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Assessing the Bankruptcy Risks of China's Emerging Port Industries: Modeling and Early Warning

Wang Ying ✉, *Igor A. Mayburov* , *Yulia V. Leontyeva*

Ural Federal University
named after the First President of Russia B. N. Yeltsin,
Yekaterinburg, Russia

✉ *van.in@urfu.ru*

Abstract. Vigorously developing emerging marine industries are an important way for China to implement the strategy of "Sea Power Nation", and improving the ability of port enterprises to prevent financial and tax risks is a key link in accelerating the high-quality development of the marine economy. The research objective of this paper is to construct a reasonable early warning financial model for emerging port industries in Guangdong, Hong Kong, and Macao Greater Bay Area. The research hypothesis is that the original Z-SCORE model and F-SCORE model are not able to accurately predict the financial risk of emerging marine industries. The data of typical port enterprises are utilized to compare the financial risk; after that risk assessment and early warning are carried out. This paper adopts the Delphi method to assign weights to different indicators and utilizes the Analytic Hierarchy Process method to derive a financial and tax early warning model applicable to Guangdong, Hong Kong, and Macao Greater Bay Area. The results of the study found that the traditional "Z-score model" and "F-score model" are less applicable to the emerging industries in the ports of Guangdong, Hong Kong, and Macao Greater Bay Area. This paper will construct a financial and tax risk control model corresponding to the development of port emerging industries and provide early warning when exceeding a certain threshold to help enterprises develop better. In addition, this paper also puts forward policy suggestions for risk management of emerging port industries from the aspects of system improvement and government-enterprise linkage.

Key words: port emerging industry; financial early warning model; Y-score model; F-score model; Delphi method; Analytic Hierarchy Process method.

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1. Introduction

At present, the Chinese government has strongly supported the rapid development of the marine industry, especially the emerging marine industry, and regarded it as an important hand in accelerating the strategy of "Ocean Power". According to the data issued by State Oceanic Administration of China (SOA), the contribution of marine industry is more than 8.9 trillion yuan per year, with an average annual growth rate of more than 8.1 %, and the GDP accounted for more than 9 % of China's gross domestic product (GDP).

The marine industry, the marine emerging industry is an important field for breeding new industries and leading new growth, and at the same time, as a new point of economic growth, it is becoming more and more prominent, and it also shows that the national level is becoming more and more enriched in the top-level design and arrangement of the marine economy [1].

In 2023, the GDP of the emerging marine industry is more than 9.46 trillion RMB, with an average annual growth reaches 7.1 %. However, the development is not smooth. in early 2020, affected by the

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epidemic, China's port cargo and container throughput declined year-on-year, but then both continued to rebound, and port throughput was overall lower than expected due to the epidemic. The scale, technology and model of the marine emerging industry are still at an immature stage, and its development is also characterized by great uncertainty.

The main risks are as follows:

Firstly, legal risk and compliance risk. Environmental protection in overseas ports, overseas projects will have additional expenditure increase, project stoppage and rework. Piraeus Port had its expansion plan rejected because it did not provide sufficient environmental impact assessment.

Secondly, social and cultural risks, the transnational business activities of port enterprises have to face the dual risks of organizational culture and national culture. the construction of a fence in an industrial park had triggered a controversy among residents in 2018, and the attack on the personnel of the Guinea project of COSCO Shipping Port in 2021.

Thirdly, there are market risks caused by changes in interest rates and exchange rates, strategic risks caused by overly aggressive overseas investment, operational risks caused by natural disasters, strikes, etc., uncontrolled project cost management, and financial risks caused by poor port operations, and so on. Therefore, marine emerging industries need to formulate their own personalized development strategy.

Taking the selected enterprises in this paper as an example, their development is characterized by high investment, long return cycle, high policy sensitivity and high uncertainty of maritime operation, so this kind of enterprises belongs to high-risk, high-yield and high-debt industries.

At present, when China's modern port enterprises carry out financial early warning, they generally start from a qualitative point of view, through certain financial characteristics of the enterprises. However, due to the interference of internal and external factors, there will be certain errors in the qualitative analysis.

In order to reduce the judgment error, it is necessary to combine the qualitative and quantitative analysis methods for calculation. Quantitative analysis is generally carried out through the construction of financial early warning model. The financial early warning model can discover the hidden problems of the enterprise financial operation system within a certain range in a timely manner to avoid the financial risk from becoming a financial crisis [2].

The purpose of our study is to construct a reasonable financial early warning model for port emerging industries in Guangdong, Hong Kong, and Macao Greater Bay Area.

Research hypothesis:

H1: Verify through empirical analysis that the original F-SCORE financial early warning model and Z-SCORE financial early warning model are not applicable to the forecasting of the new industries in the ports of Guangdong, Hong Kong, and Macao Greater Bay Area.

H2: Through empirical analysis, it is verified that the newly constructed Y-SCORE model in this paper is applicable to the financial forecasting of new industries in the ports of Guangdong, Hong Kong, and Macao Greater Bay Area.

2. Literature Review

Xhu & Chen [3] used 19 companies as samples to make predictions using a single financial indicator and pioneered a one-dimensional judgmental early warning model. Although the model was able to predict the future performance of the firms, the prediction accuracy was not high because only a single financial variable was introduced for the analysis.

Altman et al. [4] used multivariate analysis techniques to analyze the operating data of 33 firms before their bankruptcies during the period 1946–1954. By gradually updating and correcting a series of reference variables, he firstly proposed a multivariate financial early warning model.

The size of Z value can reflect the financial status of the enterprise, and the enterprise managers can judge whether there is a crisis in the enterprise by the size of Ohlson [5] and others established a multivariate logistic regression based on the method of probabilistic regression (Logit) model. The logit method he used overcame the problems in traditional discriminant analysis and resulted in a substantial increase in this model.

Jing [6] combed through the development status of Chinese enterprises, selected 67 financial crisis companies, and further researched based on the "Z-score model" by using principal component analysis, and put forward the Y-value model, which has an accuracy rate of about 86 %.

Yang et al. [7] used feed-forward neural network to conduct financial early warning research on enterprises, which has strong foresight.

Pendharkar [8] used BP artificial neural network algorithm for the first time to analyze the comprehensive ability of the enterprise's operation, and the accuracy rate reached more than 90 %. Deep learning data mining methods based on the combination of artificial intelligence and big data have also appeared in China in recent years. All the above studies aim to help enterprises discover financial crises in a timely manner.

Lepetit et al. [9] used the traditional Z-score model as a basis to revisit the Z-score model with the bank bankruptcy risk as a topic and concluded that the traditional method is inaccurate in its prediction.

Ko et al. [10] used Taiwan's solar industry as a case study and found that solving evidential coefficients of financial ratios for the distressed companies.

Elliott et al. [11] builds a double hidden Markov model (DHMM) based on the original Z-score model from the corporate accounting ratio assessment of Z-scores and published credit ratings to extract information about a firm's "true" credit quality. This approach is more conducive to forecasting accuracy.

Chiaramonte et al. [12] examines the accuracy of the Z-value, a widely used proxy indicator of bank robustness examines the accuracy of the Z-value, a widely used proxy indicator of bank robustness, using a sample of European banks from 12 countries over the period 2001–2011. Specifically, we analyze the Z-value and CAMELS-related covariates. we find that the Z-score is at least as good as the CAMELS variable in identifying crisis events, both in the whole period and in the crisis period (2008–2011), but has the advantage of being less demanding on the data. Finally, Z-score is more effective in situations where the bank's business model is more complex, as is the case for large commercial banks.

Li et al. [13] builds on the previous work by studying the four largest banks in New Zealand as a case study. Improvements were made to the z-score model and the study found that the LOO z-score modeling approach can provide early warning information and is more accurate than the z-score model.

Zhu et al. [14] used the Z-score model to assess the financial risk of IoT-only enterprises and found that using the annual reports of IoT enterprises and industry reports, and applying the Z-score model, the study found that the main sources of risk faced by IoT enterprises are mainly focused on exogenous legal risk.

Li [15] used model based on data mining for financial risk detection. CHAID algorithm has been used for development of the EWS. Developed EWS can be served like a tailor-made financial advisor in decision making process of the firms with its automated nature to the ones who have inadequate financial background. Besides, an application of the model implemented which covered 7853 SMEs based on Turkish Central Bank (TCB) 2007 data. By using EWS model, 31 risk profiles, 15 risk indicators, 2 early warning signals, and 4 financial road maps has been determined for financial risk mitigation.

