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Predicting Stock Price Crash Risk in China: A Modified Graph WaveNet Model

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Highlights

- The model modifies the graph attention network using Graph WaveNet.
- The GAT-WaveNet model demonstrates superior performance in predicting stock price crash risk of Chinese firms.
- Using node-rolling approach effectively addresses the small sample size issues.
- Investors can obtain remarkable returns by constructing long-short investment portfolios.

Abstract:

The stock price of a firm is dynamically influenced by its own factors as well as those of its peers. In this study, we introduce a Graph Attention Network (GAT) integrated with WaveNet architecture—termed the GAT-WaveNet model—to capture both time-series and spatial dependencies for forecasting the stock price crash risk of Chinese listed firms from 2012 to 2023. Utilizing node-rolling techniques to prevent overfitting, our results show that the GAT-WaveNet model significantly outperforms traditional machine learning models in prediction accuracy. Moreover, investment portfolios leveraging the GAT-WaveNet model substantially exceed the cumulative returns of those based on other models.

Keywords: Stock price crash risk, Graph neural networks, Graph attention networks, Machine learning

JEL codes: C52, C55, G11, G17, G32, M41

1. Introduction

Stock price crash risk has been receiving extensive attention from regulators, academics and investors. In the short run, it can swiftly diminish investor wealth. In the long run, it erodes confidence in the stock market, adversely affecting capital movement within the real economy (Bond and Devereux, 1988; Zhou and Huang, 2019). Thus, accurate prediction of stock price crash risk is of paramount importance. It equips policymakers with the necessary insights to preempt and mitigate the risk of market crashes in a timely and effective manner.

Although existing studies have explored various methods to predict stock price crash risk (Kim et al., 2014; Sevim et al., 2014), they predominantly concentrate on individual or macroeconomic factors (Chang et al., 2017; Dichtl et al., 2023), neglecting intercorrelations among firms within the same industrial chain or similar sectors. Instances of such interlinkages include industry or regional proximity, customer-supplier relationships (Cheng and Li, 2021), and common shareholders, as highlighted by Ye et al. (2021) and others. These intercorrelations among firms prove to be effective predictors of stock price crash risk. Fortunately, with the surge of deep learning, Spatio-Temporal Graph Neural Network (STGNN) has demonstrated advantages over traditional econometric methods in depicting the network-like transmission path and temporal trends of stock price fluctuation (Su et al., 2017; Wang et al., 2022). However, the STGNN model fails to identify asymmetric impacts between companies, as well as address the issue of predefined graph structures.

Therefore, this study modifies the Graph WaveNet model proposed by Wu et al. (2019) to predict Chinese stock price crash risk spanning from 2012 to 2023. We introduce the Graph Attention Network (GAT) (Veličković et al., 2018) into the spatial learning network of Graph WaveNet. By incorporating the self-attention mechanism of GAT, the model dynamically learns weights that signify the interplay between nodes and the multifaceted influences emanating from their neighbors. It can also capture short-term and long-term dependencies within the time series by introducing the Temporal Convolutional Network (TCN). Furthermore, the inclusion of an adaptive adjacency matrix in Graph WaveNet architecture circumvents the limitations of predefined graph structures, bolstering the model’s adaptability, precision, and scalability. Ultimately, we formulate long-short investment portfolios using GAT-WaveNet alongside other benchmark models, aiming to assess the model’s efficacy in providing investment insights within real-world stock market scenarios.

This study contributes to existing machine learning-based prediction of stock price crash risk. Diverging from previous methods relying on support vector machines (SVM), random forests (RF), recurrent neural networks (RNN), and long short-term memory (LSTM) networks (Chatzis et al., 2018; Chen et al., 2021; Leippold et al., 2022; Kaya et al., 2023), we modify the traditional Graph Convolutional Network (GCN) in Graph WaveNet with GAT to automatically capture the network transmission linkages among firms. The GAT-WaveNet model overcomes three issues associated with using the traditional STGNN model. It recognizes the varying impact of one individual firm on other firms, mutual impact between two firms, as well as multifaceted impacts from neighbor firms. Furthermore, through the construction of a long-short portfolio based on the GAT-WaveNet model, our research also contributes to providing practical investment advice and mitigating risks in stock markets.

