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Research on Risk Spillover Effects and Early Warning Optimization of China's Real Economy and Financial System

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Abstract: *In recent years, the continuous outbreak of public health events has intensified the risk linkage effect between China's real economy and financial markets. In order to describe the risk correlation mechanism among various entities, this paper uses the time-varying Copula - △ CoVaR model to quantify the risk spillover intensity between the real economy and the financial market in the context of the COVID-19, identifies the main risk contagion sources and risk contagion paths, and constructs a comprehensive early warning indicator system and a graph attention model to optimize the early warning work. The empirical research results indicate that: firstly, the risk spillover level generated by the impact of the epidemic has characteristics of time delay, repetition, and wave like, and the initial intensity is the highest; Secondly, the impact of the epidemic will exacerbate the risk of cross market transmission and upstream and downstream transmission along the industrial chain; Thirdly, compared to traditional machine learning models, the accuracy of graph attention early warning models has been improved by 10-20%, and their predictive ability for risk events is stronger. The* research *conclusion of this article will provide reference for regulatory authorities to identify major risk industries and markets, monitor multi-stage contagion of risks in sudden public health events, and establish a sound risk warning mechanism. It has important practical significance for promoting coordinated development between China's real economy and financial markets.*

Keywords: *real economy; financial system; graph attention network; emergency events*

1. Introduction

Financial security is an important component of national security and an important foundation for stable economic development. In recent years, risks triggered by major external shocks such as global economic sanctions, geopolitical conflicts, and public health have spread rapidly between China's real economy and financial markets, which has led to serious Systematic risk. For example, during the COVID-19, the supply and demand sides of China's real economy suffered from two-way compression, the industrial chain and supply chain were forced to be interrupted, and production activities and economic development suffered from long-term negative impacts. After the significant impact on the real economy industry, the Shanghai Composite Index experienced its largest daily decline since the 2015 stock market crisis, further exacerbating the debt crisis in financial sub markets such as banks, insurance, and securities, leading to a sustained deterioration of the macroeconomic environment. At the same time, the state attaches great importance to the prevention and resolution of systemic financial risks: in October 2022, the 20th National Congress of the Communist Party of China stressed that to ensure the stability of China's real economy and financial security, it is necessary to "hold the bottom line against Systematic risk", In August 2022, the "Proposal of the Central Committee of the Communist Party of China on Formulating the 14th Five Year Plan for National Economic and Social Development and the 2035 Long Range Goals" mentioned "improving the system of financial risk prevention, early warning, disposal, and accountability, and implementing regulatory and territorial responsibilities". Therefore, the investigation of China's real economy industry and important financial markets under the unified framework will help to accurately identify the risk driving mechanism and dynamic evolution process of micro entities under the realistic background of economic integration. At the same time, it will portray the relationship and risk transmission path between the various entities from the macro system level, and expand the scope of research subjects and coverage levels of risk spillover effects during the COVID-19 epidemic It is of great practical research value and academic significance to summarize the temporal characteristics of the evolution of risk transmission during the COVID-19 epidemic. On the basis of the above research, a comprehensive early warning indicator system, a scientific risk transmission network, and a refined early warning model are constructed to comprehensively improve the accuracy and granularity of early warning work, providing a scientific reference basis for establishing a sound risk prevention mechanism and preventing future public health incidents.

In this context, this paper first uses an econometric model to accurately identify the risk spillover effects of various entities during the COVID-19 epidemic, and then constructs a connection network between China's real economy and important financial markets through the plane maximum filter graph method. Based on the level of micro entities and macro systems, this paper effectively identifies the risk contagion sources, main contagion paths, risk evolution characteristics, and the relationship between various entities, This provides a reference basis for regulatory authorities to summarize the temporal characteristics of risks induced by public health events, implement risk prevention mechanisms that are suitable for the source and transmission path of infection, and correctly evaluate the importance and role of each entity within the financial system. Finally, based on the above work, we will further combine the Value at risk indicators with the basic data of nine industries to build an early warning indicator system and enrich the various risk incentives covered by the early warning indicator system. At the same time, a macro network of risk contagion is constructed using the method of plane maximum filtering graph, and the warning indicator system and risk contagion network are inputted into the risk warning model to improve the performance, robustness, and warning granularity of the warning model, providing new ideas for regulatory authorities to achieve risk warning work targeting micro entities and macro systems.

