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Research article

Systemic risk prediction based on Savitzky-Golay smoothing and temporal convolutional networks

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Abstract: Based on the data from January 2007 to December 2021, this paper selects 14 representatives from four levels of the extreme risk of financial institutions, the contagion effect between financial systems, volatility and instability of financial markets, liquidity, and credit risk systemic risk. By constructing a Savitzky-Golay-TCN deep convolutional neural network, the systemic risk indicators of China's financial market are predicted, and their accuracy and reliability are analyzed. The research found that: 1) Savitzky-Golay-TCN deep convolutional neural network has a strong generalization ability, and the prediction effect on all indices is stable. 2) Compared with the three control models (time-series convolutional network (TCN), convolutional neural network (CNN), and long short-term memory (LSTM)), the Savitzky-Golay-TCN deep convolutional neural network has excellent prediction accuracy, and its average prediction accuracy for all indices has increased. 3) Savitzky-Golay-TCN deep convolutional neural network can better monitor financial market changes and effectively predict systemic risk.

Keywords: financial market; systemic risk forecasting; deep learning; Savitzky-Golay-TCN neural network model

1. Introduction

The global financial crisis in 2008 triggered a rethinking of systemic risks by international organizations, financial regulators, and scholars in various countries. At the same time, financial risk contagion has become increasingly normalized, including extreme risk events such as "money shortage" and "circuit breaker mechanism," which have caused the spread of online public opinion, making systemic risks spread rapidly in the capital market. In addition, China is pursuing a sustainable transition and undergoing supply-side reform, and the deep-seated contradictions of stakeholders in the society and financial industry have become more prominent [1, 2]. The Chinese central government emphasizes the need to "keep the bottom line of preventing systemic risks". Such national resolve in preventing and resolving systemic risks prioritizes the stability and soundness of economic development. Due to rigorous risk monitoring and control, China has yet to experience a large-scale systemic financial crisis. However, the increasingly interconnected international financial market and policy uncertainties urge the decision-makers to pay attention to reforming and innovating the domestic financial market [3]. An effective systemic risk prediction model is thus necessary to predict and alleviate systemic risks and ensure high-quality economic development in the future.

In early research, systemic risk was defined as a financial phenomenon within the financial system. Academics described any situation that threatens the financial system or macroeconomy or undermines public confidence in the financial system as a systemic risk [4–7]. However, the global financial crisis that broke out in 2008 caused severe damage to the world economy and made academia and regulatory authorities realize that systemic risks affect the real economy from multiple levels. As a result, a new concept of systemic risk is considered a contagion risk; that is, the collapse of one financial institution will lead to the failure of other financial institutions [8, 9] . The European Central Bank pointed out that systemic risk is a widespread risk of financial instability. It undermines the essential functions of the financial system and affects economic growth, and causes severe losses to the welfare of the entire society [10]. In 2011, the International Monetary Fund and the Financial Stability Board described the systemic risk as the risk of disrupting financial services and having a severe negative impact on the real economy due to partial or total damage to the financial system [11]. Therefore, systemic risk has two dimensions, horizontal and vertical. On the one hand, within the financial system, due to the direct or indirect connection between various institutions, there is risk contagion among financial institutions, and any institution has debt repayment or liquidity risk [12]. Its affiliated institutions were also strongly impacted, resulting in a liquidity crunch across the system. On the other hand, as risks continue accumulating within the financial system, financial institutions' intermediary efficiency and resource allocation efficiency gradually decrease, causing massive damage to the real economy [13–15].

Systemic risk prediction and prevention has been a hot research topic in academic circles recently, and traditional financial risk prediction methods are mainly studied through linear models. The early prediction method is the earliest method applied to systemic risk prediction. This method selects dependent variables that reflect financial risks and independent variables related to them and establishes a conditional equation to fit the relationship between them [16]. These include the Frankel and Rose (FR) probability model [17], the Sachs, Tornell and Velasco (STV) model [18], and the Kaminsky, Lizondo and Reinhart (KLR) signal prediction model [19]. The premise of applying the early forecasting method is that the target country accurately defines a financial crisis or systemic risk event. Still, early forecasting has significant limitations for countries like China that have never experienced a financial crisis. Although some scholars have proposed setting the critical value of financial crisis risk indicator data [20, 21] or constructing financial crisis indicators and setting certain thresholds for crisis indicators to define financial crises [22]. But, when the indicator exceeds the threshold or critical value, the prior prediction methods are in gridlock for a nuanced explanation of whether systemic risk or financial crisis will occur.

In recent years, nonlinear models have gradually replaced the application of time series and other linear models in financial forecasting and forecasting because of their ability to mine nonlinear relationships between variables, which can effectively improve the performance of financial forecasting. Yun and Moon [21] proposed a multi-range neural network model based on the empirical mode decomposition (EMD) method. Their empirical results show that the model has higher prediction accuracy than the traditional neural network model. Iturriaga and Sanz [23] combined multi-layer perceptrons and self-organizing maps to build a neural network model to study the bank failure problem in the United States. The model can predict the probability of bank failure three years in advance, and compared with the traditional model, it has higher prediction accuracy. Cao et al. [24] predicted the global stock index by establishing a LSTM prediction model of EMD and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) feature sequences. There are also many studies on stock price forecasting and futures forecasting through neural network models [25–29].

However, financial forecasting based on artificial neural networks suffers from the following problems: first, overfitting deteriorates the predictive power of the model outside the training set; second, there is gradient disappearance or gradient explosion during the optimization process, which prevents the neural network from learning effectively; and third, the local extremum problem, which makes it impossible to find the optimal global solution. Although a large number of studies have demonstrated the superiority of artificial neural networks in financial time series forecasting [4, 16, 30], each step of the artificial neural network model relies on the hidden state of the previous step for prediction, which is less parallel and has problems such as long training time and easy loss of information when processing long sequences. In recent years, TCNs have been proposed to provide new ideas for time-series modeling. TCNs can obtain exponentially growing sensory fields using inflated convolution, which is highly suitable for application scenarios requiring more comprehensive historical information. Deng et al. [31] adopted the KDTCN model to predict and explain stock price movements. Dai et al. [30] added an attention mechanism to the TCN model to model the time-varying distribution of stock price change data. The Savgol-TCN deep convolutional neural network model is based on the original TCN model by adding the prediction of the error and introducing the Savitzky-Golay filter to smooth the error. The Savitzky-Golay filter is a digital filter that can be applied to smoothen data. Its advantage is that it can improve the data accuracy without changing the signal's trend and width to increase prediction accuracy.

Given this, this paper constructs the Savgol-TCN deep convolutional neural network, predicts 14 systemic risk indicators in four dimensions of China's financial market, and analyzes its accuracy and reliability. Through the comparative analysis of the constructed Savgol-TCN deep convolutional neural network and TCN, CNN, and LSTM models, the predictability and generalization ability of the Savgol-TCN deep convolutional neural network model for systemic risk are studied. In summary, the main contributions of this paper are listed below.