Yi [16] takes listed enterprises as samples, combined with the company's financial indicators and found that. The research model in this paper can improve the performance of financial risk early warning model and enhance the reliability of the model.

Bouvatier [17] uses Z-score model pairs to compare different measurement methods using a series of alternative testing procedures focusing on U.S. and European banks during the 2007–2008 financial crisis. Further enhancements to the z-score model were made.

Tang et al. [18] predicted systematic financial risk using interpretable machine learning for effectiveness in predicting systematic financial risk.

Wang et al. [19] innovatively proposed the use of patch size distribution to detect financial crisis warning signals in spatial endogenous credit models, aiming to use spatial warning signals to study spatially extended endogenous credit systems with stochasticity. They use new method can be applied for financial early warning.

Ouyang et al. [20] argued that early warning of systemic financial risk in Chinese financial market based on Attention-LSTM model. The impact of online public opinion on systemic financial risk is investigated and an online public opinion network index is constructed for China's financial market. It was found that the LSMT type of neural network model has higher accuracy than other methods.

Zhu et al. [21] used the stepwise regression method to establish the optimal prediction equation for financial systemic risk, to establish a reasonable and practical early warning index system for financial systemic risk; moreover, the optimal prediction equation was applied to predict the financial systemic risk situation in 2011, and the prediction results showed accuracy and were applicable to the prediction of the financial system.

Tarkocin & Donduran [22] used the integrated model of RUSBoost algorithm to predict the "red" and "amber" days with a success rate 21 % higher than the average success rate of other machine learning models. The model and framework proposed in this study can be applied to the banking environment, which will enable financial institutions to integrate their internal indicators with market stress indicators.

Allaj & Sanfelici [23] involved the EWS model (Early Warning System for colleges and universities) based on Logit regression and argued that the model is effective in predicting potential market instability.

Wu et al. [24] used integrated Z-score and multilayer perceptron neural network to forecast the company and the model was able to predict well that the model can provide early warning signals of deterioration in the company's financial condition.

Xiao et al. [25] argued that most of the pay attention to financial risk of companies focuses on the accuracy of prediction and ignores evaluation, so the authors designed a new three-stage decision support research framework to discuss corporate financial risk assessment and prediction based on previous research, using the LIGHTGBM integrated model to assess the market capitalization of Chinese small and medium-sized enterprises (SMEs). It was found that OPT-LIGHTGBM can improve efficiency without loss of forecasting performance and has the best overall performance compared to existing forecasting models.

Meziani & Rezvani [26] used hierarchical analysis to assess and predict financial risks. An empirical study based on SMEs found that the hierarchical analysis method can provide an effective means of assessing the financial risk of companies.

Gonzalez-Urango et al. [27] argued that recent applications of the Analytic Network Process (ANP) in the decision-making process in the fields of economics, finance, in order to identify contingencies, current trends, It was found that ANP is particularly suitable for sustainable projects to promote the participation of various stakeholders.

Nguyen et al. [28] used the fuzzy hierarchy analysis method for comprehensive assessment of investment decisions and retrogression in private sector sustainable water supply systems using a province in Vietnam as a case study and found that the fuzzy hierarchy analysis method is effective for this and retrogression assessment, and that an investment attractiveness index can be constructed in this way. This way to construct an investment attractiveness index [28].

Murugan & KalaT [29] used a machine learning strategy to analyze large-scale data and applied K-nearest neighbor (KNN), cluster based logistic regression (LR), and cluster based XG Boost models to assess financial risk. risk assessment, the simulation results of this model yielded better large-scale data-driven financial risk results than state-of-the-art methods.

Conte et al. [30] conducts an intermediation analysis with data from 394 listed banks in 54 countries from 2002 to 2017 with the aim of investigating the role of bank financial risk-taking as an intermediation channel to explain the relationship between CSP and financial performance in the banking sector. The results show that partially moderated by bank risk-taking, where CSP improves financial performance by reducing bank risk.

Rahman & Zhu [31] conducted a study on financial early warning using machine learning techniques using Chinese A-share listed construction companies as a case study. The results confirmed Z-Score model didn't catch them. In addition, the CUSBoost classifier was found to be the most accurate model based on the AUC and AUPR metrics in the main and additional tests.

From the existing research, these financial early warning model studies have strong universality, while the development of port emerging industries has its own objective laws, which cannot use the universal model in its entirety. Therefore, the study of financial early warning model for port emerging industries has stronger application value and greater practical significance.

3. Empirical Calculations and Analysis

This section encompasses the data sources, model estimation and econometric procedures used for this study.

In this paper, we are going to analyze the financial risk of key port enterprises in Guangdong, Hong Kong, and Macao Greater Bay Area by comparing the data changes of Z-score model, F-score model, and univariate early warning model, and analyze whether there is any financial risk according to the Delphi method, assigning different models to different port enterprises. Based on the Delphi method, different weights are assigned to the three models to integrate and optimize the results of the above early warning models, to seek a healthy development path for the related port enterprises in Guangdong, Hong Kong and Macao Greater Bay Area.

3.1. Data sources

Since this paper focuses on analyzing the development of emerging industries in ports in the Guangdong, Hong Kong, and Macao Greater Bay Area of China, it takes the recent Lloyd's List Global 100 ranking of ports as its target. A total of 24 listed port companies are selected as research samples, focusing on the data of listed port companies in Guangdong, Hong Kong and Macao Greater Bay Area — Guangzhou Port Group, Yantian Port Group and Zhuhai Port Holding Group Company.

The authors collect the data required for this study by searching websites such as China Securities Network, Wanfang Database and Guotai Junan Database. Meanwhile, due to the inconsistency of statistical caliber between Hong Kong and Macao and China, for the consideration of testability of the analysis, this study will select the available scientific research data instead of website data for analysis.

This paper is written in 2024, the above researched companies have not disclosed the annual report of 2023 and the occurrence of the new crown epidemic, so the company's performance is not representative. Therefore, this paper only analyzes the financial data of 2017, 2018, 2019, 2020, 2021 and 2022, which have sufficient reference significance and real-time.

3.2. Financial early warning system indicator system structure

The selection of financial indicators must be true, which is the basis for ensuring that the financial system has application value. At the same time, it should be in line with the development law of the enterprise, which is a prerequisite to ensure the effective operation of the early warning system.

The selection of indicators in this paper focuses on listed port enterprises in the Pearl River Delta region. Based on the existing literature, combined with the specific situation and characteristics of port enterprises, the authors of this paper believe that the selection of indicators should basically follow the basic principles of financial analysis.

According to the PEST analysis method, the selected financial indicators are as follows.

1. *Solvency*. Solvency refers to the ability of an enterprise to repay debts (principal and interest) when due, including short-term solvency and long-term solvency [32]. Because of the high input and high output characteristics of port-type enterprises, analyzing their solvency can be a glimpse of whether they have enough ability to pay money and repay debts.

2. *Profitability*. Profitability is the core ability of the enterprise that investors and managers are most concerned about, and it is also the criterion of whether the enterprise can continue to operate in the market for a long time and make profits for a long time [33]. The market generally believes that the higher the profit, the stronger the profitability, the enterprise has a better prospect, more sought after by investors. Sales profitability is an indicator of the level of return on corporate income.

3. The *operating capacity* of an enterprise mainly refers to the efficiency and effectiveness of its operating assets. The indicators of operational capacity mainly include inventory turnover, accounts receivable turnover and current asset turnover [34].

4. *Development potential*. Development potential is extremely important for the future development of port-based enterprises. It can objectively reflect the ability of port-based enterprises to sustain development. The selection of this indicator has a high correlation with financial risk.

5. *Non-financial indicators*. Since a single financial indicator is not comprehensive enough, non-financial indicators are introduced for calculation. Non-financial indicators are mainly selected: maritime accidents. Maritime accidents mainly refer to the occurrence of ship reefing, grounding, and other situations during navigation. Serious maritime accidents can cause great losses to port shipping companies. Sea water pollution. The introduction of pollutants into the sea due to man-made or negligence, caus-

ing damage to the ecosystem. The United Nations Convention on the Law of the Sea (UNCLOS) clearly stipulates that organizations or individuals who cause greater pollution of seawater should be punished. Therefore, sea water pollution caused by port companies can lead to a series of serious consequences. Customer satisfaction. Customer satisfaction is crucial to the future development of the company, and good customer evaluation is beneficial to the future development of the company.

