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Research on the Role of ESG Indicators on Financial Risk Early Warning in Financial Industry Based on Deep Learning Modeling

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Abstract

With the promotion of green financial policies and the implementation of the "dual carbon" goal, ESG indicators have gradually become an important tool for measuring corporate sustainability. As a pioneer in information disclosure, the relationship between ESG performance and financial risk in the financial industry has attracted attention. This study takes Chinese listed companies in the financial industry as a sample, constructs a risk early warning system covering financial and ESG indicators based on 2019-2024 data, and introduces Logistic regression, Random Forest and LSTM deep learning models for comparison. The results show that the predictive performance of the three models is improved after the inclusion of ESG factors, with the LSTM model performing the best on indicators such as AUC and F1. Further analysis shows that the governance dimension of ESG contributes most significantly to risk early warning, while the environmental and social dimensions contribute relatively weakly. Based on the above results, the study proposes to incorporate ESG indicators into the risk management framework, improve the quality of information disclosure, and strengthen the application of AI technology and talent cultivation, in order to improve the risk identification and prevention and control capabilities of financial institutions.

Keywords

ESG indicators; financial risk early warning; deep learning; LSTM model; financial sector.

1. Introduction

In recent years, with the promotion of the "dual-carbon" goal and green financial policies, the consideration of corporate sustainability has been strengthened globally, and the ESG indicator system has gradually become an important standard for measuring the long-term value of enterprises. China's financial regulators have also issued a number of guidelines to require financial institutions to strengthen ESG information disclosure and risk management, the Investor Relations Management Guidelines for Listed Companies issued by the Securities and Futures Commission (SFC) incorporates ESG into information disclosure, and the Study on Preparation of Special Report on ESG of Listed Companies of Central Enterprises issued by the State-owned Assets Supervision and Administration Commission (SASAC) builds an ESG evaluation system that contains 14 level 1 indicators and 45 level 2 indicators [1]. As of 2023, the number of ESG disclosures of A-share listed companies in China has exceeded 2,200, of which the disclosure coverage rate of listed companies in the financial industry is as high as 93.55%, which is much higher than that of other industries [2]. It can be seen that the financial industry is a pioneer in ESG practice, and stakeholders are particularly concerned about ESG management of financial institutions.

Against the backdrop of an increasingly complex business environment, financial institutions are facing increased credit and market risks, and there is an urgent need to establish a scientific early warning system for financial risks. Traditional risk early warning models mostly rely on financial statement indicators, but this tends to reflect only the short-term financial situation of enterprises, with insufficient consideration of non-financial risk factors. The use of ESG indicators to quantify corporate environmental and social responsibility is expected to capture early warning information beyond financial indicators, thus improving risk identification capabilities. In addition, with the development of artificial intelligence technology, the application of deep learning in financial risk control is promising.AI Innovation Lab points out that the use of deep learning models for multi-dimensional data fusion can realize real-time monitoring of corporate ESG performance and risk early warning, thus improving the agility and scientificity of risk control. Therefore, this paper will explore the feasibility of combining deep learning and traditional methods for early warning of financial risks in the financial industry, with a view to providing empirical evidence and suggestions for financial enterprises to prevent risks.

2. Literature Review

2.1. Research on the relationship between ESG and financial risk.

Stakeholder theory suggests that the sustainable development of enterprises relies on the fulfillment of responsibilities for environmental protection, social responsibility and corporate governance, and that excellent ESG performance can enhance corporate reputation and reduce financing costs and potential default risk. Empirical studies by most scholars at home and abroad show that corporate ESG performance is significantly negatively correlated with default risk.Korzeb Z et al. (2025) found that the better a company's environmental performance, the lower its default risk [3]; Atif and Ali (2021) also confirmed that companies with higher ESG disclosure levels are less likely to default [4]. In China, studies have similarly shown that ESG has a mitigating effect on risk: Zhang Lin et al. (2021) introduced ESG factors into a logistic model, which significantly improved the model prediction accuracy [5]; An Zhanran et al. (2024) pointed out that high ESG-scoring firms have a lower potential default risk [6]; Liu Xuejuan et al. (2023), using a sample of 417 A-share listed firms, found that firms' ESG performance is significantly negatively related to default probability [7]. Similar conclusions are also confirmed in empirical cases: a study of listed companies in the manufacturing industry shows that the inclusion of ESG indicators in early warning models can effectively improve the prediction accuracy [8]. In conclusion, existing studies generally support the conclusion that ESG has a buffering effect on financial risk, indicating that the consideration of ESG factors in risk management has theoretical and practical significance.