1) The Savitzky-Golay filter is introduced into the TCN model, and the Savgol-TCN deep convolutional neural network model is proposed for financial forecasting with time series for the first time.

2) Based on the same Savgol-TCN deep convolutional neural network, the predictability and generalization ability in systemic risk prediction are proved.

3) The 14 systemic risk indices based on the Savgol-TCN deep convolutional neural network were compared with the TCN, CNN, and LSTM models, and the proposed model reflects superior prediction capability.

The rest of the paper is organized as follows. Section 2 presents the problem description and research hypotheses. The quantum game analysis is unfolded in Section 3. Section 4 displays numerical analysis and explains the theoretical results. Finally, Section 5 concludes the paper and gives corresponding policy recommendations.

2. Research design

2.1. Model building/ description

2.1.1. Savitzky-Golay filtering algorithm

The Savitzky-Golay (Savgol, hereafter for brevity) filtering algorithm is widely used in data stream smoothing and denoising. It is a filtering method based on regional polynomial least squares fitting in the time domain. Its biggest feature is to remove signal noise while keeping the shape and width of the signal unchanged [32]. And on the same curve, different window widths can be selected at any position to meet the needs of different smoothing and filtering. Especially when dealing with time sequence data, it has obvious advantages for sequence processing in different stages. Noise samples from aperiodic and nonlinear sources also work well.

Define a width window $n = 2m + 1$ to measure the original curve from left to right. Consider a set of data with $2m + 1$ points centered on the data point y_t, and fit this set of data points based on a degree of $k - 1$ polynomial, as shown in Eq (1).

$$y = a_0 + a_1 x + a_2 x^2 + \cdots + a_{k-1} x^{k-1}. \tag{1}$$

To make the equation have a solution, generally, let $n \geq k$. For a given data set with 2m+1 data points, there are 2m+1 equations, respectively. The fitting equation can therefore be expressed in matrix form. Let the data value vector be Y, the coefficient matrix be A, the independent variable matrix is X, and the residuals be ε. The equation can be expressed as follows.

$$Y = AX + \varepsilon. \tag{2}$$

The matrix A is solved by the least squares method as $\hat{A}$; its value is shown in the formula (3). The predicted value of the fitted data is $\hat{Y}$, and its value is shown in the formula (4).

$$\hat{A} = (X^T X)^{-1} X^T Y, \tag{3}$$

$$\hat{Y} = X\hat{A} = X(X^T X)^{-1} X^T Y. \tag{4}$$

The window slides from left to right until all data points are fitted. The fitted curve has the original high-frequency components removed.

2.1.2. Temporal Convolutional Networks

The Temporal Convolutional Network (TCN) model is based on the CNN model, using Causal Convolution, Dilated Convolution, and Residual block to improve CNN; compared with CNN, LSTM, and GRU, TCN has a lighter network structure, and can change the receptive field of the network according to the filter size, which is more conducive to the prediction of time series. The principle of the TCN model is as follows.

Set filter $F = \{f_1, f_2, \cdots, f_k\}$, The input sequence is $S = \{s_1, s_2, \cdots, s_t\}$, The output sequence information is $Y = \{y_1, y_2, \cdots, y_t\}$, where $s_i(i = 1, 2, \cdots, t)$ are column vectors. At time t, the dilated convolution of s_t is defined as

$$F(s_t) = (S *_d F(s_t) = \sum_{i=1}^{K} f_i \cdot s_{t-d(K-i)}, \tag{5}$$

where d is the inflation factor, and K is the filter size. The formula for the receptive field is

$$R_F = (K-1)d + 1.$$

The TCN model introduces a residual module to solve the problems of gradient explosion and network degradation in deep traditional neural networks. Figure 1 presents the residual module of the TCN model. This residual structure can avoid losing more information in the feature extraction process and improve the model's accuracy.

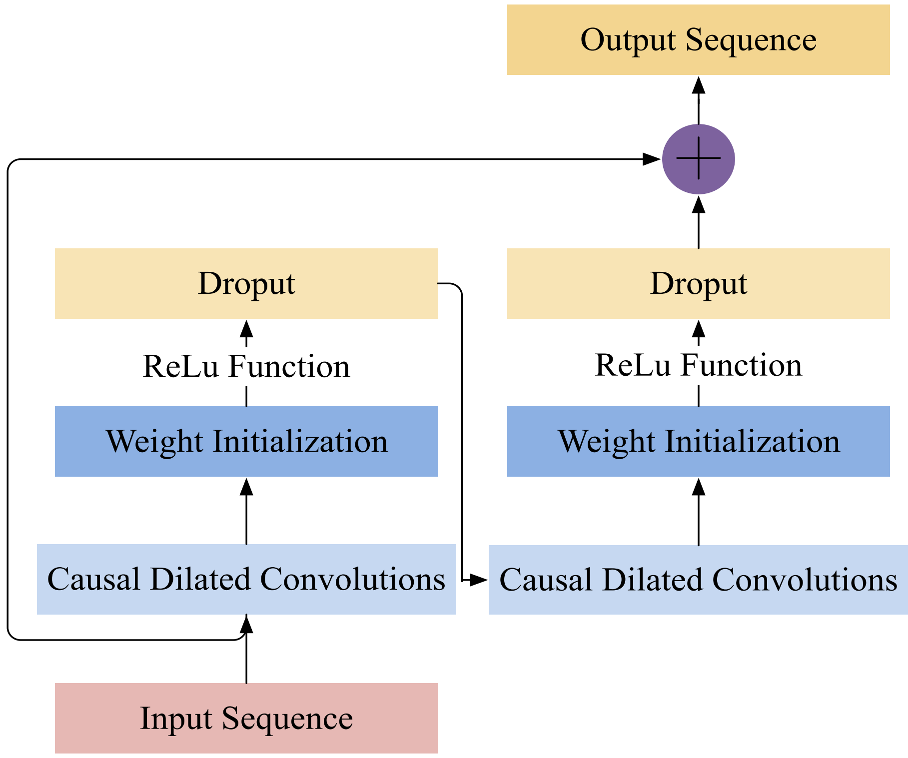

Figure 1. The residual module of the TCN model.

2.2. Systemic risk prediction model

The algorithm flow chart of the Savgol-TCN error correction systemic risk prediction method proposed in this paper is shown in Figure 2, and the specific steps are as follows.