3.3. Establishment of financial early warning data model based on Analytic Hierarchy Process (AHP)

Analytic Hierarchy Process (AHP) in the 1970s based on the application of network system theory and multi-objective comprehensive evaluation method [35]. Hierarchical analysis method is systematic, effective, and clear. Now it is widely used in enterprise management, decision-making and evaluation.

1. According to the AHP method to determine the weight of each indicator 1. Building a tree hierarchy model. The structural model is the financial early warning evaluation index system. The indicator system is divided into three layers respectively as the target layer, guideline layer and program layer. The specific financial early warning indicator system is layered as follows (Table 1).

2. When comparing two factors in this article, quantitative scaling is required. The scaling method in this article is as follows (Table 2).

Table 1. **Financial early warning indicator system**

Target layer A	Criteria Level B Measurement Level C		Criteria Level B Measurement Level C
Fiscal service pre police refer to mark body Tie	Financial indicator	Profitability B_1	Net sales profit margin C_1
			ROE C_2
			ROA C_3
			Gross profit margin C_4
			Earnings per share C_5
		Operational capability B_2	Inventory turnover rate C_6
			Accounts receivable turnover ratio C_7
			Current asset turnover ratio C_8
		Solvency B_3	Current ratio C_9
			Quick ratio C_{10}
		Development potential B_4	Sales growth rate C_{11}
			Capital preservation growth rate C_{12}
	Non-financial indicators B_5		Marine accident C_{13}
			Seawater pollution C_{14}
			Customer satisfaction C_{15}

Construct a judgment matrix (1). By scoring the importance of pairs of indicators in the same module, we can get the judgment matrix for pairwise comparison.

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \quad (1)$$

This article will use the Delphi method to assign corresponding weights to the target indicators. Choosing the right experts is an important factor affecting the accuracy of the results of the Delphi method. This research will be oriented to experts with rich theoretical and practical experience in universities and society to ensure that the answers are highly representative.

Finally, 50 qualified experts were selected for scoring. A total of 50 questionnaires were collected in the first round, and the enthusiasm of experts was 100 %; in the second round, a total of 50 questionnaires were collected, and the enthusiasm of experts was 100 % (Table 3).

3. Calculate the geometric mean of the elements in each row of each judgment matrix (Table 4):

$$\overline{w_i} = \sqrt[n]{\prod_j a_{ij}}, \quad (2)$$

$$w = \left(\overline{w_1}, \overline{w_2}, \overline{w_3}, \ldots, \overline{w_n}\right)^T. \quad (3)$$

Do normalization processing, that is,

$$w_i = \frac{\overline{w_i}}{\sum_{i=1}^{n} \overline{w_i}}, \quad (4)$$

Where: w is the vector; $\overline{w_i}$ is the geometric mean of the vector.

Table 2. **Scale meaning**

Seals	Meaning
1	Indicates that two factors have the same importance compared to each other
3	Indicates that one factor is more important than the other
5	Indicates that compared with two factors, one factor is obviously more important than the other factor
7	Indicates that one factor is more strongly important than the other when comparing two factors
9	Indicates that compared with two factors, one factor is more important than the other factor.
2,4,6,8	Is the median value of the above adjacent judgments

Table 3. **BiSpecific screening conditions for model evaluation system consulting experts**

Filter entries	Specific conditions
Profession	Including marine economics and other related majors
Work area	Relevant university teachers and port practitioners
Working years	More than 10 years
Educational qualifications	Master's degree or above
Job title	Lecturer, intermediate professional title or above

Table 4. **Index weight table**

Index Matrix Weight W Consistency Test	Index Matrix Weight W Consistency Test					Index Matrix Weight W Consistency Test	Index Matrix Weight W Consistency Test
A	B_1	B_2	B_3	B_4	B_5		λmax=5.0972 CI=0.0243 CR=0.0217
B_1	1	1/3	1/3	1/2	1/3	0.083	
B_2	3	1	1	1	1/2	0.200	
B_3	3	1	1	1	1/2	0.200	
B_4	2	1	1	1	1	0.212	
B_5	3	2	2	1	1	0.304	
B_1	C_1	C_2	C_3	C_4	C_5		λmax=5.1013 CI=0.0253 CR=0.0226
C_1	1	1/2	1	1/2	1/2	0.123	
C_2	2	1	3	1	1/2	0.233	
C_3	1	1/3	1	1/2	1/2	0.114	
C_4	2	1	2	1	1	0.247	
C_5	2	2	2	1	1	0.283	
B_2	C_6	C_7	C_8				λmax=3.0092 CI=0.0046 CR=0.0079
C_6	1	3	2			0.540	
C_7	1/3	1	1/2			0.163	
C_8	1/2	2	1			0.297	
B_3	C_9	C_{10}					λmax=2 CI=0 CR=0
C_9	1	2				0.667	
C_{10}	1/2	1				0.333	
B_4	C_{11}	C_{12}					λmax=2 CI=0 CR=0
C_{11}	1	2				0.667	
C_{12}	1/2	1				0.333	
B5	C_{13}	C_{14}	C_{15}				λmax=3.0183 CI=0.0091 CR=0.0158
C_{13}	1	2	3			0.723	
C_{14}	1	1	1			0.316	
C_{15}	0	1	1			0.276	

4. Result

Based on the above calculations it is possible to construct the following function for evaluating the financial position of a company.

$$\begin{aligned} Y = {} & 0.01X_1 + 0.019X_2 + 0.009X_3 + \\ & +0.021X_4 + 0.024X_5 + 0.108X_6 + \\ & +0.033X_7 + 0.06X_8 + 0.134X_9 + \\ & +0.067X_{10} + 0.142X_{11} + 0.071X_{12} + \\ & +0.167X_{13} + 0.073X_{14} + 0.064X_{15}. \end{aligned} \tag{5}$$

Where Y is the newly constructed model result formula.

Different marine emerging enterprises can be based on this model for financial early warning research, Y value and enterprise financial risk there is a linear correlation, the enterprise can be based on their own development to develop financial early warning risk value, Y value the smaller the probability of financial risk occurs when the value is less than *0*, the risk of the probability of occurrence of the risk will be higher.

4.1. Comparison between the model based on hierarchical analysis and the "Z-SCORE, F-SCORE" model

4.1.1 Z-value and F-value analysis of key port enterprises in Guangdong, Hong Kong, and Macao Greater Bay Area

Currently, the financial early warning model of Altman [4] is commonly used in the business world to determine whether a company has the possibility of bankruptcy.

Atman first invoked the multivariate analysis method to check the discriminative model and constructed the multivariate discriminative model "Z-score model" and judged the financial status of enterprises according to the Z-value by studying 33 enterprises that filed bankruptcy petitions and the same number of non-bankrupt enterprises during 1946–1965 and used the Z-value and F-value in the "Z-score model" to determine the financial status of enterprises.

Zhing [6] and others [35] proposed the "F-score model" based on the "Z-score model" by adding cash flow indexes in combination with the characteristics of China's capital market. This model is widely used in the financial early warning of modern enterprises.

The basic formula of "*Z*-score model" is:

$$Z = 0.012X_1 + 0.014X_2 + \\ +0.033X_3 + 0.006X_4 + 0.999X_5, \quad (6)$$

Where X_1 — working capital/total assets, X_2 — retained earnings/total assets, X_3 — earnings before interest and taxes/total assets, X_4 — capital market value/total liabilities, X_5 — sales revenues/total assets and the criteria for judging: $Z < 1.81$ — bankruptcy zone; $1.81 \le Z < 2.67$ — gray zone; $2.67 < Z$ — safety zone [36].

The basic formula of "*F*-score model" is:

$$F = -0.174 + 0.109X_1 + 0.1074X_2 + \\ +1.9271X_3 + 0.0302X_4 + 0.4961X_5, \quad (7)$$

Where X_1 — working capital/total assets, X_2 — retained earnings/total assets, X_3 — (net income after tax + depreciation)/average total liabilities, X_4 — capital market capitalization/total liabilities, X_5 — (net income after tax + interest + depreciation)/average total assets.

The judgment criteria are: if $F < 0.0274$, it indicates that there is a financial crisis in the company; if $F > 0.0274$, it is predicted that the company can operate normally, but in the region of (0.0501,0.1049) is an area of uncertainty, then it is necessary for managers to carry out further analysis in order to find out whether the company's finances are indeed going to enter into difficulties.

Z-value and *F*-value analysis of key port enterprises in Guangdong, Hong Kong and Macao Greater Bay Area is presented in Tables 5–10.