2. Literature Review

The risk relationship between industries mainly includes risk spillover effects based on micro entities and risk dependency structures based on macro systems. In terms of micro entities, the risks induced by major events impacting one entity will overflow to other entities through related risk transmission mechanisms. Early research often used Conditional Value at Risk (CoVaR) and Marginal Expected Shortfall (MES) to explore the risk impact caused by exogenous shocks from the perspective of the macro system and its internal entities at all levels. However, CoVaR (Adrian and Brunnermeier, 2008) measures the value at risk of other financial entities or financial systems when a specific financial entity is in extreme situations, lacking quantification of the degree of risk contribution[1]. Therefore, Adrian and Brunnermeier (2011) further proposed ΔCoVaR, which reflects the difference between the Value at risk of a financial entity in crisis and its normal state, can better measure the marginal contribution of a single entity to Systematic risk[2]. Except for measuring the risk spillover effect between two entities In addition to CoVaR, Acharya (2012), Acharya (2017) and Brownlees (2017) successively proposed MES, Systemic Expected Shortfall (SES) and Systematic risk Index Shortfall Kill (SRISK) to measure the risk marginal contribution of a single financial institution to the financial system[3][4][5]. Among them, MES, SES and SRISK include factors such as institutional size, leverage ratio and debt ratio into the review framework, so they are more suitable for studying the Systematic risk of financial institutions (Fang Yi and Shao Zhiquan, 2022), not for the subject of this study[6]. In summary, this article selects ΔCoVaR depicts the tail risk between China's real economy and financial system under sudden public health emergencies. The existing literature mainly uses Quantile regression method, DCC-GARCH model method and Copula function method to calculate CoVaR. Specifically, Quantile regression method is difficult to completely describe the risk correlation of nonlinear financial return series; The DCC-GARCH model method can only measure the overall Systematic risk level, but can not measure the risk exposure and direction of a single industry. Compared with the above, Copula function method can more accurately capture the complex characteristics such as asymmetry, time variability and fat tail between return series, and better describe the dependence of tail risk among industries, and its restrictions are less, so it is unnecessary to consider the specific form of Joint probability distribution (Xie Chi et al., 2021)[7]. Therefore, this article will use the time-varying Copula-GARCH family model method to measure the performance of various industries and financial markets ΔCoVaR.

On the basis of precise measurement of risk spillover effects between micro entities, the obtained CoVaR indicators are combined with nine industry fundamental indicators to establish a more comprehensive risk warning indicator system. The PMFG method is used to construct a risk contagion network, and finally the warning indicators and risk contagion network are inputted into the warning

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model to help regulatory authorities achieve the work goal of "early screening, early warning, and early governance". For risk warning models, traditional econometric models and traditional machine learning models were mainly used in the early stages. However, traditional econometric models cannot depict the nonlinear relationships between variables, and traditional machine learning models cannot depict the correlations between variables. With the continuous development of information technology, risk warning models mainly based on deep learning models such as graph neural networks have shown better warning performance (Ren Yinghua et al., 2022; Li Xiaohan et al., 2022)[8][9]. At present, Graph Convolutional neural network (GCN) is widely used in research. Thus increasing the probability of issuing the correct warning signal.

To sum up, because the traditional econometric model is not enough to accurately describe the dynamic nonlinear characteristics of risk spillover effects and the risk levels of different entities, the prediction effect of risk events needs to be improved, and the research on Systematic risk spillover effects still has room for improvement; The risk warning indicator system lacks comprehensiveness, and the performance of the risk warning model is poor. The warning work still needs to be optimized. Therefore, this article makes the following improvements to address the above shortcomings: firstly, a time-varying Copula-GARCH family model is used to calculate the CoVaR class values between industries, and the risk spillover effects of dynamic nonlinear characteristics between industries are analyzed; Secondly, use the PMFG method to construct a risk contagion network between various industries, and analyze the network structure characteristics of the macro system based on corresponding network topology indicators to identify the risk contagion characteristics and the relationship between various entities; Third, on the basis of the above work, we will further build an early warning indicator system and map attention model that include industry fundamentals and CoVaR data, and improve the performance of risk early warning from three aspects: the comprehensiveness of early warning indicators, the scientificity of network construction, and the accuracy of early warning models. The marginal contribution of this article is mainly reflected in the following three aspects: firstly, incorporating the real economy industry and financial market into a unified framework, comprehensively characterizing the risk contagion process between macro entities from a systematic perspective. Secondly, by comparing the time-varying risk spillovers during the epidemic period and the stable period, the paper analyzes the upstream risk spillover effect, and supplements the research on the prevention and control of Systematic risk. Thirdly, a comprehensive daily risk warning indicator system is constructed, and the graph attention model is used to comprehensively depict the connection relationships between various entities within the financial system. By applying deep learning methods to the field of financial research, new research ideas are provided to solve financial risk prevention and control problems.

