents the number of paths that pass through node \( v \) by the shortest path from node \( s \) to node \( t \) in the network. \( \delta_{st} \) is the number of shortest paths from node \( s \) to node \( t \) in the network.

3.7. Closeness Centrality

The closeness centrality is expressed as the inverse of the sum of the shortest paths between this node and all other nodes in the network. The smaller the average path between a node and other nodes, the greater the closeness centrality of this node. A smaller
Li in Formula (7) means that node $i$ is closer to other nodes in the network, and thus, the inverse of $L_i$ is defined as the closeness centrality of node $i$, namely,

$$CC(i) = \frac{1}{L_i} = \left( \frac{N - 1}{\sum_{i \neq j} L_{ij}} \right)^{-1}. \quad (12)$$

3.8. Community Structure

A network community is defined as a network subgraph where the number of edges between the internal nodes is larger than the number of edges between nodes and external nodes [26], which is the meso-structure of a network and an important feature in the study of network topology and network composition. In general, a community can contain a variety of meanings, such as a module, class, or group. Girvan and Newman [27] introduced the concept of modular $Q$ functions in the course of studying complex community structures. Assuming that a complex network is divided into several communities by a community-partitioning algorithm, the proportion of interconnected edges in the community can be calculated by the following formula:

$$Q = \frac{1}{2m} \sum_{i,j} \left( w_{ij} - \frac{s_i s_j}{2m} \right) \delta(c_i, c_j), \quad (13)$$

where $w_{ij}$ is the weight between nodes $i$ and $j$ in the network, $s_i = \sum_j w_{ij}$ is the weight of node $i$, $m = \sum_{i,j} w_{ij}$ is the weight of all edges in the network, $c_i$ is the community number that node $i$ is included in, and the function $\delta(u, v)$ is defined as

$$\delta(u, v) = \begin{cases} 1, & u = v, \\ 0, & u \neq v. \end{cases}$$

4. Empirical Analysis

4.1. Data

From the Wind database, we selected 149 stocks of companies listed in China, which were divided into eight industries: real estate, agriculture, construction materials, banking, manufacturing, logistics, automobile, and steel. The closing price of each stock from 1 March 2021 to 28 February 2022 was selected as the data sample. The Evergrande debt crisis emerged in July 2021. We categorized the stages of this crisis as follows: prophase (1 March to 30 June 2022), metaphase (1 July to 30 October 2021), and anaphase (1 November 2021 to 28 February 2022). These distinctions were made according to the developmental stages and restructuring processes of the debt crisis. The main purpose of dividing this time period was to compare the changes in the complex network characteristics of the stocks before and after the debt crisis across various time frames.

4.2. Associate Network Construction

We divided the 149 stocks by serial numbers ($i = R_1, R_2, \cdots, R_{149}$) and used Formulas (1) and (2) to calculate the logarithmic return correlation coefficient matrix of the 149 listed stocks. According to the principle of thermal imaging, the interval was set to $[-1, 1]$, and the color corresponding to the minimum value $-1$ was dark blue. When the correlation was greater, the color was lighter. When the correlation coefficient was greater than 0, the corresponding color gradually changed from light blue to green and finally to yellow, that is, the color of the maximum correlation coefficient 1 was yellow, as shown in Figure 1. The thermal image maps of the three periods showed that in the prophase of the debt crisis, correlations within each industry were strong, while the correlations outside each industry were weak. In the metaphase, the thermal image map showed a small square shape on the main diagonal, and the correlations of the stock price changes of the enterprises in the industries were enhanced. By the anaphase of the debt crisis, the intra-industry autocorrelations and out-of-industry correlations reached a peak. The occurrence
of Evergrande’s debt crisis made the internal connections between different industries gradually become closer.

We conducted threshold processing on the correlation coefficient matrix and set the threshold to 0.2. When the absolute value of the correlation coefficient was less than 0.2, nodes did not connect edges, and vice versa [28]. We imported this into Gephi software to generate the associated network, as shown in Figure 2.

![Networks](image)

(a) Prophase. (b) Metaphase. (c) Anaphase.

Figure 1. Correlation matrix heat maps for three periods.

Network density refers to the proportion of actual connections (edges) in the network to the total possible connections. A higher density indicates a more densely interconnected network, whereas a lower density suggests fewer connections or a sparser network structure. The observed changes in density across the defined periods provide insights into the evolving network dynamics and interrelationships between industries during and after the Evergrande debt crisis. In Figure 2, during the initial phase of the debt crisis, as depicted in Figure 2a, cross-industry associations appeared relatively negligible, indicating limited interconnectivity between industries during this period. However, during the metaphase of the debt crisis, as shown in Figure 2b, the network density increased, and the connections between industries gradually strengthened. In the anaphase, as shown in Figure 2c, there was a discernible rise in cross-industry associations, indicating a heightened interconnectivity between industries after the crisis.