The following analysis is done based on the distribution of Z-values and F-values. According to the above table, the F value of Guangzhou Port Group has increased from 2017 to 2019, rising from –0.0124 to 0.027. Among which the F value in 2017 and 2018 is in the bankruptcy range, indicating that the possibility of financial crisis of Guangzhou Port Group is higher, the F-value in 2019 is within the normal operating range, and it is predicted that the company can operate normally.

Table 5. **Z-value of key ports (Guangzhou Port)**

Project/Year	Guangzhou Port Z value					
	2022	2021	2020	2019	2018	2017
X_1	0.398	0.366	0.315	–0.01	–0.06	–0.14
X_2	0.155	0.167	0.172	0.15	0.18	0.18
X_3	0.034	0.040	0.041	0.05	0.05	0.05
X_4	0.96	1.063	1.287	1.85	2.41	4.50
X_5	0.286	0.342	0.351	0.36	0.34	0.38
Z	0.3	0.357	0.366	0.38	0.36	0.41

Table 6. **Z-value of key ports (Yantian Port)**

Project/Year	Yantian Port Z value					
	2022	2021	2020	2019	2018	2017
X_1	0.11	0.05	0.11	0.04	0.06	0.09
X_2	0.34	0.37	0.36	0.40	0.40	0.40
X_3	0.03	0.04	0.04	0.04	0.05	0.05
X_4	2.06	3.18	4.35	3.85	3.78	6.71
X_5	0.05	0.05	0.04	0.05	0.04	0.04
Z	0.07	0.07	0.07	0.08	0.07	0.09

Table 7. **Z-value of key ports (Zhuhai Port)**

Project/Year	Zhuhai Port Z value					
	2022	2021	2020	2019	2018	2017
X_1	0.05	0.01	–0.03	0.016	–0.034	0.018
X_2	0.11	0.10	0.12	0.158	0.187	0.185
X_3	0.04	0.04	0.03	0.18	0.21	0.206
X_4	0.44	0.52	0.69	0.742	1.107	1.838
X_5	0.25	0.33	0.26	0.359	0.382	0.323
Z	0.26	0.34	0.27	0.372	0.398	0.343

Table 8. **F-value of key ports (Guangzhou Port)**

Project/Year	Guangzhou Port F value					
	2022	2021	2020	2019	2018	2017
F_1	0.05	–0.07	–0.02	–0.01	–0.06	–0.14
F_2	0.16	0.17	0.17	0.15	0.18	0.18

End of table 8

Project/Year	Guangzhou Port F value					
	2022	2021	2020	2019	2018	2017
F_3	0.11	0.11	0.09	0.07	0.07	0.08
F_4	0.96	1.06	1.29	1.85	2.41	4.50
F_5	0.06	0.06	0.05	0.02	0.02	0.02
F	0.17	0.03	0.07	0.03	0.00	–0.01

Table 9. **F-value of key ports (Yantian Port)**

Project/Year	Yantian Port F value					
	2022	2021	2020	2019	2018	2017
F1	0.11	0.05	0.11	0.04	0.06	0.09
F2	0.34	0.37	0.36	0.40	0.40	0.40
F3	0.16	0.18	0.12	0.01	0.01	0.01
F4	2.06	3.18	4.35	3.85	3.45	6.09
F5	0.01	0.01	0.01	0.04	0.05	0.04
F	0.36	0.37	0.36	0.06	0.07	0.18

Table 10. **F-value of key ports (Zhuhai Port)**

Project/Year	Zhuhai Port F value					
	2022	2021	2020	2019	2018	2017
F1	0.05	0.01	–0.03	0.02	–0.03	–0.02
F2	0.11	0.10	0.12	0.02	–0.03	0.02
F3	0.04	0.05	0.03	0.16	0.19	0.19
F4	0.44	0.52	0.69	0.15	0.14	0.14
F5	0.05	0.05	0.03	0.74	1.11	1.84
F	0.01	–0.02	–0.10	0.52	0.03	0.03

According to the annual report disclosed by Guangzhou Port, revenue in 2019 increased by 18 % year-on-year, exceedingly nearly 10 billion yuan. It can be seen from the annual report that ROA is the highest in the past three years, so the F model conclusion is basically inconsistent with the operating status of Guangzhou Port, and the analysis is less accurate.

4.1.2 Model analysis based on the newly constructed Y-score

In this paper, to eliminate the influence of the index scale, it is necessary to standardize the value of each index to get the standardization matrix. For the positive indicators, i. e., the larger the value, the better the indicator, the processing method is as follows:

$$x_{ij}^{*} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}}, \quad (8)$$

Where x_{ij}^{*} is the standardized matrix.

The indicator system of this paper is constructed with reference to the financial indicator system obtained by the Delphi expert consultation method of most scholars in this paper, and five basic types of evaluation indicators reflecting the financial status and operating results of enterprises are selected: solvency indicators, profitability indicators, operating capacity indicators, growth capacity indicators and non-financial indicators. To satisfy the continuity, comparability, and authenticity of the data.

The data in this paper comes from Google database, and the division of the enterprises of the line port is based on the standard of the industry classification issued (Table 11–13).

Table 11. **Standardized values for Guangzhou Port**

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
2022	–1.24	0.74	–0.39	–0.98	0.71	–0.92	–0.62	–1.84	1.70	1.74	–0.46	–0.39	–0.41	1.79	0.00
2021	1.35	1.60	0.60	–0.61	1.57	–0.28	1.76	–0.33	–0.57	–0.45	–0.32	–0.63	2.04	–0.45	0.00
2020	–1.00	–0.54	0.57	–0.69	–0.14	–0.10	–0.08	0.06	0.17	0.25	–0.21	–0.68	–0.41	–0.45	0.00
2019	–0.15	–0.04	1.37	–0.22	–0.14	–0.57	–1.21	0.77	0.38	0.18	1.99	–0.67	–0.41	–0.45	0.00
2018	0.73	–1.06	–1.16	1.36	–1.00	–0.07	–0.01	0.58	–0.53	–0.56	–0.79	0.57	–0.41	–0.45	1.58
2017	0.32	–0.70	–0.98	1.14	–1.00	1.93	0.16	0.77	–1.15	–1.16	–0.23	1.80	–0.41	–0.45	–1.58

Table 12**. Standardized values for Yantian Port**

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
2022	–0.87	0.74	–0.39	–0.98	0.71	–0.92	–0.62	–1.84	1.70	1.74	–0.46	–0.44	–0.41	–0.41	1.58
2021	–0.52	1.60	0.60	–0.61	1.57	–0.28	1.76	–0.33	–0.57	–0.45	–0.32	–0.87	–0.41	–0.41	–1.58
2020	–0.48	–0.54	0.57	–0.69	–0.14	–0.10	–0.08	0.06	0.16	0.25	–0.20	1.90	–0.41	–0.41	0.00
2019	–0.68	–0.04	1.36	–0.22	–0.14	–0.57	–1.21	0.76	0.38	0.18	1.99	–0.66	–0.41	2.04	0.00
2018	1.18	–1.06	–1.16	1.35	–1.00	–0.07	–0.01	0.58	–0.53	–0.56	–0.79	0.05	2.04	–0.41	0.00
2017	1.37	–0.70	–0.98	1.14	–1.00	1.93	0.16	0.76	–1.15	–1.16	–0.22	0.01	–0.41	–0.41	0.00

Table 13. **Standardization for Zhuhai Port**

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
2022	1.06	–0.49	0.19	–0.63	0.39	–1.82	–1.83	–1.53	1.29	1.52	–1.18	–0.39	–0.41	–0.41	–0.41
2021	0.20	1.93	1.09	–0.64	1.78	0.07	–0.21	–0.08	0.28	0.13	1.74	0.63	–0.41	–0.41	–0.41
2020	–0.07	–0.49	0.01	–0.64	–0.08	0.24	0.37	–0.73	–1.03	–0.91	–0.45	–0.62	2.04	2.04	–0.41
2019	–1.10	–0.81	1.03	–0.64	–0.36	0.94	0.87	0.35	0.21	0.04	0.12	1.72	–0.41	–0.41	–1.22
2018	–1.19	0.18	–1.06	1.06	–0.73	0.82	0.85	1.01	–1.34	–1.26	0.30	–0.35	–0.41	–0.41	1.22
2017	1.10	–0.33	–1.26	1.50	–1.01	–0.25	–0.05	0.98	0.59	0.48	–0.53	–0.99	–0.41	–0.41	1.22

However, through the *Y*-Score model, we can know that the value for that year is positive, which is consistent with the current operating conditions. Under the *Z* model prediction, Guangzhou Port will be in the range where companies will go bankrupt from 2017 to 2019, which is quite different from the normal operating status of Guangzhou Port.