2.2. Research on risk early warning models and algorithms.

Traditionally, financial risk early warning mostly uses methods such as univariate analysis, Altman Z-Score model or Logistic regression model (Pan Zeqing, 2018)[9], which have low sample requirements and high interpretability, but have limited ability to deal with high-dimensional and nonlinear data. Therefore, machine learning algorithms (e.g., support vector machines, decision trees, random forests, etc.) have been widely introduced into the field of risk assessment in recent years. In financial risk early warning, the random forest model tends to outperform a single linear regression model, and one study found that the early warning accuracy of random forest is significantly higher than that of logistic regression [10]. In addition, with the development of deep learning, neural network models are beginning to be used for risk prediction. xu et al. (2024) proposed and optimized a risk prediction model based on Long Short-Term Memory Network (LSTM), and experiments proved that the model significantly outperforms Random Forests, XGBoost, and traditional BP neural networks in terms of the AUC metrics [11]. This indicates that the deep learning model has higher generalization ability and prediction performance when dealing with complex time series data. For financial risk control, CNN and LSTM can also be combined: CNN is good at automatically extracting features from

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structured data such as financial statements, and LSTM is able to capture long-term dependencies in the time series, and combining the two (CNN-LSTM) can further improve default prediction accuracy [12]. In summary, established studies have compared the effects of different methods in terms of algorithms, and generally found that deep learning-based models are better than traditional models in terms of metrics, but in practical applications it is necessary to combine with specific scenarios for comprehensive consideration.

3. Research Design

3.1. Data sources and sample selection

Based on Wind, CSMAR, CNINFO and other databases to obtain the financial and ESG data of listed companies in China's financial industry (banking, insurance, securities, etc.) from 2019-2024. Companies treated by ST/*ST are used as high-risk samples, and companies not treated by ST are used as the control group. The sample screening process is shown in Figure 1: firstly, the companies with missing data are excluded, and the companies that are ST/*ST in 2023 and not ST in 2021-2022 are selected as the risk group (41 companies), and the same proportion of non-ST companies are selected as as the healthy group, totaling 100 samples. This is consistent with the practice of constructing financial crisis early warning samples using ST labels in existing studies.