The remainder of the study is structured as follows: Section 2 introduces the methodology. Section 3 details the data processing and variable construction. Section 4 provides a brief analysis of the empirical results and additional tests. Finally, we conclude in Section 5.

2. Methodologies

2.1 Framework of GAT-WaveNet

The Graph WaveNet model proposed by Wu et al. (2019) excels in capturing spatial data relationships and handling long time-series sequences. Our implementation follows their framework, featuring multiple stacked spatial-temporal layers and an output layer (see Figure 1). The enhanced stacked spatial-temporal layers, comprising a gated temporal convolution layer (Gated TCN) and a Graph Attention Network (GAT), constitute the primary innovation of our model.

The specific process is as follows. Input data first undergoes a linear transformation, enhancing its feature representation. It then passes through two parallel ResNet layers: TCN-a preserves the original data as a residual connection, while TCN-b extracts time-dependent features via the gated TCN. After the gated TCN, the GAT layer updates node features by incorporating adjacent node information. Subsequently, these enriched features are merged with the original input, feeding into the next layer. This iterative process continues through the hidden layers, facilitated by skip connections that aggregate data from each layer. Finally, the data reaches the output layer for final processing and prediction.

To prevent overfitting, we use common deep learning techniques such as Dropout and employ the Adam optimizer with mini-batch gradient descent and weight decay for L2 regularization. To address gradient vanishing and expedite convergence, we incorporate Batch Normalization, ensuring consistent feature distributions after extraction for a stable and efficient optimization process.

[Insert Figire 1 here]

2.1.1 Graph Attention Network (GAT)

(1) Graph: $G=(V,E)$ is a graph, where $V=\{v_1,v_2\cdots v_N\}$ is the set of nodes and E is the set of edges. And the adjective matrix can be denoted by $A_{n\times n}\in R^{N\times N}$:

$$A_{ij} = \begin{cases} 1, & if < v_i, v_j > \in E \\ 0, & if < v_i, v_j > \notin E \end{cases} \quad (1)$$

where A_{ij} is a symmetric matrix if G is an undirected graph, while A_{ij} is an asymmetric matrix if G is a directed graph.

(2) Attention coefficients: For node v_i, there is a feature vector h_i, whose length corresponds to the number of features, and its each element equals the value of its feature. If node v_j serves as a neighbor of v_i, then we denote $j \in H_i$. The correlation coefficients between v_i and its neighbors are defined as:

$$e_{ij} = a\left(\left[Wh_i \,||Wh_j\right]\right), j \in \{H_i\} \quad (2)$$

Then, the correlation coefficients (e_{ij}) pass through the LeakyReLU activation function, and are normalized using the $softmax$ function. Therefore, attention coefficients (α_{ij}) are expressed as:

$$\alpha_{ij} = softmax(LeakyReLU(e_{ij})) \quad (3)$$

(3) Linear combination of the features: the attention coefficients serve as weights to compute a linear combination of the augmented features, which aims to obtain the aggregate influence of neighboring nodes on each node itself.

$$h_i' = \sigma(\textstyle\sum_{j \in H_i} \alpha_{ij} W h_j) \quad (4)$$

where h_i' represents the node's feature vector after considering the influence of neighboring nodes through the GAT process. σ represents the activation function. We use the ELU (Exponential Linear Unit) function because it preserves gradients well (Cheng and Li, 2021). The entire process above is referred to as a single-head GAT. To stabilize the learning process of self-attention, we employ a muti-head attention mechanism:

$$h_i' = ||_{k=1}^{K} \sigma(\textstyle\sum_{j \in H_i} \alpha_{ij} W h_j) \quad (5)$$

Multi-head attention captures a broader range of patterns than single-head GAT. It performs multiple attention calculations and aggregations.