According to the company's annual report, affected by the epidemic in 2020, the company's asset-liability ratio was 48.28 %, a year-on-year increase of 14.45 %; the current ratio was 0.95, and the quick ratio was 0.8; the total debt was 8.891 billion yuan, of which short-term debt was 3.182-billion-yuan, short-term debt accounts for 35.79 % of total debt. At the same time, short-term debt is relatively large and there is a gap in existing funds. During the reporting period, broad money funds were 2.9-billion-yuan, short-term debt was 3.18-billion-yuan, broad money funds/short-term debt was 0.91, and broad money funds were lower than short-term debt. Performance will improve after 2021, and the Y-score model is in line with the current situation.

According to the table above, the F values of Yantian Port from 2017 to 2019 are all greater than 0.0274, indicating that there is no possibility of bankruptcy. However, through the "*Z*-score model" analysis, Yantian Port III's performance has not rebounded in recent years, and the probability of financial crisis in the future is high, and the possibility of bankruptcy is very high.

4.2. Normalization on the Y-value

The Y-values obtained after normalization are shown below (Figure 1–3).

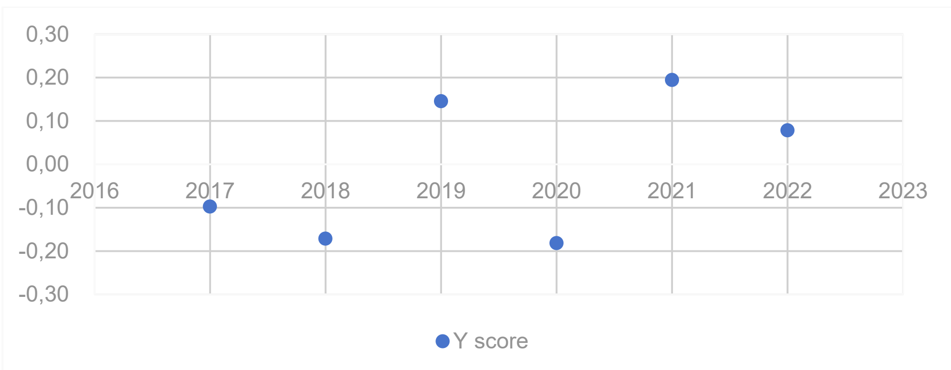

Figure 1. Y-value for Guangzhou Port

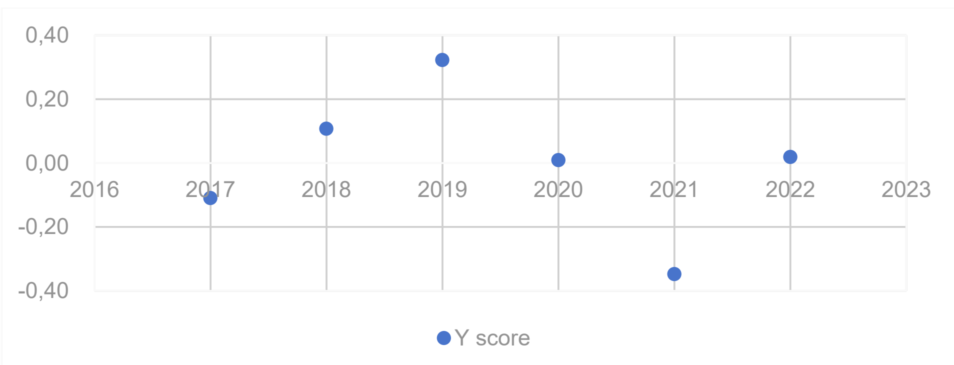

Figure 2. Y-value for Yantian Port

Figure 3. Y-value for Zhuhai Port

However, through the annual reports disclosed by Yantian Port Group from 2017 to 2019 and the financial analysis conducted above, Yantian Port has made relatively good profits in recent years, has no risk of bankruptcy, and its performance has been increasing year by year, so the *Y*-Score model is more in line with the 2017 operating conditions in 2019.

The 2020 annual report shows that the net profit attributable to shareholders of listed companies is 388 million yuan, a year-on-year increase of 8.05 %; the basic earnings per share is 0.19 yuan. And the gross profit margin has remained around 50 % in the past three years. The lower value obtained by the *Y*-score model in 2021 is more consistent with the company's operating conditions that year. Yantian Port completed operating income of 75.4603 million yuan in 2021, a year-on-year decrease of 7.11 %; it achieved a net profit of –32.9462 million yuan, a year-on-year decrease of 19.1306 million yuan.

According to the above table, by comparing the *F* value and *Z* value of Zhuhai Port, the F-value of Zhuhai Port in recent years from 2017 to 2019 has all been greater than 0.0274, indicating that the company has no bankruptcy risk. The Z values are all less than 1.23. Under the prediction of the *Z* model, the company is about to go bankrupt, but according to the annual report disclosed by the company, Zhuhai Port has vigorously developed new energy glass, wind power investment projects, etc. with the support of the government, and has achieved relatively high returns. Even in 2020, amid the COVID-19 epidemic Despite the adverse impact, the company's cargo throughput still reached 139 million tons.

Therefore, the prediction results of "*Z*-score model" and "*F*-score model" are less accurate. In contrast, the *Y*-score model prediction is more accurate. At the same time, in the first half of 2022, Zhuhai Port achieved operating income of 2.790 billion yuan, a year-on-year decrease of 8.85 %, and net profit attributable to shareholders of listed companies was 175 million yuan, a year-on-year decrease of 30.16 %. The prediction of the *Y*-score model is negative, and the prediction is more accurate.

4.3. Main findings

Through specific analysis and calculation.

Firstly, the traditional "*Z*-score model" is not applicable to emerging industry enterprises in the ports of the Guangdong-Hong Kong-Macao Greater Bay Area, and the analysis indicators are too few and the comprehensiveness is too weak. The evaluation model based on the analytic hierarchy process can cover the financial indicators of most port enterprises, and the addition of non-financial indicators in this article can predict the risks of port enterprises more accurately, and enterprises can change according to the differences of individual companies.

Secondly, the *Z*-score model is a functional model for all enterprises and has poor applicability to a certain industry or enterprise. Compared with the AHP, which has a wider range of applications, the AHP is not limited to financial warnings, but can also be applied to other aspects of the company. Finally, the analytic hierarchy process can analyze the problem of a certain indicator independently, but the Z-score model and the F-score model cannot specifically analyze the problem of a certain indicator individually.

In summary, this article has certain reference significance for managers of emerging port industries in the Guangdong-Hong Kong-Macao Greater Bay Area and related stakeholders. Future research can optimize the critical value of the financial early warning model based on more port enterprises, thereby improving the accuracy of financial early warning.

5. Discussion

Firstly, the establishment of a financial early warning system is essential for the development of enterprises. The financial early warning system mainly relies on the analysis of relevant financial indicators, but the analysis of statements and indicators is a lagging means and is easily affected by the subjective judgment of relevant financial personnel, according to studies conducted by Yang et al. [7] and Altman [4].

However, this model can make objective and reliable evaluation of the financial data of the enterprise and the relevant data in the industry through some mathematical calculations, to find out the risk situation of the enterprise at this stage [35, 36], thus avoiding the inadequacy of man-made operations, but also through the form of numerical values to reflect the degree of risk faced by the enterprise, to provide more intuitive data for the relevant management personnel.

Therefore, the backward risk early warning analysis system directly affects the accuracy and precision of enterprise risk prediction [37, 38].

Secondly, port-type enterprises should introduce data visualization technology in the financial risk early warning system, the introduction of the *Y*-score model for analysis, effectively ensuring the timeliness of the risk communication, to avoid the further expansion of the risk from the source.

Thirdly, it breaks the traditional manual financial checking mode, and the combination of charts, text, tables visualization presentation makes the massive data information of the company's expense more intuitive, image, and at the same time, it makes the company's office expenses involved in the department, the maximum amount of the occurrence of the number of people in the department, the monthly expenditure, quarterly expenditure, the year-on-year growth rate, the chain growth rate, and other important data to realize the real-time statistical analysis, and extends the coverage of the monitoring data [39, 40].

The coverage of monitoring data is expanded. Abnormal situations are determined intelligently, and early warnings are automatically issued to relevant departments and financial personnel, prompting the relevant departments and business approvers to pay attention to abnormal risks in a timely manner. Finally, the occurrence of financial crisis is a slow process [40–42].