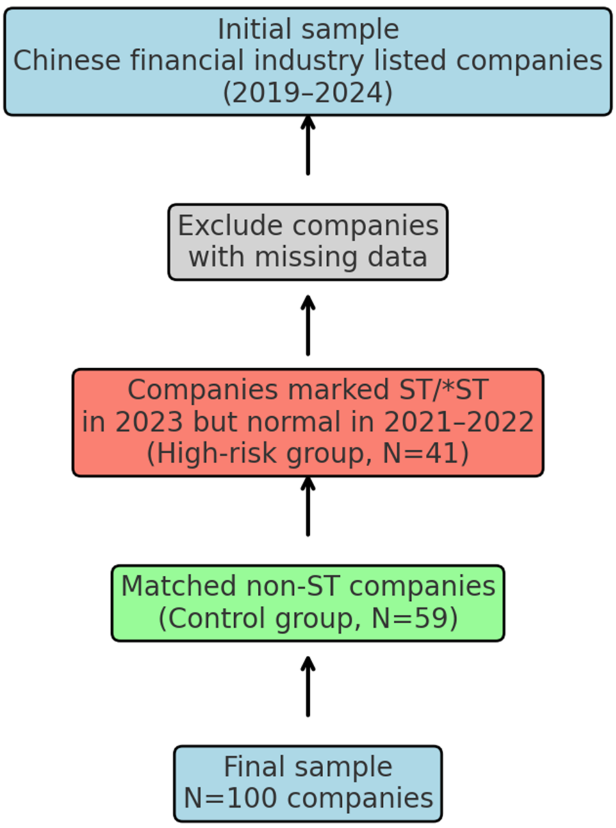

Figure 1. Flowchart of sample selection process

3.2. Indicator Selection and Early Warning System Construction

The early warning indicator system constructed in this paper includes two major categories: first, financial indicators, including the enterprise's solvency, profitability, and operational ability, such as gearing ratio, current ratio, ROE, capital intensity, etc.; second, non-financial ESG indicators, which comprehensively consider the environmental (Environment), social (Social) and corporate governance (Governance) dimensions. Governance) dimensions. The environmental dimension can be selected from indicators such as carbon emission intensity, pollutant emissions, energy saving and emission reduction investment; the social dimension includes employee training rate, R&D investment rate, public welfare donation intensity, customer satisfaction, etc.; and the governance dimension is selected from indicators such as the proportion of independent directors, shareholding concentration, and executive compensation incentives.

When constructing the indicator system, we try to balance the weights of all three, avoiding favoring one dimension, to ensure a comprehensive reflection of corporate ESG performance. All indicators are processed with missing values and standardized before calculation to eliminate the influence of the scale. This paper constructs the early warning system of financial indicators (14) and ESG indicators (3), see Table 1 for details.

Table 1. Structure of Financial and ESG Indicators Used in Risk Prediction Models

first indicator	Secondary indicators	Specific indicators
Financial Indicators	solvency	Current ratio, quick ratio, cash ratio, gearing ratio
	managerial ability	Total Asset Turnover, Fixed Asset Turnover, Capital Intensity
	profitability	Return on net assets, earnings per share, return on assets
	growth	Total assets growth rate, net profit growth rate
	cash flows	Net cash flow from operations, cash flow debt ratio
ESG indicators	Environment (E)	carbon intensity
	Social (S)	Employee Satisfaction
	Governance (G)	Proportion of independent directors

3.3. Model construction

In this paper, two types of models, traditional and deep learning, are used for financial risk early warning analysis, respectively. Traditional methods include Logistic regression and Random Forest.

(1) Logistic regression model of the form:

$$P(Y=1 \mid x)=\frac{1}{1+\exp(-(\beta_0+\sum_{i=1}^{n}\beta_i x_i))} \tag{1}$$

where $P(Y=1 \mid x)$ is the probability that the sample belongs to category 1.

β_0 is the model intercept term, β_i is the regression coefficient of the i th independent variable (characteristic), x_i is the value of the i th independent variable, and n is the number of independent variables. The solution is obtained by maximum likelihood estimation.

(2) Random Forest Model

Random forest is an integrated learning method, the basic idea of which is to build multiple decision trees, each of which votes independently, and then the votes are aggregated (majority voting) to complete the classification.

Suppose there are T trees:

$$\hat{Y} = majorityVote(h_1(x), h_2(x), ..., h_T(x)) \tag{2}$$

Where $h_T(x)$ is the classification result of the first t decision tree on the sample x ,T is the total number of trees in the forest, and $\hat{Y}$ is the final predicted classification label (0 or 1), the decision tree is constructed based on random sampling of the "feature subset" and the "sample subset" (Bagging + feature perturbation). The "Gini impurity reduction" due to the features x_i is calculated for each tree at node splitting:

$$impor\tan ce(x_i) = \sum_{t=1}^{T} \sum_{s \in S_i^t} \triangle Gini(s) \tag{3}$$

s_i^t is all the nodes in the first t tree split using the variable x_i ,$\triangle Gini(s)$ is the purity boost resulting from the variable's split at that node, and finally all feature importance is normalized to sum to one.