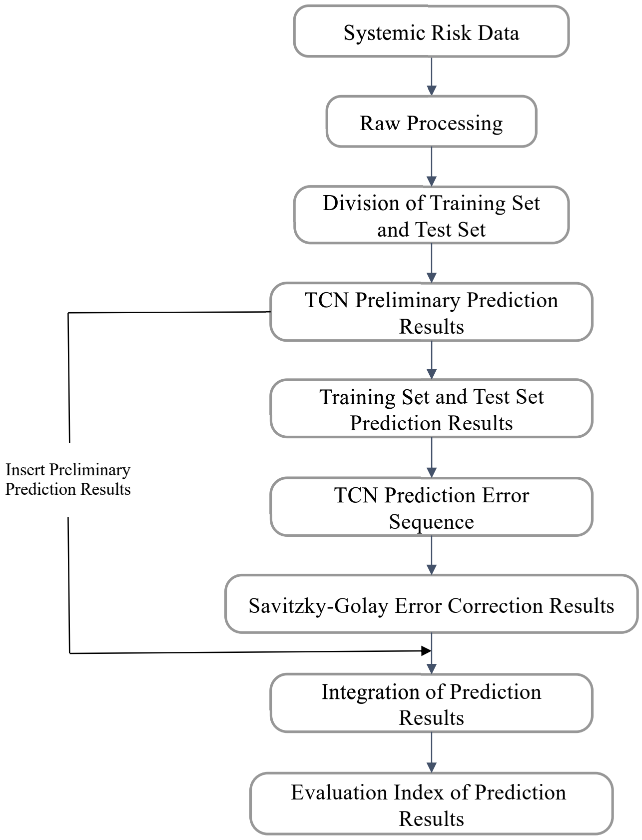

Figure 2. The algorithm flow chart of the Savgol-TCN error correction systemic risk prediction method.

The specific steps are as follows. First, all the original systemic risk sequences P before the input time t are preprocessed. Then, the convolution kernel in the spatial dimension of TCN is used to extract the spatial characteristics of each component of the systemic risk. Next, the convolution kernel in the time dimension is used to extract the features of the change of the systemic risk over time. The mapping relationship between the input sequence and the systemic risk is established. Then, the initial prediction output result is obtained at the moment t. Then, use the prediction model trained in the previous step to take all the historical data before time t as the input set, get the prediction result and calculate the error set E of all systemic risks before time t. Then use Savitzky-Golay smoothing to smooth the prediction error set to obtain a less volatile and more stable error sequence. Finally, the initial prediction output results and the error sequence are integrated, and the model prediction result evaluation index is output.

2.3. Model checking

During the network training process, the mean square error (MSE) is used as the loss function to calculate the Euclidean distance between the model-predicted value and the actual value. As shown in formula (6),

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{6}$$

where y_i is the test value, $\hat{y}$ is the real value, and n is the number of samples. This paper selects the root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}, \tag{7}$$

and the mean absolute percentage error (MAPE) as the evaluation indicators for the prediction results:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \hat{y}_i}{y_i}| \times 100\%. \tag{8}$$

RMSE is consistent with the unit of the predicted variable, the error results are more intuitive and easy to interpret, and RMSE is very sensitive to the situation where the predicted value deviates from the actual value and is widely used in prediction evaluation. Furthermore, compared with RMSE, MAPE is not affected by dimensions, which is conducive to the direct comparison between different models and is an important indicator to measure the prediction accuracy of models.

Besides, the mean absolute error (MAE) is also used. MAE measures the average magnitude of the errors in a set of predictions without considering their direction. It is the average of the absolute differences between prediction and actual observation over the test sample, where all individual differences have equal weight. Using the two indicators at the same time can more comprehensively evaluate the prediction accuracy of the model. The calculation formulas are expressed as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \times 100\%, \tag{9}$$

We ran the model 30 replicates to avoid chance and calculated the average metric as the final comparison criterion.

3. Data sources and sample selection

3.1. Data sources

In order to more comprehensively and accurately evaluate the applicability of the Savgol-TCN deep convolutional neural network model to China's systemic risk prediction, this paper considers the selection of large, medium, and small institutions from the three sectors of banking, insurance, and securities. A total of 52 listed companies were selected as samples of Chinese financial institutions, including 23 banks, 25 securities companies, and four insurance companies. Referring to the research of Giglio et al. [33], the systemic risk indicators of 14 sub-categories and four categories of extreme risk, contagion effect, volatility and instability, liquidity, and credit risk of individual institutions were selected. The data range is from January 2007 to December 2021, and the CSI 300 index is chosen to measure financial market returns. The book leverage and market leverage are calculated from the total assets, total liabilities, and other data provided by the quarterly reports of listed companies. Finally, the weight of each institution in the overall calculation is measured by the proportion of the company's market value. The data comes from the Cathay Pacific and Wind databases. In the demonstration, 80% of the data is used as the training set, and the remaining 20% is used as the test set. In order to preserve the relationship between the time series data, the method of using time series cross-validation is used for verification. Construct a feature set with the time window as December, and predict the index value of the following month.

3.2. *Variable definitions*

3.2.1. Institutional extremum risk

Institutional extreme risk focuses on the change of extreme characteristics of institutional returns. This paper selects four indicators: conditional value at risk, conditional value at risk, marginal expected loss (MES), and financial system catastrophe risk to describe the extreme risk of financial institutions.

1) Conditions Value-at-Risk (CoVaR). Adrian and Brunnermeier [34] put forward the basis of VaR, which focuses on reflecting the risk spillover of a single financial institution to other institutions or the entire financial market. Under the confidence level, the CoVaR level of the institution in the future period is:

$$Pr(X^i < VaR^i) = q.$$

The CoVaR level of the financial system in the event of a financial institution crisis is:

$$Pr(X^{syst} < CoVaR^i | X^i = VaR^i) = q,$$

where X^{syst} represents the rate of return of the financial system, and CoVaR can measure the impact of a single institution on the financial system as a whole when a crisis occurs, thereby quantifying the importance of a single institution to the financial system. In this paper, when estimating CoVaR, the confidence level is set to 0.05, and the Dynamic Conditional Corelational Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model is used to calculate the dynamic CoVaR.

2) The difference between the CoVaR ($\Delta CoVaR$). It represents the difference between the financial system CoVaR when the institution is in an extreme state and the financial system CoVaR in a normal state.

$$\Delta CoVaR^i = CoVaR^i(q) - CoVaR^i(0.5),$$

Referring to Adrian and Brunnermeier [34], here, the extreme state of the institution is set at the 0.05th percentile of its rate of return, the normal state is set at the 0.5th percentile of the rate of return, and the financial system conditions of the financial institution in the two states are calculated at Poor risk.

3) MES Acharya et al. [8] proposed based on expected loss ES, which reflects the marginal contribution of a single institution to systemic financial risk when the yield of the entire financial market drops significantly. The expression for the MES is

$$MES^i = E[R^i | R^m < q],$$

where $\mathbf{R}^m$ represents the financial market rate of return, the confidence is set to 0.05, and the dynamic MES is calculated using the DCC-GARCH model.

4) The financial system catastrophe risk (Catfin). Allen et al. [35] proposed calculating the extreme tail at-risk value VaR of the cross-section through the generalized Pareto distribution, the biased generalized error distribution, and the nonparametric method, respectively, and then calculating the average value to obtain the Catfin index value.

3.2.2. Contagion effects

The contagion effect reflects the transfer and diffusion of systemic financial risks among financial institutions by analyzing the degree of correlation between institutions. This paper selects the absorption ratio, absorption ratio difference, and average correlation mean to measure the contagion effect of systemic financial risk.