Fourthly, the occurrence of financial crisis in a company is a slow process, and the stability of the prediction will fluctuate with the business performance, so managers should pay attention to the development of the enterprise in time.

6. Conclusion and Policy Implications

The conjecture of hypothesis *H1* and hypothesis *H2* of this paper is correct. The authors found that the original *F*-score and *Z*-score models are not suitable for the financial forecasting of the new industries of the ports in Guangdong, Hong Kong and Macao Greater Bay Area through research.

The Y-score model obtained through empirical research in this paper is consistent with the financial early warning forecast of the Guangdong-Hong Kong-Macao Greater Bay Area according to the calculation in this article, marine accidents account for the largest proportion in the financial risk early warning model. Therefore, to reduce the risk of bankruptcy of emerging industry enterprises in ports and achieve reasonable and normal operation of enterprises, managers must start to establish Maritime accident early warning mechanism.

Before conducting maritime transportation, managers should conduct feasibility analysis and scientific predictions on maritime weather, transportation routes, etc. Strict supervision will be carried out on projects with large amounts of money and long construction or transportation periods to reduce the possibility of marine accidents. While vigorously developing emerging marine industries, we must also establish methods for handling maritime accidents. Once a maritime accident occurs, companies can actively cooperate with the government to handle scientifically and respond efficiently.

As a high-risk, high-profit enterprise for port enterprises, company managers should take the lead in establishing a risk warning department that combines internal control and financial warning and formulate a standardized process for financial warning based on their own development. Clarify different accounting responsibilities and division of labor, strictly supervise, and implement hierarchical management. The modernized internal control mechanism of an enterprise is an important yardstick for standardizing and restricting corporate behavior. It is also an important means to improve the effectiveness of financial crisis early warning and has positive significance for the realization of the value of the system.

The financial department has established a financial indicator early warning system based on the analytic hierarchy process. When abnormal analysis results occur, the risk warning department needs to cooperate with other departments to investigate hidden dangers. If the abnormal situation is controllable, then the financial warning department should propose corresponding solutions. If the abnormal situation is uncontrollable, department leaders should promptly inform business managers to tighten cash flow, and employees should remain highly alert mentally to prevent financial crises from coming.

Further strengthen the personnel management of risk warning departments. Most corporate financial crises occur because relevant personnel lack crisis awareness. Employees should be trained and assessed regularly. Companies should introduce the Analytical Hierarchy Process into the company's financial early warning model based on their actual situation.

The theoretical knowledge of financial early warning is updated from time to time. Because employees must remain highly vigilant mentally. The normative behavior of employees can coordinate the relationship between financial warning and production and operation, thereby expanding the profitability of the company and prompting the company to create more profits. This model must be written to combine financial early warning with internal control. The effect of risk prevention is reflected in the performance of each participant, and company risks are closely linked to personal development through incentives, punishments, and other methods.

As an important part of local development, emerging port industries are an important source of local fiscal revenue. The government should take the lead in accelerating the construction of a core port enterprise management platform, which will help promote the development of emerging industries in the entire city's ports.

At the same time, enterprises have increased investment in insurance funds for key targets. Form a new model of "Government + Enterprise + Insurance" to prevent corporate crises. Because the development of most emerging port industries requires a large amount of capital flow, financial crises will occur once a company's capital flow breaks.

The capital income generated from operating activities and the expenditures generated from investment activities strengthen the supervision of target companies and provide timely notification of abnormal business that occurs in the company. Under the normal operation of the enterprise, ensure the balance between capital expenditure and income, block unreasonable capital allocation, and improve the efficiency of capital use.

At the same time, a new mechanism covering budget indicators, fund payments, and early warning supervision has been established with enterprises to strictly prevent enterprise managers from tampering with data and whitewashing the calculation results of financial early warning models. Only when financial warning is running can it play its due role.

References

1. Tian, J. Deng, W., Yuan, J. (2023). Evaluation of sports tourism competitiveness of urban agglomerations in Guangdong-Hong Kong-Macao Greater Bay Area. *Heliyon,* Vol. 9, Issue 12, e22780. https://doi.org/10.1016/j.heliyon.2023.e22780

2. Koycungil, A.S., Ozgulbas, N. (2012). Financial early warning system model and data minging application for risk detection. *Expert Systems with Applications,* Vol. 39, Issue 6, 6238–6253. https://doi.org/10.1016/j.eswa.2011.12.021

3. Zhu, R., Chen, F. (2024). Tax and financial credit risks — Empirical evidence from Chinese investment enterprises. *Finance Research Letters,* Vol. 61, 104917. https://doi.org/10.1016/j.frl.2023.104917

4. Altman, E.L. (1968). Financial Rations, Discriminant Analys is and Prediction of Corporate Bankruptcy. *Journal of Finance,* Vol. 9, Issue 4, 589–609. https://doi.org/10.2307/2978933

5. Ohlson, J.A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research,* Vol. 18, No. 1, 109–131. http://dx.doi.org/10.2307/2490395

6. Jing, A. (2023). The technology and digital financial risk management model using intelligent data processing. *Optik,* Vol. 273, 170410. https://doi.org/10.1016/j.ijleo.2022.170410

7. Yang, B., Li, L.X., Ji, H., Xu, J. (2001). An early warning system for loan risk assessment using artificial neural networks. *Knowledge-Based Systems,* Vol. 14, Issue 5–6, 303–306. https://doi.org/10.1016/S0950-7051(01)00110-1

8. Pendharkar, P.C. (2005). A threshold-varying artificial neural network approach for classification and its application to bankruptcy prediction problem. *Computers & Operations Research,* Vol. 32, Issue 10, 2561–2582. https://doi.org/10.1016/j.cor.2004.06.023

9. Lepetit, L., Strobel, F. (2015). Bank insolvency risk and Z-score measures: A refinement. *Finance Research Letters,* Vol. 13, 214–224. https://doi.org/10.1016/j.frl.2015.01.001

10. Ko, Y.-Ch., Hamido, F., Tianrui, Li. (2017). An evidential analysis of Altman Z-score for financial predictions: Case study on solar energy companies. *Applied Soft Computing,* Vol. 52, 748–759. https://doi.org/10.1016/j.asoc.2016.09.050

11. Elliott, R.J., Siu, T.K., Fung, E.S. (2014). A Double HMM approach to Altman Z-scores and credit ratings. *Expert Systems with Applications,* Vol. 41, Issue 4, Part 2, 1553–1560. https://doi.org/10.1016/j.eswa.2013.08.052

12. Chiaramonte, L., Croci, E., Poli, F. (2015). Should we trust the Z-score? Evidence from the European Banking Industry. *Global Finance Journal,* Vol. 28, 111–131. https://doi.org/10.1016/j.gfj.2015.02.002

13. Li, X., Tripe, D., Malone, C., Smith, D. (2020). Measuring systemic risk contribution: The leave-one-out z-score method. *Finance Research Letters,* Vol. 36, 101316. https://doi.org/10.1016/j.frl.2019.101316

14. Zhu, L., Li, M., Metawa, N. (2021). Financial risk evaluation Z-score model for intelligent IoT-based enterprises. *Information Processing & Management,* Vol. 58, Issue 6, 102692. https://doi.org/10.1016/j.ipm.2021.102692

15. Li, H. (2024). Research on financial risk early warning system model based on second-order blockchain differential equation. *Intelligent Decision Technologies,* Vol. 18, No. 1, 327–342. https://doi.org/10.3233/IDT-230318

16. Yi, W. (2012). Z-score model on financial crisis early-warning of listed real estate companies in China: a financial engineering perspective. *Systems Engineering Procedia,* Vol. 3, 153–157. https://doi.org/10.1016/j.sepro.2011.11.021

17. Bouvatier, V., Lepetit, L., Rehault, P.-N., Strobel, F. (2023). Time-varying Z-score measures for bank insolvency risk: Best practice. *Journal of Empirical Finance,* Vol. 73, 170–179. https://doi.org/10.1016/j.jempfin.2023.06.002

18. Tang, P., Tang, T., Lu, C. (2024). Predicting systemic financial risk with interpretable machine learning. *The North American Journal of Economics and Finance,* Vol. 71, 102088. https://doi.org/10.1016/j.najef.2024.102088

19. Wang, J., Zeng, C., Han, X., Ma, Z., Zheng, B. (2023). Detecting early warning signals of financial crisis in spatial endogenous credit model using patch-size distribution. *Physica A: Statistical Mechanics and its Applications,* Vol. 625, 128925. https://doi.org/10.1016/j.physa.2023.128925