(3) LSTM (Long Short-Term Memory) model

LSTM is a recurrent neural network (RNN) structure for processing time-series data, which solves the long-range dependency problem on the basis of traditional RNNs and is particularly suitable for modeling the impact of corporate historical financial data and ESG score sequences on future financial risks. For time series data, LSTM is able to capture the long-distance dependence information in the dynamic change process of enterprise financial indicators and ESG, so this paper tries to input enterprise calendar year indicators as sequences into the LSTM network. At the same time, a convolutional layer (CNN) is introduced for extracting local patterns of multidimensional features. One-dimensional convolution can be used to perform sliding convolution for different indicator dimensions, and then the extracted feature sequences are fed into LSTM for time modeling, and finally the risk probability is output through the fully connected layer. Cross-validation method was used to determine the hyperparameters during model training, and AUC, F1 score, etc. were used as evaluation metrics. All models are trained and validated on the same training set/test set division to ensure the fairness of comparison. The specific calculation formula is as follows:

The LSTM cell consists of three "gates" that control the memorization and forgetting of information.

① Input Gate determines how much information is updated to the "Memory State" by the current input x_t .

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

② Forget Gate, which determines how much of the previous memory state is retained C_{t-1}

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5}$$

③ Output Gate (Output Gate), determines how much of the current cell state is output as a hidden state.

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$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

④ State update (Memory Cell), integrating past memory and current input to update the current cell state.

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{7}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{8}$$

$$h_t = o_t \odot \tanh(C_t) \tag{9}$$

where x_t is the input features (e.g., financial metrics vs. ESG scores) at the t th time step, h_t is the hidden state (output) at the current moment, σ is the Sigmoid function, $\odot$ is the Hadamard product (elementwise multiplication), C_t is the unit state (memory), W_i, W_f, W_o, W_c is the weight matrix, b_i, b_f, b_o, b_c is the bias term, and finally, the LSTM feeds the hidden state h_T at the last time step into the fully-connected layer, which outputs the classification probability $\hat{Y} = sigmoid(W \cdot h_T + b)$

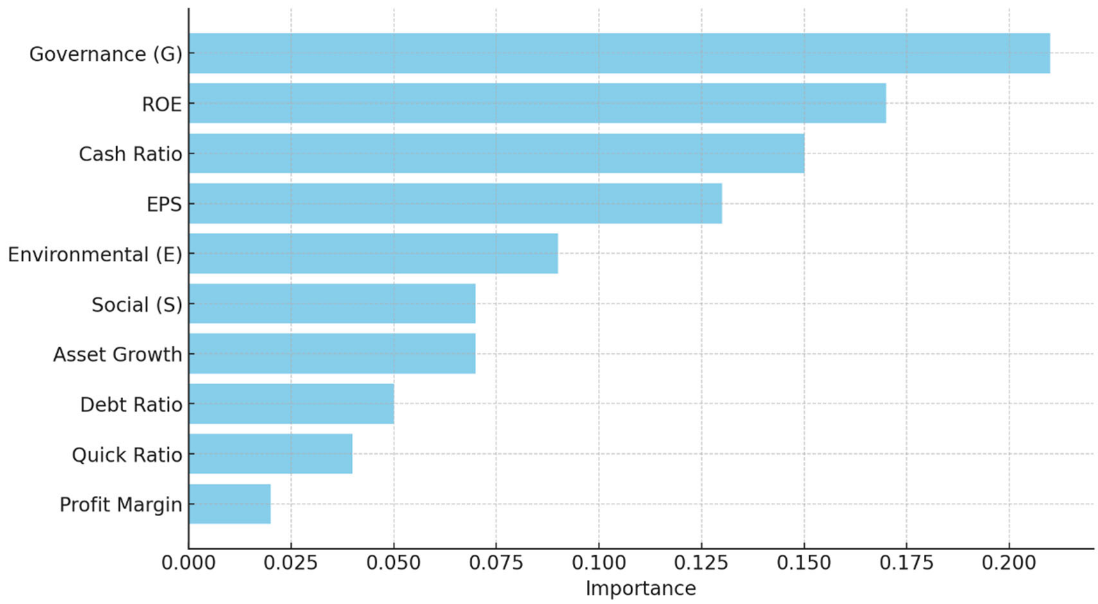

Figure 2. Feature importance in deep learning model

4. Empirical Analysis

In the experiment, the prediction performance of different models was first compared (see Table 2). It can be seen that the deep learning model has better classification ability.The AUC and F1 scores of the LSTM model are higher than those of the random forest and logistic regression models. In this study, the models with ESG metrics have different degrees of improvement in AUC and F1 than the models without ESG, indicating that ESG information provides a valuable addition to risk early warning. Specifically, the AUC of the Logistic model is

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0.85 and the F1 is 0.82, the Random Forest can be improved to AUC= 0.90 and F1= 0.87, while the LSTM model can even reach AUC= 0.92 and F1= 0.90.