1) Absorption rate. Kritzman et al. [36] extracted the first $k(k < N)$ principal components from N financial institutions and calculated the variance contribution rate of principal components. The calculation formula is

$$Abs(k) = \frac{\sum_{i=1}^{k} Var(PC_i)}{\sum_{i=1}^{N} Var(PC_i)}.$$

This paper calculates the absorption ratio from the 252-day long-term moving window by establishing a moving window. This indicator represents the degree of interpretation of a certain amount of variance to the total variance of the original variable. The larger the value, the greater the correlation of each institution. The faster the contagion, the higher the systemic monetary risk.

2) Absorption rate difference. Construct an indicator reflecting systemic monetary risk from the difference between the absorption ratio of the short-term moving window and the long-term moving window, and its expression is

$$\Delta Abs = Abs(k)_{short} - Abs(k)_{long}.$$

This paper sets the moving window from the perspective of year and month, the long-term moving window is 252 days, and the short-term moving window is 22 days to obtain the absorption ratio difference.

3) Average correlation means. Pollet and Wilson [37] obtained the average correlation mean of financial institutions by calculating the correlation coefficient between financial institutions and taking the average value. The calculation formula is:

$$\rho = \frac{N \sum x_i y_i - \sum x_i \cdot \sum y_i}{\sqrt{N \sum x_i^2 - (\sum x_i)^2} \cdot \sqrt{N \sum y_i^2 - (\sum y_i)^2}}.$$

ρ represents the average correlation mean between institutionsthe larger the average correlation means, the greater the systemic financial risk in the financial market.

3.2.3. Volatility and instability

High financial leverage contributes to volatility, instability, and systemic financial risk. Therefore, we select four indicators: return volatility, book leverage, market leverage, and scale concentration to reflect market volatility and fluctuation.

1) Return volatility. The monthly standard deviation of the average daily returns of individual stocks of 45 institutions is calculated to construct the individual fluctuation sequence of financial institutions. Then the overall return volatility is obtained by weighting the market value ratio of a single financial institution.

2) Book leverage, an indicator of the total book leverage of 45 financial institutions, is constructed from the ratio of total liabilities to total assets, which reflects the repayment ability of the institutions and predicts the impact on the macroeconomy when the market is highly leveraged.

3) Market leverage. A market leverage index measuring 45 financial institutions is constructed from the ratio of total liabilities to total market capitalization, which reflects the repayment ability of the institutions to predict the impact on the macroeconomy when the market is highly leveraged. When the economy is stable, appropriate leverage can help solve the shortage of funds in the real economy, promote enterprise production, and drive consumer demand. Still, excessive debt is prone to debt risks and crises.

4) Scale concentration. This indicator reflects the size distribution of financial enterprises by constructing the Herfindahl index

$$Herfindahl = n\frac{\sum_{i=1}^{N} ME_i^2}{\left(\sum_{i=1}^{N} ME_i\right)^2}$$

to reflect the size distribution of financial enterprises.

3.2.4. Liquidity and credit risk

Since the second half of 2012, China's liquidity and credit risk have increased significantly. Therefore, we select individual stock liquidity, credit spread, and term spread to characterize liquidity and credit risk.

1) Individual stock liquidity. It is usually expressed by the turnover rate, which reflects the stock's liquidity. This indicator is calculated by the ratio of the daily trading volume to the number of tradable shares in a certain period in the stock market.

2) Credit spreads. Calculating the credit spread based on the spread between the Shanghai Interbank Offered Rate (SHIBOR) and government bond yields is an essential measure of financial market risks. When the credit spread expands, it means that the financial market is tight, which leads to an increase in institutional borrowing costs and increased financial market risks.

3) Term spread. Calculated from the yield spread between the 10-year Treasury bond and the 3-month Treasury bond, the narrowing of the term spread means that the possibility of economic depression and more significant market risk increases, which is an important measure of financial market risk. The relevant variable settings are shown in Table 1.

Figure 3 shows the changes of four representative indicators, MES, Average-Cor, Volatility, and AIM, from January 2007 to December 2021, representing the individual risks, linkage, and contagion effects, volatility, and instability of financial institutions, respectively as well as liquidity and credit profiles. To facilitate the observation of the time series characteristics of each indicator, we standardized the four indicators. We found that, in general, the changes in the four indicators were similar, and they appeared in the stage of the global financial crisis in 2008 and the stage of China's stock market boom and busted in 2015. The subprime mortgage crisis broke out in the United States in August 2007. Due to the severe disconnection between the virtual and real economies, the Internet bubble, and other reasons, the crisis spread to the world, triggering the global financial crisis. Therefore, the financial crisis from 2007 to 2008 had the most extensive impact and violent fluctuations. In 2015, the stock market crisis saw a sharp drop in the index in just 53 trading days, and the limit of 1,000 shares occurred many times. Compared with the financial crisis, the outbreak occurred faster, the scope of influence was small, and the impact time was relatively short, showing an apparent peak shape. However, observing the specific change trend of each indicator, there are certain differences between indicators. Judging from the fluctuation trend when the financial crisis broke out in 2008, AIM and Volatility showed a clear downward trend, while MES and Average Correlation showed an upward trend; from the sequence of the peaks of various indicators of the stock market crash in 2015, AIM and Volatility peaked earlier, MES is relatively late, and the Average Correlation peak is not apparent. It can be seen that a single indicator has its trend characteristics and may only reflect systemic financial risks in a particular aspect. Therefore, it is necessary to consider multiple indicators to reflect systemic financial risks accurately.

Table 1. Descriptive statistics of systemic risk indicators/systemic risk metrics.

Indicators category	Variable name	Variable meaning	Variable definition
Institutional extremum risk	CoVaR	Conditions CoVaR	$Pr(X^{syst} < CoVaR^i \| X^i = VaR^i) = q$
	ΔCoVaR	The difference between the CoVaR	$\Delta CoVaR^i = CoVaR^i(q) - CoVaR^i(0.5)$
	MES	MES	$MES^i = E[R^i \| R^m < q]$
	Catfin	financial system catastrophe risk	A Nonparametric Method to Calculate the Tail Value at Risk of a Section
Contagion effects	Ab.	Absorption rate	$Abs(K) = \frac{\sum_{i=1}^{K} Var(PC_i)}{\sum_{i=1}^{N} Var(PC_i)}$
	ΔAbs	Absorption rate difference	$\Delta Abs = Abs(K)_{short} - Abs(K)_{long}$
	Average_Cor	Mean correlation coefficient	$\rho = \frac{N\sum x_i y_i - \sum x_i \cdot \sum y_i}{\sqrt{N\sum x_i^2 - (\sum x_i)^2} \cdot \sqrt{N\sum x_i^2 - (\sum y_i)^2}}$
Volatility and instability	Volatility	Return volatility	The monthly standard deviation of the daily average return of individual stocks
	Book_lev	Book leverage	Total Liabilities/Total Assets
	Market_lev	Market leverage	Total liabilities/Total market value
	Size_concen	Scale concentration	Herfindahl=$N\frac{\sum_{i=1}^{N} ME_i^2}{(\sum_{i=1}^{N} ME_i)^2}$
Liquidity and credit risk	AIM	Individual stock liquidity	stock turnover ratio
	Credit_spread	Credit spreads	SHIBOR and Treasury Bond Yield Spread
	Term_spread	Term spread	10-year and 3-month Treasury bond yield spread