Through a comparison of the correlation networks across the defined periods, significant variations were observed. Specifically, the average node degree within Evergrande’s network was notably lower during the early phase of the debt crisis (prophase), implying fewer direct connections or correlations with other nodes (industries). Conversely, the average node degree within Evergrande’s network notably increased during the later phase (anaphase) of the debt crisis, indicating an elevated level of connectivity or associations with other nodes.

It can be seen from Figures 1 and 2 that (1) the cross-industry association was not significant in the prophase of the debt crisis but gradually increased after the debt crisis of Evergrande, and (2) by comparing the correlation networks of the three periods, the average
node degree of Evergrande’s network was the lowest in the prophase of the debt crisis, while the average node degree of Evergrande’s network increased in the anaphase.

Figure 2. Associated networks of three periods.

4.3. Statistics of Network Topology Properties

In order to analyze the topological properties of the associated networks during the three different periods, we used Formulas (4), (6) and (7) to calculate the average degree (AD), average clustering coefficient (ACC), and average path length (APL) of the associated networks, respectively. Gephi software was used to calculate the graph density (GD) of the association network, and the calculation results are shown in Table 1. The results show that (1) the average degree of the network and the average clustering coefficient gradually increased in the prophase, metaphase, and anaphase, which also validated our view from the thermal imaging analysis, that is, the cross-industry connections gradually increased, and (2) the gradual decline in the average path length indicates that the debt crisis made the distance between nodes in the network gradually shrink and the graph density gradually increase.

Table 1. Characteristics of network structure in the three periods.

<table>
<thead>
<tr>
<th>Period</th>
<th>AD</th>
<th>ACC</th>
<th>APL</th>
<th>GD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prophase</td>
<td>37.074</td>
<td>0.439</td>
<td>1.784</td>
<td>0.25</td>
</tr>
<tr>
<td>Metaphase</td>
<td>51.45</td>
<td>0.578</td>
<td>1.671</td>
<td>0.348</td>
</tr>
<tr>
<td>Anaphase</td>
<td>58.523</td>
<td>0.618</td>
<td>1.627</td>
<td>0.395</td>
</tr>
</tbody>
</table>
4.4. Node Degree Analysis of the Networks

In order to determine whether the networks in the three periods were small-world networks or scale-free networks, we used Formulas (9) and (10) to carry out a fitting analysis on the node degrees of the three networks, as shown in Figure 3 and Table 2. The goodness-of-fits in the prophase, metaphase, and anaphase of the debt crisis were 0.9688, 0.9865, and 0.9782, respectively. The results show that (1) all the networks in the three periods obeyed the power-law distribution and were scale-free networks, and (2) before the debt crisis, the scale-free characteristics of the network were optimal, and the goodness-of-fit decreased with time.

![Degree distribution graph of the three periods of associated networks.](image)

Figure 3. Degree distribution graph of the three periods of associated networks.

<table>
<thead>
<tr>
<th>Time Periods</th>
<th>$\alpha$</th>
<th>$\gamma$</th>
<th>$R$</th>
<th>adj-R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prophase</td>
<td>66.78</td>
<td>0.429</td>
<td>0.9727</td>
<td>0.9688</td>
</tr>
<tr>
<td>Metaphase</td>
<td>78.51</td>
<td>0.291</td>
<td>0.9930</td>
<td>0.9865</td>
</tr>
<tr>
<td>Anaphase</td>
<td>96.48</td>
<td>0.269</td>
<td>0.9808</td>
<td>0.9782</td>
</tr>
</tbody>
</table>

4.5. Network Destructibility

In order to further understand the impact of Evergrande’s debt crisis on the resilience of China’s stock market network, we chose random and deliberate patterns to attack the nodes of the network. A random pattern involved random attacks on the number of nodes in the network. The deliberate pattern was arranged according to the betweenness centrality of nodes from the largest to the smallest. After each node with the largest betweenness centrality was excluded, Formula (11) was used to recalculate the betweenness centrality of the network. Both methods used Formula (8) to calculate the connectivity efficiency of the network, and we stopped the attack when the network crashed, that is, when the
connectivity efficiency was 0. Figure 4 shows that (1) irrespective of whether it was a deliberate pattern or a random pattern, the network connectivity efficiencies $E$ during the three periods showed an exponentially decreasing trends; (2) in the metaphase of the debt crisis under deliberate attacks, the network fluctuated and declined at 0.42 and 0.7; and (3) from the two attack patterns, it can be seen that the network of the prophase collapsed more easily, while the network of the anaphase was more stable. Based on the above views, it could be concluded that the occurrence of the Evergrande debt crisis made the cross-industry connections in the financial market increase and the connectivity efficiency of the network became higher.