3. Theoretical Model

This article uses the PMFG method to construct a daily graph structure network to prevent the formation of dense graphs due to excessive connections between nodes. The warning indicator system and risk contagion network are inputted into the GAT model to achieve precise dual signal risk warning work based on classification tasks.

After constructing a graph structure network model using the planar maximum filtering graph method, the daily industry fundamentals and CoVaR data indicators are input as node feature vectors:

$$\vec{h} = \{\vec{h_1}, \vec{h_2}, \dots, \vec{h_n}, \vec{h_i} \in R^F\} \tag{1}$$

Among them, is the feature vector of the i-th node, n is the number of nodes, and F is the number of features for each node. The matrix constructed in this article has an input vector of 15 * 10.15 represents the number of industries, and 10 represents the number of industry characteristics. This process will perform one hot encoding on the node feature vectors to form a feature matrix composed of 15 node feature vectors.

The advantage of the GAT model lies in its ability to autonomously learn and assign weights to nodes with different features. Therefore, in order to obtain sufficient high-dimensional feature expression ability, the input feature vectors are linearly changed and attention coefficients are learned:

$$e_{ij} = a(W\vec{h_i}, W\vec{h_j}) \tag{2}$$

Among them, W is the weight parameter, j is the first-order neighbor node of node i, and is the attention coefficient, indicating the importance of node j's features to node i. A() is a function that

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calculates the correlation between the characteristic vectors of node i and j. In order to facilitate the calculation and comparison of the obtained attention coefficient, the softmax function is used for normalization to obtain a new attention coefficient. Is the neighbor node and set of node i, and is a nonlinear Activation function.

$$a_{ij} = \mathrm{softmax}(e_{ij}) = \frac{\exp(\mathrm{LeakyReLU}(e_{ij}))}{\sum_{k\in N_i}\exp(\mathrm{LeakyReLU}(e_{ij}))} \tag{3}$$

Based on the obtained attention coefficient, the GAT model assigns different weights to different neighboring nodes through the attention coefficient, ultimately achieving feature weighted summation of node features.

$$\overrightarrow{h^*_\imath} = \sigma(\textstyle\sum_{j\in N_i} a_{ij}\, W\overrightarrow{h_j}) \tag{4}$$

Among them, is the new feature of node i output by the GAT model, which integrates the information of its neighboring nodes. () is the Activation function.

Output a new node feature matrix composed of 15 node feature vectors:

$$\overrightarrow{h^*} = \{\overrightarrow{h^*_1}, \overrightarrow{h^*_2}, \dots, \overrightarrow{h^*_n}, \overrightarrow{h^*_\imath} \in R^{F*}\} \tag{5}$$

Finally, the risk signal is issued by the new node feature matrix. Considering that the early warning model needs to have forward-looking recognition ability, this article determines a lead time of one month for the issuance of early warning signals. According to Table 2 below, set the time range label of the month before the severe epidemic period to 1, representing risk warning; The remaining period labels are set to 0, indicating no risk. The warning model in this article is a dual signal,. Among them, 0 represents a safety signal and 1 represents a warning signal.

4. Data Description

Given the authoritative and universal nature of the China Securities First Class Industry Classification Standard, this article refers to its classification standards and selects nine industries from the China Securities First Class Classification to represent the real economy. In addition, important financial sub markets such as the stock market, securities market, bond market, banking market, insurance market, and currency market were selected for risk spillover research (Fang Yi et al., 2021)[10].

This article calculates daily logarithmic returns based on various industry indices. To prevent the fitting effect of time-varying Copula models from being poor due to small data units, the logarithmic returns are increased by 100 times, as shown in formula (6).

$$Y_t = (\mathrm{In}P_a\text{- } \mathrm{In}P_b) * 100 \tag{6}$$

The data range is from December 9, 2019 to January 20, 2023. The period from December 9, 2019 to May 6, 2020, and from December 13, 2021 to December 6, 2022 were severe periods of the epidemic. The period from May 7, 2020 to December 10, 2021 and from December 7, 2022 to January 20, 2023 is a stable period. The risk warning indicator constructed in this article consists of CoVaR class and industry fundamental data, where industry fundamental data consists of daily opening price, daily closing price, daily highest price, daily lowest price, daily yield, daily rise and fall, daily rise and fall, daily transaction amount, and daily trading volume. The input feature vectors are normalized to eliminate differences caused by different dimensions and units.

There are many GARCH family models and time-varying Copula models. Based on the principle of minimizing AIC, this article ultimately chooses the AR (0) - GARCH (1,1) - t distribution model and combines it with the time-varying t-Copula function to calculate VaR and △CoVaR values.