2.1.2 WaveNet

(1) Self-adaptive Adjacency Matrix: We redefine the self-adaptive adjacency matrix proposed in Wu et al. (2019):

$$A_{ij} = f\left(Relu\left(E_1 {E_2}^T + I\right)\right) \quad (6)$$

where E_1 is the source node embedding and E_2 is the target node embedding. $E_1, E_2 \in R^{N \times d}$ are $N \times d$ matrices, where N represents the number of nodes, and d represents the dimension of node (embeddings). EE^T is activated with the $Relu$ function following Wu et al. (2019) to map values to $[0, +\infty)$, and a custom function f is used to convert non-zero values to 1.

(2) Temporal Convolution Network: It is a novel model for extracting time series dependencies based on one-dimensional convolution, following the RNN, LSTM, and GRU models. Its main architectural diagram is depicted in Figure 2:

[Insert Figure 2 here]

2.2 Sample construction

Because GAT-WaveNet is a compound model with both TCN and GAT layers, the input h takes the form of a four-dimensional tensor, precisely with the dimensions $[B, C, N, L]$. Here, B indicates the batch numbers, C represents the hidden dimension, N signifies the node numbers within the graph, and L denotes the sequence length. The product of $B \times N \times L$ represents the total number of data, whereas the batch number multiplied by the batch size equals the number of samples. Consequently, as the number of nodes N in the graph structure increases, the available number of samples decreases.

In practice, dealing with too many nodes leads to a limited number of samples, resulting in poor generalization. To avoid overfitting problems due to the lack of samples, we propose a node-rolling method to extract both global and local relationships. The samples are split into three distinct subsamples (training, validation, test) with a ratio of 0.7/0.2/0.1, while maintaining temporal ordering. Detailed discussions of the node-rolling method are in Appendix A.

To compare the prediction effectiveness of our GAT-WaveNet model with other benchmark models (Logisti, SVM, RF, LSTM), we adopt the widely used evaluation measures, including Accuracy, Precision, Avg-Precision, F1-score, AUC-ROC and AUC-PR. The definitions of these measures are displayed in Table B1 of Appendix B.

3. Data and Variables

3.1 Predictive factors

Leippold et al. (2022) assert that factors commonly used to forecast stock price in the United States exhibit limited effectiveness in China, primarily due to China's distinctive market attributes, such as a predominantly retail investor base. They construct an indicator system encompassing 94 stock-level and 11 macroeconomic characteristics for Chinese stock market. Although based on their framework, we prioritize showcasing our model's inherent superiority over identifying the most predictive factors. Thus, we selectively focus on basic firm-level indicators, including total assets, inventory, current ratio, beta, the number of outstanding shares, et al. Through this rigorous factor selection process, we ultimately retain 57 basic factors (listed in Table B2-B3 of Appendix B). We choose non-financial, non-ST firms listed from 2011-2023, with no missing values for critical variables. Finally, our dataset comprises a total of 1219 firms, spanning from January 2011 to September 2023, with a forecast period from January 2012 to October 2023. All the data is sourced from the Wind database.

3.2 Measurement of stock price crash risk

We apply the percentile method and definition following Chatzis et al. (2018). This method associates crash events with extremely severe stock price declines. The stock price crash risk of a specific stock ($event_{it}$) is defined as follows: If the weekly returns fall below the 5th percentile of the rolling one-year time window at least once within the current month, $event_{it}$ equals 1. Otherwise, it is set to 0.

To address the issue of infrequent stock crash events, we incorporate weighted adjustments into the traditional Binary CrossEntropy loss function. These weights are determined based on the proportion of positive samples, facilitating an effective resolution to this problem.