20. Ouyang, Z.-S., Yang, X.-Y., Lai, Y. (2021). Systemic financial risk early warning of financial market in China using Attention-LSTM model. *The North American Journal of Economics and Finance,* Vol. 56, 101383. https://doi.org/10.1016/j.najef.2021.101383

21. Zhu, K., Liu, D., Wu, J., Sun, L. (2012). The research of the regional financial risk early-warning model integrating the regression of lagging factors. *AASRI Procedia,* Vol. 1, 428–434. https://doi.org/10.1016/j.aasri.2012.06.067

22. Tarkocin, C., Donduran, M. (2024). Constructing early warning indicators for banks using machine learning models. *The North American Journal of Economics and Finance,* Vol. 69, 102018. https://doi.org/10.1016/j.najef.2023.102018

23. Allaj, E., Sanfelici, S. (2023). Early Warning Systems for identifying financial instability. *International Journal of Forecasting,* Vol. 39, Issue 4, 1777–1803. https://doi.org/10.1016/j.ijforecast.2022.08.004

24. Wu, D., Ma, X., Olson, D.L. (2022). Financial distress prediction using integrated Z-score and multilayer perceptron neural networks. *Decision Support Systems,* Vol. 159, 113814. https://doi.org/10.1016/j.dss.2022.113814

25. Xiao, J., Wen, Z., Jiang, X., Yu, L., Wang, S. (2024). Three-stage research framework to assess and predict the financial risk of SMEs based on hybrid method. *Decision Support Systems,* Vol. 177, 114090. https://doi.org/10.1016/j.dss.2023.114090

26. Meziani, A.S., Rezvani, F. (1990). Using the analytical hierarchy process to select a financing instrument for a foreign investment. *Mathematical and Computer Modelling,* Vol. 13, Issue 7, 77–82. https://doi.org/10.1016/0895-7177(90)90130-F

27. Gonzalez-Urango, H., Mu, E., Ujwary-Gil, A., Florek-Paszkowska, A. (2024). Analytic network process in economics, finance and management: Contingency factors, current trends and further research. *Expert Systems with Applications,* Vol. 237, 121415. https://doi.org/10.1016/j.eswa.2023.121415

28. Nguyen, M.-T., Vu, Q.-H., Truong, H.-H., Nguyen, H.-H. (2023). A comprehensive evaluation of private sector investment decisions for sustainable water supply systems using a fuzzy-

analytic hierarchy process: A case study of Ha Nam province in Vietnam. *Heliyon,* Vol. 9, Issue 9, e19727. https://doi.org/10.1016/j.heliyon.2023.e19727

29. Murugan, S., Kala, T.S. (2023). Large-scale data-driven financial risk management & analysis using machine learning strategies. *Measurement: Sensors,* Vol. 27, 100756. https://doi.org/10.1016/j.measen.2023.100756

30. Conte, D., Bussoli, C., Hemmings, D. (2024). Responsible risk-taking and the CSP-financial performance relation in the banking sector: A mediation analysis. *Research in International Business and Finance,* Vol. 69, 102293. https://doi.org/10.1016/j.ribaf.2024.102293

31. Rahman, M.J., Zhu, H. (2024). Predicting financial distress using machine learning approaches: Evidence China. *Journal of Contemporary Accounting & Economics,* Vol. 20, Issue 1, 100403. https://doi.org/10.1016/j.jcae.2024.100403

32. Yu, H., Su, T. (2024). ESG performance and corporate solvency. Finance *Research Letters,* Vol. 59, 104799. https://doi.org/10.1016/j.frl.2023.104799

33. Prol, J.L., Paul, A. (2024). Profitability landscapes for competitive photovoltaic self-consumption. *Energy Policy,* Vol. 188, 114084. https://doi.org/10.1016/j.enpol.2024.114084

34. Chiaramonte, L., Dreassi, A., Pisera, S., Khan, A. (2023). Mergers and acquisitions in the financial industry: A bibliometric review and future research directions. *Research in International Business and Finance,* Vol. 64, 101837. https://doi.org/10.1016/j.ribaf.2022.101837

35. Zhu, W., Zhang, T., Wu, Y., Li, S., Li, Z. (2022). Research on optimization of an enterprise financial risk early warning method based on the DS-RF model. *International Review of Financial Analysis,* Vol. 81, 102140. https://doi.org/10.1016/j.irfa.2022.102140

36. Chen, L., Zhang, C. (2023). The impact of financial agglomeration on corporate financialization: The moderating role of financial risk in Chinese listed manufacturing enterprises. *Finance Research Letters,* Vol. 58, 104655. https://doi.org/10.1016/j.frl.2023.104655

37. Afshan, S., Leong, K.Y., Najmi, A., Razi, U., Lelchumanan, B., Cheong, C.W.H. (2024). Fintech advancements for financial resilience: Analysing exchange rates and digital currencies during oil and financial risk. *Resources Policy,* Vol. 88, 104432. https://doi.org/10.1016/j.resourpol.2023.104432

38. Saputra, W.H., Prastyo, D.D., Kuswanto, H. (2024). Machine Learning Modeling on Mixed-frequency Data for Financial Growth at Risk. *Procedia Computer Science,* Vol. 234, 397–403. https://doi.org/10.1016/j.procs.2024.03.020

39. Tian, S., Li, S., Gu, Q. (2023). Measurement and contagion modelling of systemic risk in China's financial sectors: Evidence for functional data analysis and complex network. *International Review of Financial Analysis,* Vol. 90, 102913. https://doi.org/10.1016/j.irfa.2023.102913

40. Kandpal, B., Backe, S., del Granado, P.S. (2024). Power purchase agreements for plus energy neighbourhoods: Financial risk mitigation through predictive modelling and bargaining theory. *Applied Energy,* Vol. 358, 122589. https://doi.org/10.1016/j.apenergy.2023.122589

41. Cafferata, A., Casellina, S., Landini, S., Uberti, M. (2023). Financial fragility and credit risk: A simulation model. *Communications in Nonlinear Science and Numerical Simulation,* Vol. 116, 106879. https://doi.org/10.1016/j.cnsns.2022.106879

42. Yang, L., Cui, X., Hamori. S., Cai, X. (2023). Risk spillover from international financial markets and China's macro-economy: A MIDAS-CoVaR-QR model. *International Review of Economics & Finance,* Vol. 84, 55–69. https://doi.org/10.1016/j.iref.2022.11.006

INFORMATION ABOUT AUTHORS

Wang Ying

Post-Graduate Student, Department of Financial and Tax Management, Ural Federal University named after the first President of Russia B. N. Yeltsin, Yekaterinburg, Russia (620002, Yekaterinburg, Mira street, 19); ORCID https://orcid.org/0009-0007-8225-028X e-mail: 1127486294@qq.com

Igor Anatolyevich Mayburov

Doctor of Economics, Professor, Head of the Department of Financial and Tax Management, Ural Federal University named after the first President of Russia B. N. Yeltsin, Yekaterinburg, Russia (620002, Yekaterinburg, Mira street, 19); ORCID https://orcid.org/0000-0001-8791-665X e-mail: mayburov.home@gmail.com

Yulia Vladimirovna Leontyeva

Candidate of Economic Sciences,, Associate Professor, the Department of Financial and Tax Management, Ural Federal University named after the first President of Russia B. N. Yeltsin, Yekaterinburg, Russia (620002, Yekaterinburg, Mira street, 19); ORCID https://orcid.org/0000-0003-4676-9926 e-mail: uv.leonteva@mail.ru

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Оценка рисков банкротства развивающихся портовых отраслей Китая: моделирование и раннее предупреждение

Ван Ин ✉, ***И. А. Майбуров*** , ***Ю. В. Леонтьева***

Уральский федеральный университет
имени первого Президента России Б. Н. Ельцина,
г. Екатеринбург, Россия

✉ *van.in@urfu.ru*

Аннотация. Стремительный рост развивающихся портовых отраслей является важным способом реализации Китаем стратегии «Океанская держава». При этом повышение способности портовых предприятий предотвращать финансовые и налоговые риски является ключевым звеном для ускорения высококачественного развития морской экономики. Целью статьи является построение модели раннего финансового предупреждения для новых портовых отраслей в Гуандуне, Гонконге и районе Большого залива Макао. Гипотеза исследования заключается в том, что исходные модели Z-SCORE и модель F-SCORE не способны точно предсказать финансовый риск морских развивающихся отраслей. Данные типичных портовых предприятий используются для анализа и сравнения финансового риска по разным моделям, после чего проводится оценка рисков банкротства и разрабатывается модель раннего предупреждения. В работе используется метод Дельфи для присвоения весовых коэффициентов различным показателям, а метод аналитического иерархического процесса используется для получения финансовой и налоговой модели раннего предупреждения, применимой к провинциям Гуандун, Гонконг и Макао. Результаты исследования показали, что традиционные модели Z-SCORE и F-SCORE менее применимы к развивающимся отраслям в портах. В работе разработана модель управления финансовыми и налоговыми рисками в соответствии с развитием новых портовых отраслей и обеспечено раннее предупреждение при превышении определенного порога, чтобы помочь предприятиям лучше развиваться. В статье также обосновываются предложения по политике управления рисками в новых портовых отраслях с точки зрения совершенствования системы и связи между государством и предприятиями.