5. Risk spillover effects across industries and markets

This section of the study is based on the micro subject perspective, using the time-varying Copula-GARCH family model to accurately characterize the risk spillover effects between two entities. It explores the risk spillover effects of the two periods from the perspective of overall dynamic correlation between industries and markets, as well as the characteristics of risk transmission between industries. It also prepares for the construction of a comprehensive risk warning indicator system. According to the △CoVaR between various industries and financial markets, the trend of △CoVaR

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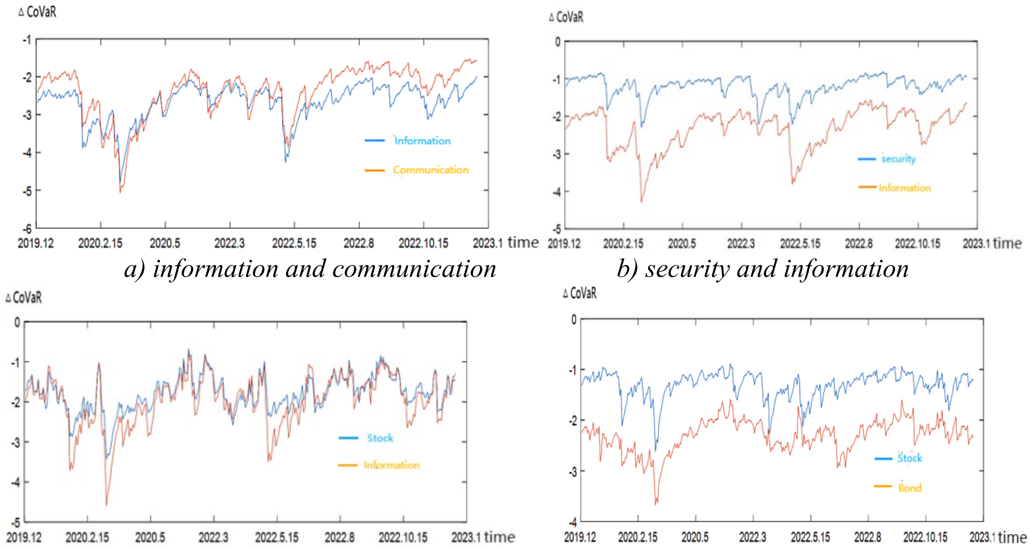
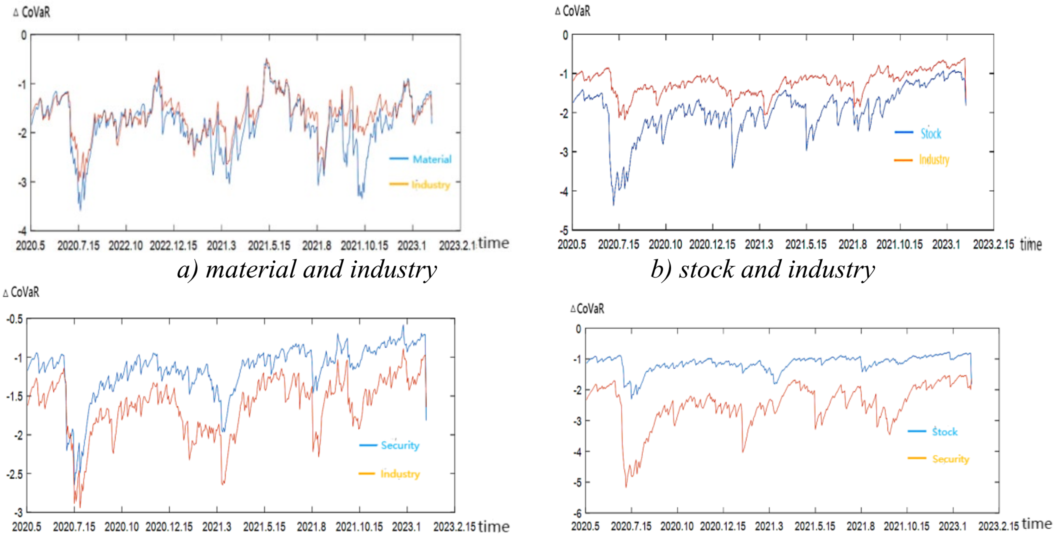
within the real economy, financial markets, and between the real economy and financial markets is very similar, with the main difference being the intensity of risk spillovers. Therefore, figure 1 and figure 2 only shows the risk spillover intensity and dynamic relationship between industries and markets with higher risk spillover intensity during the two periods, and analyzes the trend characteristics.