![Figure 4](image)

**Figure 4.** Network destructibility of the three periods.

### 4.6. Minimum Spanning Tree of Metaphase

We used Formula (3) to calculate the distance matrix of the metaphase of the debt crisis, and used the Prim algorithm to build the minimum spanning tree network of the stock market, as shown in Figure 5. For this network, we used Formula (12) to calculate the proximity centrality of this network, and then used Formula (13) to classify the community structure of this network. Then, this network was divided into 15 communities. There were 29 nodes with a near centrality of 1, and the steel industry accounted for the largest number of listed enterprises among these 29 nodes, followed by the banking and real estate industries. In this network, Evergrande was the enterprise with the highest near centrality. Therefore, our study showed that (1) after the debt crisis of Evergrande, Evergrande became the core node of the network; (2) the steel industry occupied a prominent position in the minimum spanning tree network; and (3) as the core node, Evergrande was located in the 14th community, which included eight enterprises: Country Garden, Three Gorges New Materials, Zaisheng Technology, Bank of Chongqing, Minsheng Bank, China CITIC Bank,
Shandong Iron Steel, and Zhuhai Zhongfu. According to a Pearson’s correlation coefficient analysis, Country Garden, Zaisheng Technology, and China CITIC Bank had high correlation coefficients with Evergrande. That is to say, these eight enterprises were impacted more by the Evergrande debt crisis. The regulatory authorities should immediately pay attention to the chain reaction brought about by the crisis event and manage the financial risks of such enterprises.

Figure 5. The minimum spanning tree in the metaphase of the debt crisis. Different colors under the same sub-tree are used to distinguish between different branches. Different sub-trees may have the same color branches.

5. Conclusions

This study constructed complex networks of the stock market and analyzed the impacts of major debt crisis events on the topology of the networks. We divided the occurrence of the debt crisis into three periods, namely, the prophase, metaphase, and anaphase of the debt crisis. We constructed complex networks for these three periods and studied their respective network topological characteristics and destructiveness. The studies showed the following: (1) In the prophase of the debt crisis, the correlations within industries were strong, but the correlations outside the industry were weak, indicating that the cross-industry connection was not close. When the debt crisis broke out, the correlations within industries and the correlations outside industries gradually increased and reached the highest value in the anaphase of the debt crisis, indicating that the occurrence of the Evergrande debt crisis caused more cross-industry connections. (2) The study of the network topological characteristics illustrated that the average clustering coefficient, graph density, and average degree increased with time, while the average path was the opposite, indicating that the node pairs were more closely related. (3) The destruction resistance studies concluded that the initial value of the connectivity efficiency in the three periods gradually increased. After the two kinds of attacks, the debt crisis resistance performance of the anaphase was the best. In the metaphase of the debt crisis, there were two fluctuations under deliberate attack, but the overall resilience and connectivity was better than that in the prophase of the debt crisis. This shows that the occurrence of the Evergrande debt crisis gradually enhanced the network’s resistance and connectivity.

We constructed the minimum spanning tree network for the correlation coefficient matrix in the metaphase of the debt crisis and found that the network was dominant in the steel industry during this period. In this network, Evergrande was located in the 14th community and was one of the nodes with the highest closeness centralities, indicating that the debt crisis of Evergrande had the greatest impact on enterprises in the 14th community.

The debt crisis of Evergrande was highly contagious, and the steel industry related to Evergrande became core nodes in the network. We should further prevent the chain reaction of risks in the debt crisis.
Previous studies often narrowly focused on singular methodologies, such as network topology characteristics, destructiveness, or community structure when analyzing network impacts. Few studies specifically examined the impact of the Evergrande debt crisis on the stock market complex network. Our study took a unique approach by integrating multiple methodologies—network topological analysis, destructiveness assessment, and community structure evaluation—to investigate the stock market network across three distinct phases of the major debt crisis: prophase, metaphase, and anaphase. Through this comprehensive analysis, we observed dynamic changes in the network structure and connectivity efficiency during these critical phases.

Our comparative analysis revealed noticeable shifts in the inter-industry correlations across different phases of the debt crisis, particularly highlighting strengthened cross-industry connections following the outbreak of the Evergrande debt crisis. This indicates increased contagion effects across sectors. In contrast to previous research, our study integrated various analytical approaches to offer a comprehensive examination of how the Evergrande debt crisis affected the complex stock market network.

This study significantly contributed to understanding how major debt crises, such as the Evergrande event, influence stock market interconnectivity and resilience. Our integrated methodology illuminates the evolving network dynamics during crisis periods, providing valuable insights for financial institutions and policymakers to develop effective risk management and crisis response strategies.

It is important to acknowledge this study’s limitations, including our focus on a specific debt crisis event (Evergrande), which may limit the generalizability. Additionally, our analysis relied on certain network modeling assumptions and parameter choices. Future studies could extend this work by exploring broader implications of debt crises on global financial networks and investigating additional methodologies for network analysis and risk assessment.

Author Contributions: K.L. proposed the method in this study, S.L. collected data and wrote the manuscript, W.Z. analysed the results and provided financial support, C.Z. conceived the numerical experiments. All authors reviewed the manuscript. All authors have read and agreed to the published version of the manuscript.

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