4. Empirical Results Analysis

4.1 Baseline results

Table 1 shows the prediction results for our method and traditional methods. From the metrics dimension, all models perform well in terms of accuracy and AUC-ROC metrics, while other metrics vary significantly. From the model dimension, the GAT-WaveNet model and RF model perform significantly better than other models. The findings reveal that when employing the node rolling approach to extract global relationships, GAT-WaveNet exhibits outstanding performance in terms of Recall, F1-Score and AUC-ROC[1] compared to other benchmark models.

The aforementioned results solely analyzed the average performance of different models. Moving forward, we present the time-varying performances of these models, referring to Hou et al. (2021). The results are illustrated in Figure 3, which indicate that our model demonstrates the highest performance in terms of F1-Score, AUC-ROC and AUC-PR. These consistent findings further underscore the superiority of the GAT-WaveNet model.

[Insert Table 1 here]

[Insert Figure 3 here]

4.2 Robustness tests

We perform additional tests to verify our model's predictions, focusing on whether our methodological innovations enhance crash risk predictions. We first assess if the node rolling method effectively addresses insufficient sample sizes. Next, we evaluate if the model better captures local spatial correlations. Finally, we investigate if the GAT component enhances the predictive capabilities of our model. These tests confirm our model's robustness, with the first two emphasizing sample handling and the latter focusing on model enhancement.

Firstly, we compare the performance of GAT-WaveNet models with and without node rolling. Columns (1) and (2) in Table 2 show that GAT-WaveNet with global node-rolling significantly performs better than that without node-rolling. It is

[1] Due to the severe sample imbalance issue, where the proportion of stock price crash instances is relatively small, and the identification of positive samples is of utmost importance, we prioritize metrics that are sensitive to positive cases. Therefore, F1-score, AUC-ROC and AUC-PR are the main reference metrics.

confirmed that node-rolling well addresses the issue of poor model performance due to limited samples.

Secondly, to explore whether GAT-WaveNet model can capture local spatial dependencies, we restrict the sample firms to the same industry. Using the SWS[2] industry's first-level classification, we select 106 companies in the Pharmaceutical and Biological Industry (Industry Code: 801150.SI), which has the most companies in our sample. Setting N to 25 for rolling within the industry[3], we obtain 568 samples. In addition, we also construct a subsample by randomly selecting 106 companies. Columns (3) and (4) in Table 2 indicate that when input companies are in the same industry, GAT-WaveNet can effectively capture local spatial connections, resulting in a significant improvement in its predictive capabilities. To provide additional evidence for this conclusion, we restrict samples to the same industry for other benchmark models. The results are presented in Table C1 of Appendix C.

Thirdly, to investigate whether the GAT enhances the predictive capabilities, we compare the WaveNet model with and without GAT. Columns (1) and (5) of Table 2 show that the model incorporating GAT has an advantage over the model without GAT in global information extraction. Similarly, for local information extraction, Columns (3) and (6) show that the model utilizing GAT performs better than the model without GAT in terms of F1-Score and AUC-ROC. These findings confirm that employing GAT to capture spatial dependencies improves the model's performance. Finally, we alter the core parameters to further validate the reliability of the model. See Table C2 in Appendix C for more details.

[Insert Table 2 here]

4.3 Comparison of investment portfolio performance

To investigate whether the GAT-WaveNet model can provide valuable investment advice in real stock markets, we compare the performance of GAT-WaveNet with other benchmark models in terms of cumulative returns under the same investment strategy. Following Dichtl et al. (2023) and Gu et al. (2020), we rank stocks based on their predicted crash probabilities in descending order and divide them into five equal groups. Subsequently, we assess whether there is a significant difference in monthly average returns between the top group (short position) and the bottom group (long position). A t-test is employed to compare the means of the two groups. The results are shown in Table 3.

[2] The SWS industry classification standard used in this study is released by Shenyin & Wanguo Securities (SWS) Research Co., Ltd and it consists of all the firms listed on the China A-share market. The SWS industry classification standard 2021 contains 31 primary industries, 124 secondary industries and 395 tertiary industries.