a) information and communication *b) security and information*

c) stock and information *d) stock and bond*

Figure 1: Image of risk spillovers between high-risk industries and markets during the epidemic period



a) material and industry *b) stock and industry*

c) security and industry *d) stock and security*

Figure 2: Risk Spillover Image between High Risk Industries and Markets during Stable Times

As shown on the figure 1 and figure 2 ,the analysis of the overall risk dynamic spillover situation between the industry and the market shows that the impact of the epidemic shock has time delay and repeatability, and the shock fluctuation presents a wave like feature. For example, △CoVaR reached its peak in all industries and markets 2-3 months after the COVID-19 hit and 1-2 months after the stable period lasted; After a period of impact or stabilization, the △CoVaR between the industry and the market has experienced multiple local peaks, and the intensity of the initial △CoVaR peak is higher than that of the mid-term and later stages. The reason for this is that in the early stages of the outbreak of the epidemic, the economic downturn was fierce, and risks spread rapidly and strongly between industries and markets; Afterwards, local outbreaks of the epidemic occurred one after another throughout the country, with periods of impact alternating with periods of stability. After a period of sustained external major shocks and favorable policy adjustments, positive or negative impacts continued to accumulate, leading to risk outbreaks and fluctuating levels of risk spillovers. It is worth noting that during a stable period, the economy begins to recover, and the rising market also carries huge risks. Therefore, regulatory agencies should not only focus on the decline of the market caused by

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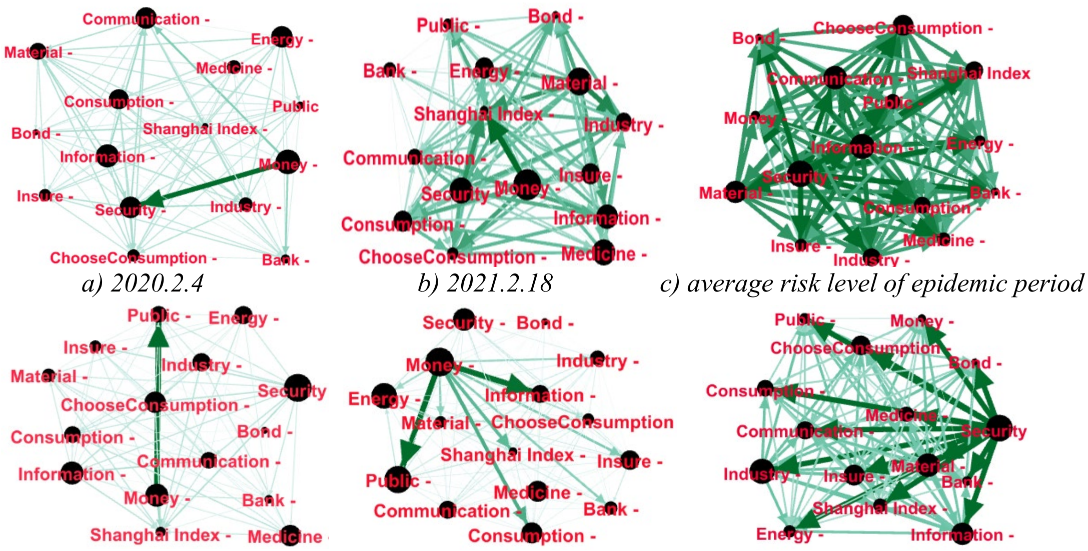
extreme shocks, but also monitor the situation of the rising market during a stable period.

Further analysis based on the characteristics of risk contagion between industries and markets reveals that risk contagion channels mainly include the following two categories: cross market contagion and industry chain related contagion. In terms of cross market contagion, the impact of the epidemic will increase the inter market linkage effect and risk resonance effect with common risk exposure. For example, the bidirectional risk spillover between the stock market and the securities market shows a strong positive dynamic correlation trend, and the intensity of risk spillover is high in both periods. The reason for this is that in the early stages of sudden public health emergencies, the impact of the epidemic will lead to a high level of panic among investors. Investors often transfer assets from high-risk stock and securities markets to other low-risk markets to reduce risks, enhancing the linkage effect between the stock and bond markets in the same economic environment; With the spread of the epidemic and the rebound of local epidemics leading to economic shutdowns, the stock and securities markets will simultaneously bear the impact of macroeconomic downturn and irrational investor behavior, exacerbating their risk resonance effect. In terms of industrial chain related contagion, the impact of the epidemic will increase the risk spillover effect between upstream and downstream industries with high correlation. The bidirectional risk spillovers between information, communication, materials, and industrial industries reflect a strong positive dynamic correlation trend. The reason for this is that the impact of the epidemic will squeeze the supply and demand sides in both directions. During the epidemic, production activities are restricted for a long time and on a large scale, resulting in a serious shortage of supply side supply, and a significant decline in demand side demand due to the macroeconomic downturn.