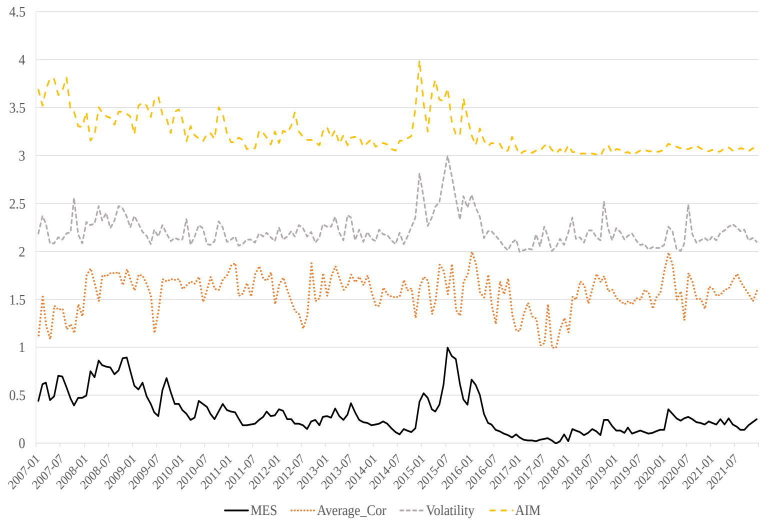

Figure 3. The changes of four representative indicators.

4. Empirical tests

4.1. Variable descriptive statistics

Through the calculation of the monthly data of 52 financial institutions, the data of each single systemic financial risk measurement indicator is obtained. The statistical description of each indicator is shown in Table 2.

Table 2. Descriptive statistics of systemic risk indicators.

Indicators category	Variable name	Variable meaning	Min.	Max.	Mean	Std. Dev.
Institutional extremum risk	CoVaR	Conditions Value at Risk	0.015	0.249	0.033	0.021
	ΔCoVaR	The difference between the CoVaR	0.006	0.058	0.024	0.012
	MES	MES	0.011	0.077	0.033	0.015
	Catfin	Catastrophe risk in the financial system	0.044	0.212	0.099	0.040
Contagion effects	Abs	Absorption rate	0.622	0.931	0.823	0.070
	ΔAbs	Absorption rate difference	-0.119	0.207	0.082	0.057
	Average_Cor	Mean correlation coefficient	0.264	0.856	0.594	0.123
Volatility and instability	Volatility	Return volatility	0.009	0.215	0.026	0.031
	Book_lev	Book leverage	0.716	0.941	0.919	0.035
	Market_lev	Market leverage	3.612	21.220	13.070	4.413
	Size_concen	Scale concentration	2.342	4.073	3.145	0.362
Liquidity and credit risk	AIM	Individual stock liquidity	5.534	115.400	33.420	23.310
	Credit_spread	Credit spreads	0.106	3.002	1.170	0.592
	Term_spread	Term spread	-0.557	2.414	1.017	0.597

There are specific differences in the values of different systemic risk indicators. Among them, the market leverage and individual stock liquidity calculated from total liabilities and market capitalization have the largest mean and standard deviation. Their value fluctuations are relatively large, ranging from

3.612 to 21.220 and 5.534 to 115.400, respectively. The value of the return volatility has the smallest fluctuation range, and the fluctuation range is between 0.009 and 0.215. The values of systemic risk indicators of the same category are relatively close. The three indicators of extreme institutional risk are calculated from each institution's daily rate of return. Therefore, the three indicators of MES, $CoVaR$, and $\Delta CoVaR$ have the most similar fluctuations.

4.2. Empirical results analysis

Fourteen Systemic risk indicators were added to the Savgol-TCN deep convolutional neural network model constructed in this paper for training and prediction. In addition, three evaluation indicators, MSE, MAE, and MAPE, were used for evaluation. The empirical results are shown in Tables 2-4.

To verify the superiority of the Savgol-TCN deep convolutional neural network model constructed in this paper, this paper compares and analyzes the TCN, CNN, and LSTM in the table and the Savgol-TCN deep convolutional neural network model of this method and compares the errors of each experiment. For indicators estimated by statistical methods such as $CoVaR$ and MES, Catfin, and average correlation mean to refer to the studies of Acharya et al. [8], Adrian and Brunnermeier [34], Allen et al. [35], and Patro et al. [38]. The commonly used systemic risk index can represent the level of systemic risk, so this paper uses it to predict the systemic risk level.

Table 3. Systemic risk index forecast results (MSE)

Index	Savgol-TCN	TCN	LSTM	CNN
CoVaR	0.0003	0.0006	0.0003	0.0005
ΔCoVaR	0.0003	0.0007	0.0003	0.0005
MES	0.0003	0.0008	0.0007	0.0006
Catfin	0.0009	0.0015	0.0014	0.0016
Abs	0.0010	0.0035	0.0022	0.0031
ΔAbs	0.0021	0.0034	0.0026	0.0030
Average_Cor	0.0052	0.0084	0.0066	0.0079
Volatility	0.0004	0.0006	0.0004	0.0005
Book_lev	0.0017	0.0036	0.0011	0.0025
Market_lev	0.0502	0.1474	0.0822	0.1682
Size_con	0.0072	0.0264	0.0091	0.0219
AIM	0.6935	0.8942	1.2121	1.0290
Credit_spread	0.0143	0.0399	0.0147	0.0264
Term_spread	0.0264	0.0318	0.0094	0.0293

Tables 3–5 report the prediction effect evaluation results of the systemic risk indicator test set, respectively. As can be seen from Tables 2–4, the prediction accuracy of the Savgol-TCN deep convolutional neural network model is significantly improved compared with the TCN, CNN, and LSTM models. Compared with the TCN model, only the Savgol-TCN deep convolutional neural network model is used. The prediction accuracy of all systemic risk indicators has been steadily improved. The LSTM neural network prediction accuracy for AIM is not as good as that of the TCN model. TCN, LSTM, and CNN cannot show advantages in predicting systemic risk indicators, and the prediction accuracy is uncertain. Based on the 14 Systemic risk indicators, the Savgol-TCN deep convolutional neural network model, compared with other models (TCN, LSTM, CNN), decreases

MSE, MAE, and MAPE in 14 prediction indices, indicating that The Savgol-TCN deep convolutional neural network model predicts better.

Table 4. Systemic risk index forecast results (MAE).