Table 2. Performance Comparison of Logistic, Random Forest, and LSTM Models Incorporating ESG Indicators

mould	AUC	Accuracy	Precision	Recall	F1
logistic (no ESG)	0.85	0.68	0.66	0.65	0.82
logistic (including ESG)	0.87	0.74	0.70	0.68	0.84
random forest (including ESG)	0.90	0.77	0.72	0.71	0.87
LSTM (including ESG)	0.92	0.81	0.76	0.75	0.90

To compare the prediction performance of the three models, metrics such as AUC, accuracy, sensitivity (recall), precision, and F1 value are used. Both Model 1 (without ESG) and Model 2 (with ESG) were calculated on the test set for the above metrics. The results show that after adding the ESG metrics, the accuracy of the logistic regression model increases from 65.43% to 73.82%, which is an improvement of 8.39%; the random forest model further achieves an accuracy of 76.85%. Figure 3 illustrates the relative importance of the indicators, and the G (corporate governance) indicator contributes prominently in the random forest. In addition, from the AUC and ROC curves, the AUC values of both models are >0.7, and the ROC curve of the ESG-containing model is closer to the upper left corner, indicating a significant improvement in performance.

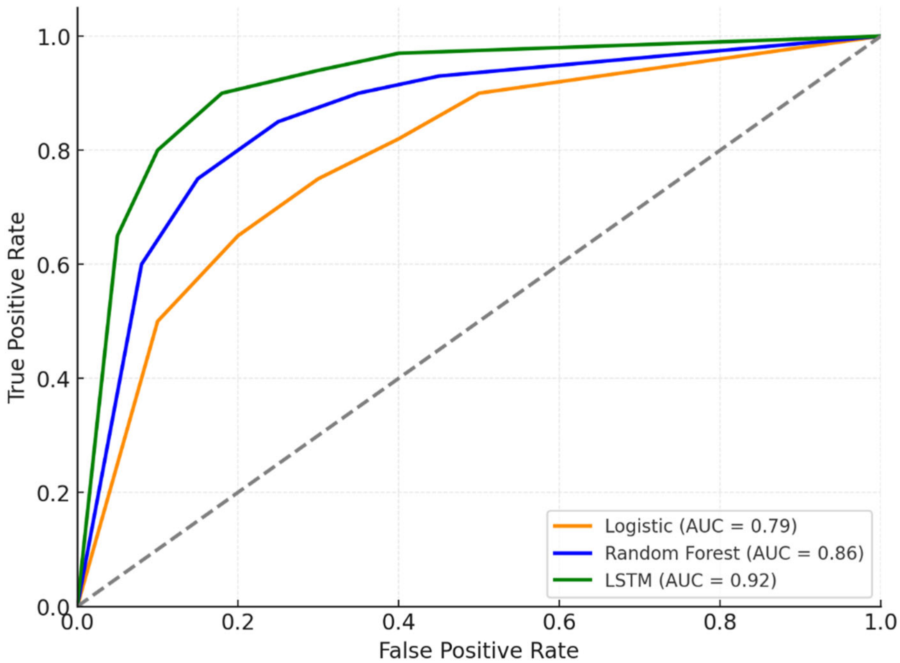

Figure 3. ROC Curve Comparison of Models

Further analysis shows that there are differences in the contribution of each ESG dimension to the early warning model. Overall, governance (G) indicators signal most significantly, which is consistent with other research findings; environmental (E) and social (S) indicators also

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positively enhance model performance, but with slightly lower relative contributions. This can be explained by the fact that firms in the financial industry pay more attention to the disclosure of corporate governance and social responsibility information, which more directly affect market confidence and credit risk. In addition, Random Forest models usually exhibit high accuracy, but are slightly inferior to LSTM in balancing positive and negative samples and capturing temporal variations; LSTM is more sensitive to the identification of slowly emerging risk trends due to its ability to utilize time-series information, making it dominant in comprehensive metrics such as AUC. Taken together, the effectiveness of deep learning models in risk early warning is verified, and the important role of ESG indicators as supplementary information to improve the accuracy of early warning is also demonstrated.