6. Risk transmission network

After conducting an overall analysis, industry refinement analysis, and inter industry correlation analysis of individual risk spillovers at the micro level, this article will conduct a macro system analysis from the risk transmission paths, in order to assist in improving risk prevention mechanisms from the micro entity and macro system levels, and prepare for the network construction part of risk warning.

To characterize the differences in risk tolerance among various entities, identify the main risk spillovers and the risk transmission paths within nodes and systems, and draw a risk transmission path map of the average risk spillover intensity at important time points and two periods for comparative analysis. The results are shown in the figure 3 and figure 4.



a) 2020.2.4 *b) 2021.2.18* *c) average risk level of epidemic period*

d) 2022.7.5 *e) 2022.12.7* *f) average risk level of stable period*

Note: The color depth of the edges in Figure 3 represents the size of the weight. The darker the color of the edges, the greater the weight and the greater the risk overflow intensity. The size of a node represents the size of its occurrence, and the larger the node, the higher its occurrence, which is the main risk spillover industry or market.

Figure 3: Key time points and average risk spillover transmission path diagram

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Observing Figures (a), (b), and (c), the average risk spillover intensity is the highest during the epidemic period and the lowest during the downward trend of the market. Therefore, it is necessary to strengthen the attention to the daily industry and market, as well as the upward trend of the market; Observing Figures (d), (e), and (f), the average risk spillover intensity is the highest during the stable period of the epidemic, and the lowest during the upward trend of the market. Therefore, it is necessary to strengthen daily risk supervision of the industry and market. In addition, due to the implementation of relatively loose monetary policy, the risk potential of the currency market is relatively high.

After analyzing the important nodal analysis, it is found that the risk characteristics of each entity are relatively stable, that is, the main risk bearers and spillovers have hardly changed in the two periods. Specifically, the information, materials industry, and securities market are the main risk spillovers. The reason is that the information industry, as a highly valued industry in China in recent years, has attracted a large number of talents and capital. At the same time, it has also increased the possibility of the industry overheating leading to the bursting of the foam to a certain extent. On the other hand, external uncertain factors such as foreign policy sanctions and new breakthroughs in China's core information technology can cause significant fluctuations and instability in the risk of information industry spillovers; The material industry is undergoing a transition from traditional materials to new materials, and the characteristics of the period exacerbate its risks; The securities market has the characteristics of high activity, varying levels of practitioners and credit, and many internal non-standard operations. It is also greatly influenced by investor sentiment and asset allocation mechanisms, which to some extent increases the risk hidden dangers of the securities market.

The asset allocation mechanism has intensified the cross market contagion of risks, leading to the bond and banking markets becoming the main risk bearers. The reason for this is that bonds have a more stable cash value in their future discount flows compared to other financial assets, so the bond market itself is more robust. And when the economy is unstable, investors will increase the proportion of bond investment in their assets by changing their asset portfolio, to some extent transferring risk to the bond market; For the banking market, currently larger banks are mainly controlled by the state, and the state will timely regulate financial instruments such as monetary policy, deposit reserve ratio, interest rates and exchange rates based on macroeconomic conditions, ensuring bank credit and business standards to a certain extent. And interbank business transactions are becoming increasingly close, and when faced with external shocks, the market will use a series of means to diversify risks internally.

7. Risk warning model

On the basis of accurately measuring the risk spillover effects between micro entities and constructing a risk contagion network, this article will further construct a comprehensive warning indicator system and warning model that covers industry fundamentals and CoVaR data, in order to help regulatory authorities improve their forward-looking prevention capabilities for risk events. Specifically, first, because VaR focuses on measuring the risk of a single entity, it combines VaR with the data of nine industry fundamentals to build an early warning indicator system. Then, it uses the PMFG method to build a risk contagion network. Finally, it inputs the early warning indicators and risk contagion network into the GAT model for early warning of risk events, and optimizes the early warning work from three aspects: the comprehensiveness of early warning indicators, the scientificity of network construction, and the accuracy of early warning models. In order to verify the accuracy of the risk early warning indicator system and the selection of the risk early warning model, this paper selects the classification accuracy, recall, false alarm, the area of the ROC curve (AUC) value and the Cross entropy Loss function to evaluate the actual prediction effect of the model, and selects the fivefold cross method to divide and train the sample data, And use principal component analysis to reduce the dimensionality of information features. For the prediction results of the two category early warning model, the above evaluation indicators are calculated by constructing a Confusion matrix.The results are shown in the table 1.