Index	Savgol-TCN	TCN	LSTM	CNN
CoVaR	0.0027	0.0062	0.0028	0.0048
ΔCoVaR	0.0025	0.0074	0.0028	0.0054
MES	0.0032	0.0078	0.0059	0.0059
Catfin	0.0079	0.0151	0.0120	0.0151
Abs	0.0104	0.0369	0.0207	0.0320
ΔAbs	0.0196	0.0335	0.0243	0.0296
Average_Cor	0.0527	0.0827	0.0686	0.0811
Volatility	0.0040	0.0064	0.0042	0.0050
Book_lev	0.0155	0.0369	0.0079	0.0233
Market_lev	0.4501	1.4929	0.7224	1.8080
Size_con	0.0722	0.2768	0.0899	0.2212
AIM	5.6736	7.6389	9.9136	8.9762
Credit_spread	0.1277	0.3870	0.1344	0.2767
Term_spread	0.2577	0.3136	0.0916	0.2832

Table 5. Systemic risk index forecast results (MAPE).

Index	Savgol-TCN	TCN	LSTM	CNN
CoVaR	9.3594	22.4996	9.2321	16.5611
ΔCoVaR	12.2127	42.7474	13.1731	27.2812
MES	11.4593	29.1350	18.7904	20.0723
Catfin	7.9786	17.8557	12.0536	16.3645
Abs	1.2267	4.4140	2.5754	3.9078
ΔAbs	32.9638	57.8988	54.4398	62.6208
Average_Cor	9.1944	15.7485	12.5664	15.0082
Volatility	22.6790	36.4395	22.5920	27.7508
Book_lev	1.8858	4.3950	0.9524	2.7449
Market_lev	3.7125	12.2193	5.4504	16.7460
Size_con	2.2927	8.8114	2.8612	7.1962
AIM	21.0094	31.0727	30.8383	36.2269
Credit_spread	12.7113	41.0228	13.4683	30.5531
Term_spread	79.3981	94.1137	22.2828	74.2717

Table 6 reports the average predictive effect evaluation results on the systemic risk indicator test set. It can be seen from the table that the prediction accuracy of the Savgol-TCN deep convolutional neural network model is improved compared with the TCN, CNN, and LSTM models. Detailed discussions are given below. The average MSE and MAE of the Savgol-TCN deep convolutional neural network model of the institutional extreme risk group and MAPE values are 0.0005, 0.0040, and 10.2005, respectively, compared to TCN, LSTM, and CNN models, the MSE is reduced by 0.0004, 0.0003 and 0.0003, MAE decreased by 0.0043, 0.003, and 0.0037, and MAPE decreased by 13.4303, 5.1801, and 9.4458. The average MSE, MAE, and MAPE values of the contagion effect group were 0.0031, 0.0284, and 17.4564, respectively. Compared with the TCN, LSTM, and CNN models, the MSE decreased by 0.0026, 0.0011, and 0.0019, the MAE decreased by 0.0234, 0.0101, and 0.0174, and the MAPE decreased by 10.7217, 8.5365 and 12.1746. The mean MSE, MAE, and MAPE values of the fluctuation and instability groups were 0.0159, 0.1267, and 12.6412, respectively. Compared with the TCN, LSTM, and CNN models, the MSE decreased by 0.0462, 0.0272, and 0.0367, the MAE decreased by 0.4471, 0.2297, and 0.3569, and the MAPE decreased by 14.0672, 5.9906 and 10.3368. The average MSE, MAE, and MAPE values of the liquidity and credit risk groups were 0.2872, 2.3072, and 25.9849, respectively. Compared with the TCN, LSTM, and CNN models, the MSE decreased by 0.1235, 0.2572, and 0.151, the MAE decreased by 1.0997, 2.0038, and 1.4134, and the MAPE decreased by 32.6766, 7.1083 and 31.3725.

Table 6. Comparison of systemic risk index prediction results.

	Institutional extremum risk	Contagion effects	Volatility and instability	Liquidity and credit risk
Panel A: The average MSE				
Savgol-TCN	0.0005	0.0031	0.0159	0.2872
TCN	0.0009	0.0057	0.0621	0.4107
LSTM	0.0008	0.0042	0.0431	0.5444
CNN	0.0008	0.0050	0.0526	0.4382
Panel B: The average MAE				
Savgol-TCN	0.0040	0.0284	0.1267	2.3072
TCN	0.0083	0.0518	0.5738	3.4069
LSTM	0.0070	0.0385	0.3564	4.3110
CNN	0.0077	0.0458	0.4836	3.7206
Panel C: The average MAPE				
Savgol-TCN	10.2005	17.4564	12.6412	25.9849
TCN	23.6308	28.1781	26.7084	58.6615
LSTM	15.3806	25.9929	18.6318	33.0932
CNN	19.6463	29.6310	22.9780	57.3574

Overall, the average MSE, MAE, and MAPE of the Savgol-TCN deep convolutional neural network model for all 14 indicators are 0.1251, 0.6275, and 18.4742, respectively, and the MSE is 0.0471, 0.0737 and 0.0506 lower than that of the TCN, LSTM, and CNN models, respectively. Compared with TCN, LSTM, and CNN models, MAE is reduced by 0.4312, 0.5810, and 0.4779, respectively, and MAPE is reduced by 20.0154, 7.6348, 17.481 compared with TCN, LSTM, and CNN models, respectively. Therefore, in terms of systemic risk prediction, the Savgol-TCN deep convolutional neural network model's prediction accuracy outperforms the other three models. The reason is that the causal convolution and the null convolution introduced by the TCN model could widen the sensory field. Thus, the model is conducive to mining the indicators' variation characteristics and improving the indicators' prediction accuracy.

Moreover, adding the Savitzky-Golay filter for error correction can effectively reduce the MAE and MSE of TCN model prediction results. As a result, the combined prediction model with Savitzky-Golay significantly improved MAE improvement compared with the single prediction model without Savitzky-Golay. Its improvement in the accuracy and stability of forecasting performance mainly relies on its efficiency in extracting the temporal characteristics of the forecasting errors.

4.3. *Effective visualization of models*

The 14 Systemic risk index series selected in this paper show a long-term trend, which provides a specific basis for model prediction. In addition, systemic risk indicators have the characteristics of high volatility, high noise, and nonlinearity, and it is challenging to obtain high-precision forecast results by constructing traditional linear forecasting models for them. Deep learning is more suitable for processing this kind of data.

Figure 4 is a comparison chart of the prediction effect of Savgol-TCN, TCN, CNN, and LSTM models on the risk of individual institutions. As seen in Figure 4, the Savgol-TCN deep convolutional neural network model constructed in this paper fits better than the TCN, CNN, and LSTM models and can better predict the trend of systemic risk. The overall trend of the LSTM model for CoVaR, CoVaR, MES, and Catfin is close to the actual value, and the hysteresis is better than that of the CNN model. Still, the subtle local performance is insufficient, and the prediction is too flat. The nonlinear fitting ability of the CNN model is excellent, which can reflect not only the subtle changes in the risk of individual institutions but also the overall trend, but the prediction accuracy is low. The overall trend of the prediction effect of the TCN model is close to the actual value, and the lag is better than that of the CNN model, but the subtle local prediction is insufficient and too smooth. Therefore, the Savgol-TCN deep neural network model proposed in this paper can achieve a good prediction effect on the risk of individual institutions.