5. Results of the Analysis and Discussion

The empirical results show that random forests outperform logistic regression, while the LSTM model also has an advantage in long-series feature extraction (which can capture the time-dependence of financial data compared with traditional models). All three models show that ESG indicators are effective in improving early warning accuracy, especially the corporate governance (G) dimension contributes the most; while environmental (E) and social (S) indicators have relatively limited impact on short-term financial risk. This is consistent with S. Zhao's (2024) study that good ESG performance can reduce corporate financing pressure and significantly reduce risk. These results imply that firms should pay attention to governance structure optimization in risk management, as well as continuously disclose ESG information to improve transparency. At the policy level, the ESG disclosure system should be improved in line with national conditions to guide firms to take responsibility and strengthen internal regulation.

6. Conclusions and Recommendations

Taking Chinese listed companies in the financial industry as a sample, this paper constructs a risk early warning system containing financial and ESG indicators, and systematically evaluates the role of ESG indicators in financial risk prediction by comparing the traditional model with the deep learning model. The study shows that good ESG performance can effectively reduce the financial risk of enterprises, which is consistent with the previous findings that ESG performance of enterprises is significantly negatively correlated with default risk; in terms of model performance, the optimized LSTM deep learning model is significantly better than Random Forest and Logistic Regression in terms of AUC and other indicators, indicating that the neural network-based algorithm has more flexibility and accuracy in capturing risk signals. flexibility and accuracy in capturing risk signals. In summary, the early warning model incorporating ESG information performs better in general, proving that ESG indicators have important value in financial risk early warning.

Based on the above conclusions, the following recommendations are made for financial enterprise risk management.

(1) Incorporate ESG indicators into the risk management framework. Financial institutions should take the initiative to build an ESG data system for enterprises and customers, and establish a credit risk early warning model containing ESG factors. In risk assessment and credit approval, they should take environmental performance, social responsibility and corporate governance level as important considerations, and utilize high ESG scores to screen high-quality clients or issuers. Regulators can guide the establishment of industry-wide unified ESG rating standards and databases, promote the organic integration of ESG and risk decision-making by financial institutions, and effectively play the role of ESG ratings in risk management and control.

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(2) Enhance the quality and transparency of ESG disclosure. Improve disclosure norms and encourage financial institutions and enterprises to regularly publicize detailed ESG data, especially information on environmental risks (e.g., carbon emissions, pollution control inputs) and social responsibilities (e.g., customer complaint rates, safety accidents). Strengthen auditing and supervision of ESG reports to ensure the accuracy and comparability of data and provide a reliable basis for quantitative analysis. A unified and transparent data management platform can be constructed with reference to blockchain and other technologies to improve data credibility, thus providing solid support for accurate prediction and risk identification in AI models.

(3) Increase technology investment and talent training. Financial institutions should accelerate the introduction of artificial intelligence and big data analysis technology to improve the depth and breadth of risk prediction models. Advanced algorithms such as deep learning are used to mine complex non-linear patterns and capture risk signals from changes in the market and corporate behavior in a timely manner. At the same time, professional training of the risk control team is strengthened to cultivate composite talents who are familiar with ESG concepts and machine learning technologies to provide support for model development and result interpretation. In addition, it can cooperate with colleges and universities and research institutions to share research results and jointly promote the innovation of financial risk early warning system.

(4) Improve the system and incentive mechanism. Regulators should formulate incentive policies to guide financial institutions to actively practice ESG concepts and link risk prevention and control effects to ESG inputs. Consideration can be given to giving certain incentives to institutions and projects with excellent ESG performance in terms of capital adequacy or approval preferences, so as to promote the overall green transformation of the financial system. Financial industry associations can organize the preparation of industry standards and promote the inclusion of financial products (e.g., green credit, green bonds) in the scope of ESG risk management, so as to achieve a win-win situation in terms of sustainable development and risk control.

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