[3] When extracting local features, using the rolling approach to address the sample problem inevitably leads to the loss of more microscopic local features, such as upstream and downstream industry relationships and competition relationships. However, it, meanwhile, enables the model to handle dynamic graphs, which is a valuable capability.

The results indicate that the GAT-WaveNet model predicts a positive return for the long-short investment portfolio, with a monthly return of around 2.3%. In contrast, other models do not generate significant returns. These findings demonstrate that the GAT-WaveNet model not only exhibits strong predictive ability for the crash risk, but also generates significant returns for investors. This confirms the robust performance of GAT-WaveNet and its significant practical implications.

[Insert Table 3 here]

Meanwhile, we calculate the cumulative returns of the investment portfolio. We adopt an equally weighted approach by taking long positions on stocks in the bottom group and short positions on stocks in the top group, with monthly rebalancing. Figure 4(a) depicts the cumulative returns of the investment portfolio. The results indicate that during the sample periods, the GAT-WaveNet model-based investment portfolio achieves almost 10.6 times the return of the benchmark, significantly outperforming other model-based portfolios. To delve deeper into the sources of these returns, Figures 4(b) and 4(c) illustrate the cumulative returns of the top (short) group and the bottom (long) group, respectively. These two figures confirm that the GAT-WaveNet model accurately identifies investment portfolios with high probabilities of stock price crashes, which have lower long-term investment returns, whereas portfolios with very low probabilities of stock price crashes achieve returns far surpassing the benchmark in the long term, indicating the GAT-WaveNet model can effectively identify good firms. In conclusion, our model serves as a valuable tool for investors in screening stocks for their portfolios. By buying stocks with the lowest 20% crash probability and selling those with the highest 20%, investors can obtain notable positive returns.

[Insert Figure 4 here]

5. Conclusion

This study innovatively combines the Graph WaveNet model with GAT for predicting stock price crash risk. The modified model, GAT-WaveNet, concurrently executes nonlinear feature extraction, time-dependency relationship extraction, and multi-pattern spatial dependency relationship extraction. Our results demonstrate that the GAT-WaveNet model significantly outperforms traditional machine learning models in predicting stock price crash risk. This model excels in extracting local spatial dependency relationships, particularly when stocks are confined to the same industry. To mitigate overfitting problems, we employ the node-rolling approach, effectively addressing the issue arising from a small sample size. In addition, we evaluate the cumulative return of investment portfolios informed by the GAT-WaveNet against those constructed by benchmark models. The findings reveal that portfolios based on the GAT-WaveNet model realize returns nearly 10.6-fold higher than the benchmark throughout the sample period from 2012 to 2023.

Our research has several practical implications. For investors, our model facilitates stock selection for investment portfolios. For policymakers, our model underscores the importance of firm interconnectedness, which should be adequately considered when constructing financial risk warning systems. However, our study bears certain limitations. Firstly, the use of low-frequency data limits our model's ability to capture risks associated with short-term market sentiment fluctuations. High-frequency data (weekly or daily) can be used to explore the impact patterns of short-term market liquidity shocks. Secondly, the model's large parameter count, high complexity, and significant training space occupation impose constraints on optimal parameter settings. Therefore, future research handling larger datasets and more intricate market structures should endeavor to incorporate a wider array of company samples.

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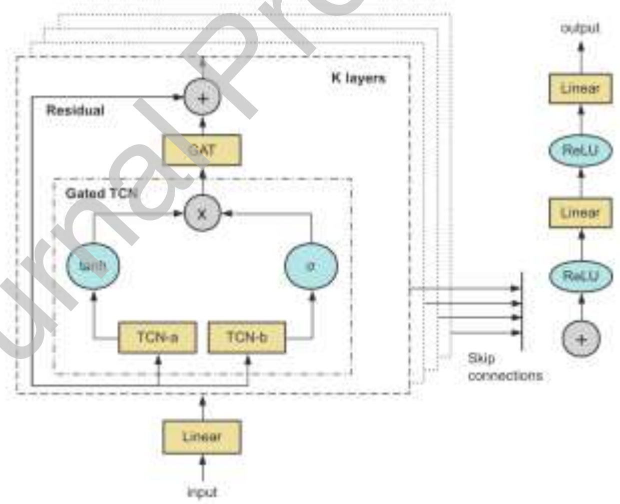


Figure 1: The GAT-WaveNet Framework. The GAT-WaveNet framework consists of K spatial-temporal layers on the left side, with an output layer on the right.