Table 1: Risk early warning model Confusion matrix

Actual label	Predicted label is Class 0	Predicted label is class 1
Actual label is class 0	TN	FP
Actual label is Class 1	FN	TP

In order to verify the risk early warning performance of the GAT model, this paper also selects the widely used Logistic, Random forest (RF), K-Nearest Algorithm (KNN), XGBoost and Support Vector

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Machine (SVM) traditional machine learning for comparative analysis. The index results of each model are shown in Table 2. From Table 2, it can be seen that for the training set, validation set, test set accuracy, test set recall, and AUC indicators, the GAT model has reached over 90%, which is more than 10% higher than the SVM model with the highest prediction accuracy among machine learning models and about 20% higher than the Logistic model with the lowest prediction accuracy; The false alarm rate of the test set is controlled within 7%, and the probability of issuing error warning signals is very low, which is significantly reduced compared to other machine learning models; The Cross entropy loss is kept below 0.2, that is, the predicted value of the model is very close to the true value, which is significantly lower than other machine learning models.

Table 2: Evaluation indicators for risk warning models with VaR

Risk warning models	Train accuracy	Validation accuracy	Test accuracy	Test false alarm	Test recall	AUC	Cross entropy loss
GAT	95.10%	94.72%	94.74%	5.76%	95.24%	0.94	0.18
Logistic	72.53%	70.37%	68.29%	31.28%	67.96%	0.68	0.46
RF	82.66%	81.21%	78.95%	21.39%	79.25%	0.78	0.37
XGBoost	79.8%	80.4%	78.68%	18.46%	76.07%	0.76	0.33
KNN	88.3%	86.1%	82.24%	19.50%	83.59%	0.81	0.29
SVM	87.71%	84.73%	80.13%	21.01%	81.37%	0.79	0.26

Conduct robustness testing on the GAT model and risk warning indicators. Because different Value at risk variables focus on different risk characteristics, VaR in node characteristics is replaced by CoVaR and △CoVaR respectively, and other variables and methods remain unchanged. By replacing variables, different risk characteristics can be emphasized, making the risk warning indicator system and risk warning model more universal. Among them, CoVaR focuses on depicting the risk level of a single entity in the financial system during a crisis; △CoVaR focuses on describing the marginal contribution of a single entity to financial Systemic risk when it is in crisis. The results after replacing variables are shown in Tables 3 and 4, and all models have similar performance to the original model after replacing indicators. From Table 3 and table 4,the accuracy of the training set, verification set and test set of the GAT model are all between 90% and 95%, and the Cross entropy loss value is about 0.2. Even after changing variables, the performance of the GAT model remains relatively stable and excellent. Therefore, based on comprehensive observation, the GAT model has a higher predictive ability for risk events and, through robustness testing, can serve as a tool for risk warning and provide decision-making reference for regulatory authorities.

Table 3: Evaluation indicators for risk warning models with △CoVaR

Risk warning models	Train accuracy	Validation accuracy	Test accuracy	Test false alarm	Test recall	AUC	Cross entropy loss
GAT	94.37%	93.23%	94.08%	6.38%	94.53%	0.93	0.16
Logistic	75.3%	71.9%	68.68%	30.48%	67.88%	0.73	0.46
RF	81.26%	79.81%	78.55%	22.49%	79.54%	0.80	0.43
XGBoost	81.32%	80.41%	80.13%	16.67%	77.25%	0.79	0.44
KNN	81.31%	80.26%	82.24%	20.10%	84.62%	0.82	0.36
SVM	84.37%	81.32%	80.13%	21.28%	81.62%	0.82	0.28

Table 4: Evaluation indicators for risk warning models with CoVaR

Risk warning models	Train accuracy	Validation accuracy	Test accuracy	Test false alarm	Test recall	AUC	Cross entropy loss
GAT	93.94%	97.62%	93.55%	6.70%	93.80%	0.92	0.18
Logistic	73.17%	72.29%	69.87%	28.92%	68.72%	0.72	0.43
RF	83.75%	80.54%	78.95%	22.43%	80.26%	0.81	0.41
XGBoost	80.14%	80.09%	79.74%	17.91%	77.46%	0.80	0.39
KNN	81.11%	80.03%	82.37%	19.41%	84.11%	0.81	0.35
SVM	86.92%	83.28%	82.24%	18.91%	83.42%	0.84	0.38

8. Conclusion and Suggestions

Controlling the global risks of China's real economy and financial market under sudden public