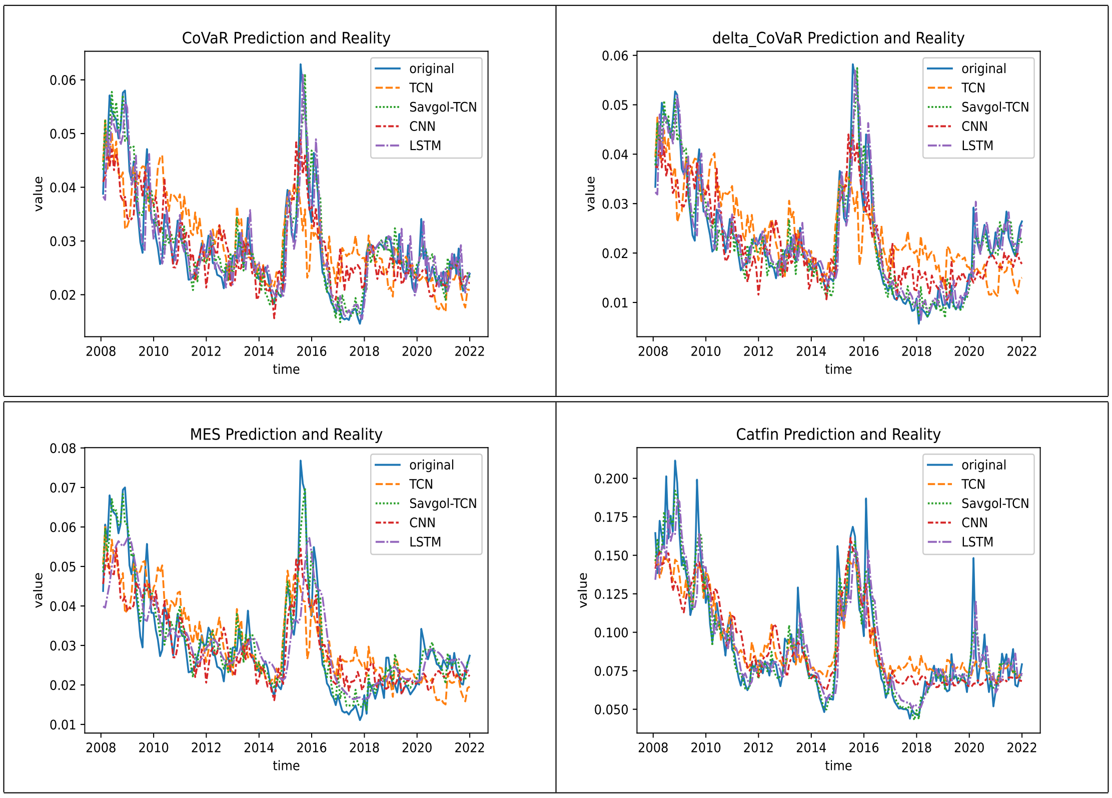

Figure 4. CoVaR, ΔCoVaR, MES and Catfin.

Figure 5 is a comparison chart of the prediction effect of Savgol-TCN, TCN, CNN, and LSTM models in the contagion effect. As can be seen from Figure 5, the Savgol-TCN deep convolutional neural network model constructed in this paper has a better fitting effect than the TCN, CNN, and LSTM models. Among them, the LSTM model has a better prediction effect than the TCN and CNN models, but there needs to be more local effect prediction. On the other hand, the Savgol-TCN model constructed in this paper coincides with the actual data curve and has a better prediction effect at the turning point of the data trend. This shows that the Savgol-TCN deep neural network model proposed in this paper can achieve a good prediction effect in the contagion effect.

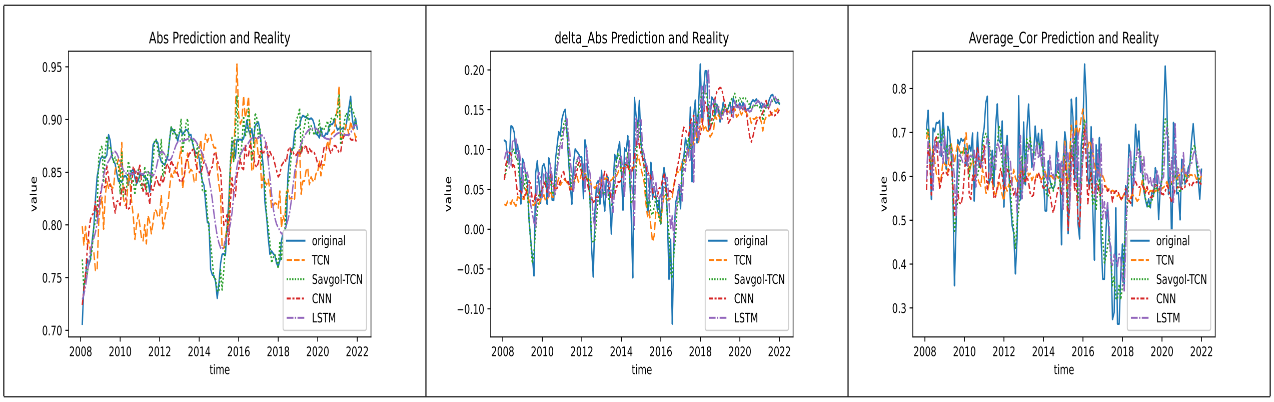

Figure 5. Abs, ΔAbs and Average_Cor.

Figure 6 is a comparison chart of the prediction effect of Savgol-TCN, TCN, CNN, and LSTM models in fluctuation and instability. As seen in Figure 6, the Savgol-TCN deep convolutional neural network model constructed in this paper has a better fitting effect than the TCN, CNN, and LSTM models, and the prediction effect of LSTM in the Volatility indicator is similar to the Savgol-TCN deep convolutional neural network. The models are close and are not as good as the Savgol-TCN deep convolutional neural network model in Book_lev, Market_lev, and Size_con, but the prediction effect is significantly better than the TCN and CNN models. This shows that the Savgol-TCN deep neural network model proposed in this paper can achieve a good prediction effect in fluctuation and instability.

Figure 7 compares the prediction effect of Savgol-TCN, TCN, CNN, and LSTM models in liquidity and credit risk. As can be seen from Figure 7, the Savgol-TCN deep convolutional neural network model constructed in this paper has a better fitting effect than the TCN, CNN, and LSTM models. The prediction effect of the TCN model in AIM, Credit_spread, and Term_spread is significantly better than that of the CNN and LSTM models, but the prediction effect is not as good as the Savgol-TCN deep convolutional neural network model. The possible reason is that the overall trend of the prediction effect of the TCN model is close to the actual value and lags. The performance is better than that of the CNN model. Still, the subtle local prediction is insufficient and too flat, resulting in a lower prediction effect than the Savgol-TCN deep convolutional neural network model. This shows that the Savgol-TCN deep neural network model proposed in this paper can achieve a good prediction effect in liquidity and credit risk.