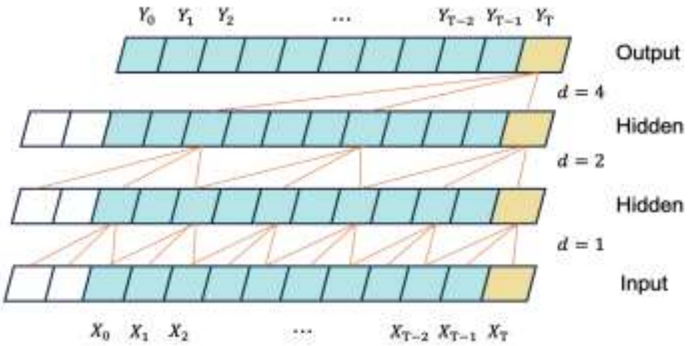
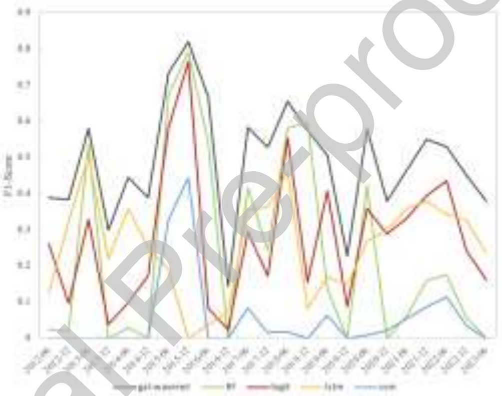
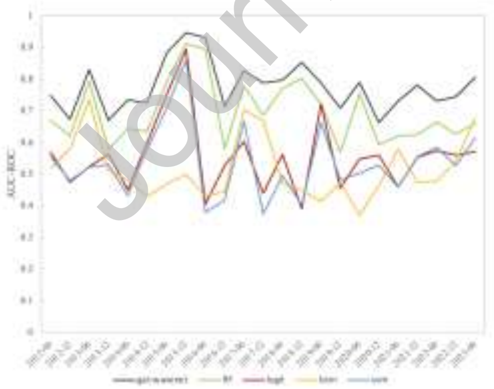


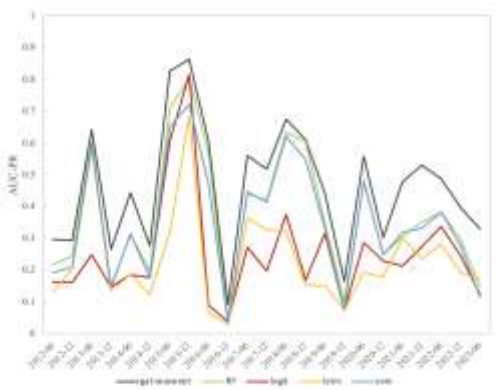
Figure 2: Temporal Convolution Layer. TCN has dilation factors (d) of 1, 2, and 4 and a filter size (k) of 3. The receptive field covers all values from the input sequence. The outputs of TCN maintain the same length as the input, effectively addressing the gradient vanishing problem. TCN also combines causal convolution with dilated convolution, allowing it to capture long-term dependencies with a growing receptive field while avoiding excessive computational overhead.