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health emergencies, deeply analyzing the spillover effects, transmission paths, and contagion characteristics of risks in the network connecting the real economy and financial market, and establishing a sound risk prevention mechanism, not only helps regulatory authorities achieve forward-looking and refined warnings, but also helps to implement macroeconomic control policies that are suitable for public health events, Preventing systemic financial risks is of great significance for maintaining the stable operation of the national macroeconomic and social stability and development. This paper selects the return rate of each industry and market during the epidemic period, the stable epidemic period and the policy opening period to conduct time-varying Copula GARCH modeling and calculate △CoVaR, and uses the PMFG method to build a risk contagion network at key time points. After that, the network topology indicators are analyzed, comprehensively depicting the Systematic risk spillover effect from the micro subject to the macro system. Finally, Select comprehensive risk early warning indicators and graph attention model to carry out risk early warning, realize significant improvement of early warning performance, and provide different perspectives of reference for prevention, governance and early warning of Systematic risk.

A summary of the dynamic evolution characteristics of risks among various industries and markets, as well as the research on refined risk warning, is drawn as follows: firstly, the impact of the epidemic shock on industries and markets is time lagged and repetitive, and the level of risk spillover shows a wave like feature. This is often manifested when the risk spillover level between the industry and the market reaches multiple local peaks after a period of shock or stability lasts for a certain period of time. And the peak risk spillover level in the initial stage is the highest, while the peak risk spillover level in the subsequent period is relatively low. Secondly, the impact of the epidemic will increase the linkage effect and risk resonance effect between industries and markets with common risk exposure, manifested as cross market contagion of risks and upstream and downstream contagion along related industry chains; Thirdly, graph attention models have better evaluation indicators and stronger predictive ability for risk events compared to logistic, RF, XGBoost, KNN, and SVM models.

Based on the above conclusions, this article proposes the following suggestions:

Firstly, summarize the temporal changes and characteristics of risk spillovers in various industries, and implement timely and effective targeted strategies when similar public health emergencies occur again. For risk spillover levels that exhibit wave like characteristics, it is necessary to accurately grasp the time nodes and stage characteristics of peaks and valleys, identify industries and markets that are at high risk spillover levels at different time points, and carry out forward-looking and periodic control to avoid risk spreading along the systemic financial network.

Secondly, for industries and markets with strong correlations, it is necessary to promptly identify and cut off their risk transmission pathways. The various entities within China's financial system are in a common economic environment and risk exposure, and the degree of business intersection and similarity in holding financial assets is becoming increasingly close. Therefore, for markets with similar structures such as stocks and securities, it is necessary to cut off the risk transmission path in a timely manner to prevent further increase in positive correlation and risk resonance between markets. For industrial chains with upstream and downstream relationships such as information and communication, materials, and industry, it is necessary to strengthen regulatory efforts on both sides at the same time. By prioritizing the smooth operation and production of downstream supply chains, the market can be stimulated to promote the operational vitality of upstream demand chains.

Thirdly, strengthen separate industry supervision and identify the main risk spillovers and bearers. When a public health emergency occurs, targeted policy tools should be selected for differential supervision based on the ranking of risk spillover intensity among various entities and the source of risk transmission pathways. We should not only pay attention to the risks and hidden dangers of high-tech industries such as information and communication, but also not ignore the risks of traditional industries such as materials and industry, especially during the transition period of traditional industries; We need to strengthen the supervision of markets prone to non-standard operations such as stocks and securities, where the qualifications and credit of practitioners are mixed. We also need to adopt macro policies to leverage the regulatory capabilities of financial instruments such as bonds and banks in the market to mitigate risks.

Fourthly, when studying systemic financial problems with multiple agents and connections, traditional econometric models are often used to study individual agents due to the limitations of conditional assumptions. Therefore, they need to be adept at using graph models to construct their complex connection relationships and analyze their topological structures based on graph theory knowledge. In addition, theories and methods from other disciplines can be combined to promote

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interdisciplinary integration and provide new ideas for research in the financial field.

The COVID-19 that broke out at the end of 2019 not only triggered a large-scale and long-term risk resonance between China's financial market and the real economy, but also caused the global economic environment to decline and production to stop for a long time. Nowadays, the policy of relaxing epidemic control has been fully implemented, and the economy is gradually recovering, with expectations of stability. However, considering that future public health emergencies may still continue to occur, regulatory authorities need to continuously improve risk prevention mechanisms and take timely measures to stabilize the economy in the face of the impact of sudden public health events, enhance the confidence of investors and consumers, and establish positive market expectations. At the same time, it is necessary to pay attention to optimizing early warning work, enriching the levels and means covered by risk warning mechanisms, and achieving early detection and governance.

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