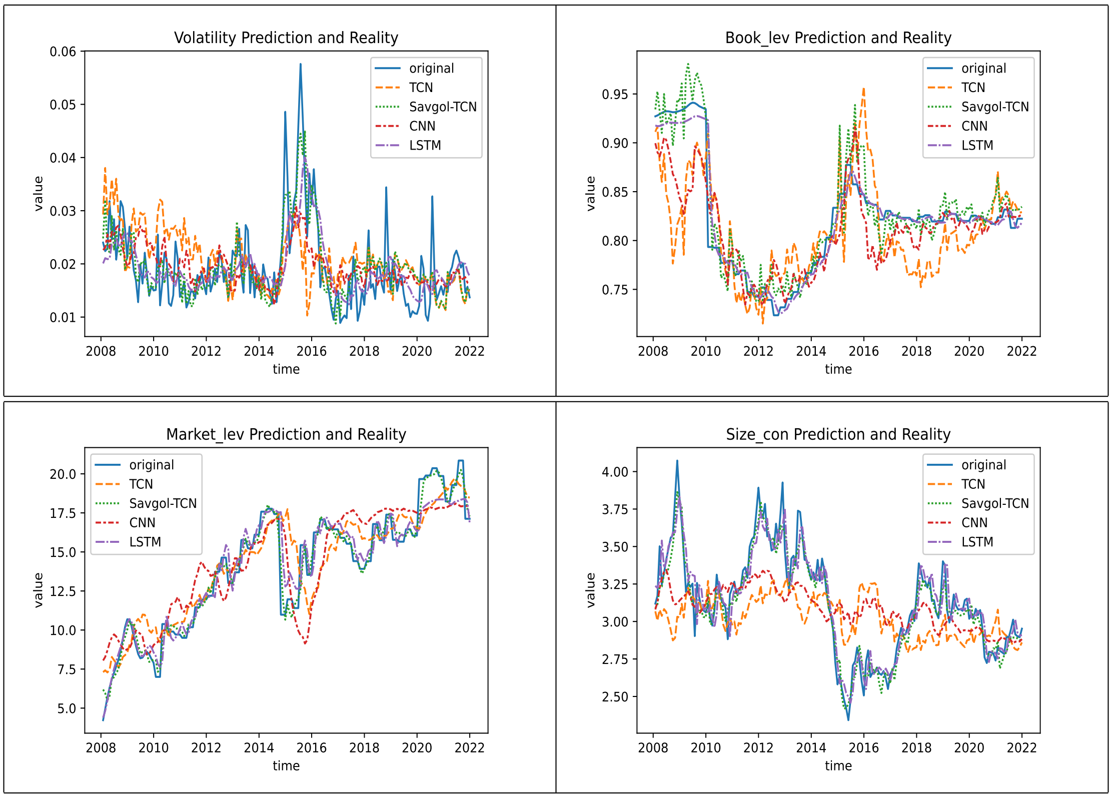

Figure 6. Volatility, Book_lev, Market_lev and Size_con.

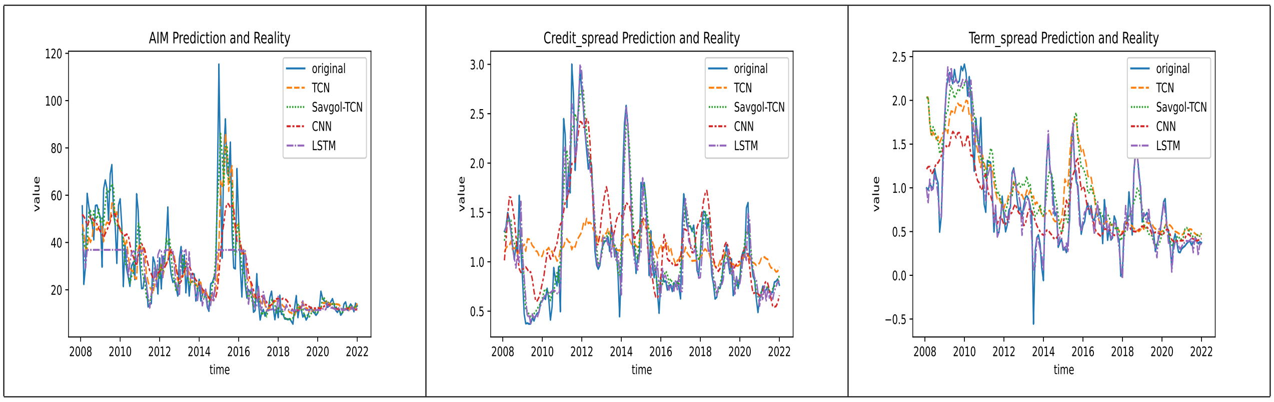

Figure 7. AIM, Credit_spread and Term_spread.

5. Conclusions and future work

Based on the monthly data from January 2007 to December 2021 in Chinas financial market, this paper established the Savgol-TCN deep convolutional neural network to predict 14 systemic risk indicators in 4 dimensions and analyzes its accuracy and reliability. It selects the extreme risk of financial institutions, the contagion effect between financial systems, the volatility, and instability of financial markets, liquidity, and systemic credit risk.

By constructing a Savgol-TCN deep convolutional neural network, the systemic risk indicators of China's financial market are predicted, and their accuracy and reliability are analyzed. The constructed Savgol-TCN deep convolutional neural network is compared with TCN, CNN, and LSTM models, and the prediction ability and generalization ability of the Savgol-TCN deep convolutional neural network model to systemic risk are studied. Conclusions are remarked as follows:

1) The Savgol-TCN deep convolutional neural network has a strong generalization ability, and the prediction effect for all indices is stable.

2) The Savgol-TCN deep convolutional neural network model can be used to predict various systemic risk indicators. Compared with TCN, CNN, and LSTM models, the Savgol-TCN deep convolutional neural network has superior predictive performance in predicting systemic risk. Its average prediction accuracy for all indices has increased.

3) The Savgol-TCN deep convolutional neural networks can better monitor financial market changes and effectively predict systemic risk states.

Given that the Savgol-TCN deep convolutional neural network has strong learning ability and model adaptability, it has substantial advantages in systemic risk prediction ability, so deep learning technology is applied to financial forecasting and forecasting in financial intelligence. In addition to systemic risk forecasting, the Savgol-TCN deep convolutional neural network model proposed in this paper can also be applied to other fields to solve complex forecasting problems, including crude oil price forecasting, stock price forecasting, etc. Although the forecasting model proposed in this paper has high forecasting accuracy, the model only takes historical data as input. Since the systemic risk indicator is affected by multiple complex factors, future work can consider introducing these factors into the proposed method.

Based on the conclusions of this study, we give the following policy recommendations. Firstly, it is necessary to strengthen the monitoring and early warning of systemic financial risk state variables, monitor various indicators and monitor systemic risk. Secondly, we should fully consider various factors affecting financial risks, build scientific and reasonable risk impact indicators and early warning methods, and accelerate the construction of early warning and prevention mechanisms in the financial industry. Finally, although this paper's systemic risk prediction model can better predict systemic risk, financial risk prediction is only the first step of financial risk supervision. To achieve effective financial risk prevention, we must also rely on macro-prudential measures and micro-risk control to achieve good prevention effects.

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