(a) Time-varying F1-score



(b) Time-varying AUC-ROC



(c) Time-varying AUC-PR

Figure 3: Comparison of Time-Varying Indicators (F1-Score, AUC-ROC and AUC-PR) among Different Machine Learning Models, including GAT-WaveNet, RF, Logit, LSTM, and SVM. There are significant fluctuations in the values of F1-score and AUC-PR. We find that during the periods when the overall performances of these metrics are poor, the proportion of actual stock market crash events is relatively low. This finding indicate that in order to ensure generalization ability to achieve overall better performance, the model will not recognize such particularly exceptional cases.

(a) The cumulative returns of the long-short investment portfolio

(b) The cumulative returns of the short investment portfolio

(c) The cumulative returns of the long investment portfolio

Figure 4: Comparison of Cumulative Returns for Long-Short, Short, and Long Portfolios. Stocks are ranked based on their predicted crash probabilities in descending order and divided into five equal groups. The investment portfolio is constructed using an equally weighted approach by taking long positions on stocks in the bottom group (with the lowest predicted price crash risk) and short positions on stocks in the top group (with the highest predicted price crash risk), with monthly rebalancing.

Table 1
Prediction Results for GAT-WaveNet and Benchmark Models.

	(1) GAT-WaveNet	(2) Logistic	(3) SVM	(4) RF	(5) LSTM
Accuracy	0.72	0.66	0.68	0.83	0.45
Precision	0.40	0.32	0.32	0.73	0.19
Recall	0.75	0.58	0.53	0.29	0.55
F1-score	0.52	0.41	0.40	0.41	0.29
Avg-Precision	0.35	0.27	0.26	0.35	0.20
AUC-ROC	0.81	0.63	0.62	0.63	0.50
AUC-PR	0.56	0.49	0.47	0.58	0.23

Note: GAT-WaveNet is the stock price crash prediction method using global rolling with N=50. Since the problem investigated in this study is a classification problem, the evaluation metrics used include accuracy, precision, recall, F1-score, average precision, AUC-ROC, and AUC-PR.

Table 2
Additional Test Results.

	(1) Node-rolling Full sample GAT	(2) **Non-node-rolling** Full sample GAT	(3) Node-rolling **Same industry** GAT	(4) Node-rolling **Random selection** GAT	(5) Node-rolling Full sample **Without GAT**	(6) Node-rolling **Same industry Without GAT**
Accuracy	0.72	0.48	0.66	0.65	0.72	0.68
Precision	0.40	0.16	0.35	0.31	0.39	0.35
Recall	0.75	0.57	0.75	0.66	0.69	0.63
F1-score	0.52	0.25	0.47	0.42	0.50	0.45
Avg-Precision	0.35	0.15	0.31	0.27	0.33	0.30
AUC-ROC	0.81	0.52	0.75	0.71	0.79	0.72
AUC-PR	0.56	0.16	0.50	0.37	0.54	0.54

Note: This table presents the results of the first three additional tests. The definition of evaluation metrics is the same as in Table 1. The following columns represent different model parameters or samples, respectively.

Table 3
T-Test Result (H0: mean(bottom)-mean(top)>0).

Model	(1) Mean	(2) Std	(3) t-value	(4) p-value
GAT-WaveNet	0.023***	0.048	5.791	0.000
Logistic	-0.001	0.031	-0.421	0.663
SVM	-0.003	0.033	-1.248	0.893
RF	0.003	0.030	1.055	0.147
LSTM	-0.001	0.034	-0.241	0.595

Note: This table presents the t-test results. Stocks are initially ranked based on their predicted crash probabilities in descending order and divided into five equal groups. Subsequently, we assess whether there is a significant difference in monthly average returns between the top group (with the highest crash probability) and the bottom group (with the lowest crash probability). The null hypothesis is mean(bottom) - mean(top) > 0. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Author Statement

We hereby declare that there is no known competing financial interests or personal relationships that could have appeared to influence the work reported in the paper entitled “Predicting Stock Price Crash Risk in China: A Modified Graph WaveNet Model”.

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