Ключевые слова: портовая развивающаяся отрасль; финансовая модель раннего предупреждения; модель Y-оценки; модель F-оценки; метод Дельфи; метод аналитического иерархического процесса.

Список использованных источников

1. *Tian J. Deng W., Yuan J.* Evaluation of sports tourism competitiveness of urban agglomerations in Guangdong-Hong Kong-Macao Greater Bay Area // Heliyon. 2023. Vol. 9, Issue 12. e22780. https://doi.org/10.1016/j.heliyon.2023.e22780

2. *Koycungil A. S., Ozgulbas N.* Financial early warning system model and data minging application for risk detection // Expert Systems with Applications. 2012. Vol. 39, Issue 6. Pp. 6238–6253. https://doi.org/10.1016/j.eswa.2011.12.021

3. *Zhu R., Chen F.* Tax and financial credit risks — Empirical evidence from Chinese investment enterprises // Finance Research Letters. 2024. Vol. 61. 104917. https://doi.org/10.1016/j.frl.2023.104917

4. *Altman E. L.* Financial Rations, Discriminant Analys is and Prediction of Corporate Bankruptcy // Journal of Finance. 1968. Vol. 9, Issue 4. Pp. 589–609. https://doi.org/10.2307/2978933

5. *Ohlson J. A.* Financial Ratios and the Probabilistic Prediction of Bankruptcy // Journal of Accounting Research. 1980. Vol. 18, No. 1. Pp. 109–131. http://dx.doi.org/10.2307/2490395
6. *Jing A.* The technology and digital financial risk management model using intelligent data processing // Optik. 2023. Vol. 273. 170410. https://doi.org/10.1016/j.ijleo.2022.170410
7. *Yang B., Li L. X., Ji H., Xu J.* An early warning system for loan risk assessment using artificial neural networks // Knowledge-Based Systems. 2001. Vol. 14. Issue 5–6. Pp. 303–306. https://doi.org/10.1016/S0950-7051(01)00110-1
8. *Pendharkar P. C.* A threshold-varying artificial neural network approach for classification and its application to bankruptcy prediction problem // Computers & Operations Research. 2005. Vol. 32, Issue 10. Pp. 2561–2582. https://doi.org/10.1016/j.cor.2004.06.023
9. *Lepetit L., Strobel F.* Bank insolvency risk and Z-score measures: A refinement // Finance Research Letters. 2015. Vol. 13. Pp. 214–224. https://doi.org/10.1016/j.frl.2015.01.001
10. *Ko Y.-Ch., Hamido F., Tianrui Li.* An evidential analysis of Altman Z-score for financial predictions: Case study on solar energy companies // Applied Soft Computing. 2017. Vol. 52. Pp. 748–759. https://doi.org/10.1016/j.asoc.2016.09.050
11. *Elliott R. J., Siu T. K., Fung E. S.* A Double HMM approach to Altman Z-scores and credit ratings // Expert Systems with Applications. 2014. Vol. 41, Issue 4, Part 2. Pp. 1553–1560. https://doi.org/10.1016/j.eswa.2013.08.052
12. *Chiaramonte L., Croci E., Poli F.* Should we trust the Z-score? Evidence from the European Banking Industry // Global Finance Journal. 2015. Vol. 28. Pp. 111–131. https://doi.org/10.1016/j.gfj.2015.02.002
13. *Li X., Tripe D., Malone C., Smith D.* Measuring systemic risk contribution: The leave-one-out Z-score method // Finance Research Letters. 2020. Vol. 36. 101316. https://doi.org/10.1016/j.frl.2019.101316
14. *Zhu L., Li M., Metawa N.* Financial risk evaluation Z-score model for intelligent IoT-based enterprises // Information Processing & Management. 2021. Vol. 58, Issue 6, 102692. https://doi.org/10.1016/j.ipm.2021.102692
15. *Li H.* Research on financial risk early warning system model based on second-order blockchain differential equation// Intelligent Decision Technologies. 2024. Vol. 18, No. 1. Pp. 327–342. https://doi.org/10.3233/IDT-230318
16. *Yi W.* Z-score model on financial crisis early-warning of listed real estate companies in China: a financial engineering perspective // Systems Engineering Procedia. 2012. Vol. 3. Pp. 153–157. https://doi.org/10.1016/j.sepro.2011.11.021
17. *Bouvatier V., Lepetit L., Rehault P.-N., Strobel F.* Time-varying Z-score measures for bank insolvency risk: Best practice // Journal of Empirical Finance. 2023. Vol. 73. Pp. 170–179. https://doi.org/10.1016/j.jempfin.2023.06.002
18. *Tang P., Tang T., Lu C.* Predicting systemic financial risk with interpretable machine learning // The North American Journal of Economics and Finance. 2024. Vol. 71. 102088. https://doi.org/10.1016/j.najef.2024.102088
19. *Wang J., Zeng C., Han X., Ma Z., Zheng B.* Detecting early warning signals of financial crisis in spatial endogenous credit model using patch-size distribution // Physica A: Statistical Mechanics and its Applications. 2023. Vol. 625. 128925. https://doi.org/10.1016/j.physa.2023.128925
20. *Ouyang Z.-S., Yang X.-Y., Lai Y.* Systemic financial risk early warning of financial market in China using Attention-LSTM model // The North American Journal of Economics and Finance. 2021. Vol. 56. 101383. https://doi.org/10.1016/j.najef.2021.101383
21. *Zhu K., Liu D., Wu J., Sun L.* The research of the regional financial risk early-warning model integrating the regression of lagging factors // AASRI Procedia. 2012. Vol. 1. Pp. 428–434. https://doi.org/10.1016/j.aasri.2012.06.067
22. *Tarkocin C., Donduran M.* Constructing early warning indicators for banks using machine learning models // The North American Journal of Economics and Finance. 2024. Vol. 69. 102018. https://doi.org/10.1016/j.najef.2023.102018

23. *Allaj E., Sanfelici S.* Early Warning Systems for identifying financial instability // International Journal of Forecasting. 2023. Vol. 39, Issue 4. Pp. 1777–1803. https://doi.org/10.1016/j.ijforecast.2022.08.004

24. *Wu D., Ma X., Olson D. L.* Financial distress prediction using integrated Z-score and multilayer perceptron neural networks // Decision Support Systems. 2022. Vol. 159. 113814. https://doi.org/10.1016/j.dss.2022.113814

25. *Xiao J., Wen Z., Jiang X., Yu L., Wang S.* Three-stage research framework to assess and predict the financial risk of SMEs based on hybrid method // Decision Support Systems. 2024. Vol. 177. 114090. https://doi.org/10.1016/j.dss.2023.114090

26. *Meziani A. S., Rezvani F.* Using the analytical hierarchy process to select a financing instrument for a foreign investment // Mathematical and Computer Modelling. 1990. Vol. 13, Issue 7. Pp. 77–82. https://doi.org/10.1016/0895-7177(90)90130-F

27. *Gonzalez-Urango H., Mu E., Ujwary-Gil A., Florek-Paszkowska A.* Analytic network process in economics, finance and management: Contingency factors, current trends and further research // Expert Systems with Applications. 2024. Vol. 237. 121415. https://doi.org/10.1016/j.eswa.2023.121415

28. *Nguyen M.-T., Vu Q.-H., Truong H.-H., Nguyen H.-H.* A comprehensive evaluation of private sector investment decisions for sustainable water supply systems using a fuzzy-analytic hierarchy process: A case study of Ha Nam province in Vietnam // Heliyon. 2023. Vol. 9, Issue 9. e19727. https://doi.org/10.1016/j.heliyon.2023.e19727

29. *Murugan S., Kala T. S.* Large-scale data-driven financial risk management & analysis using machine learning strategies // Measurement: Sensors. 2023. Vol. 27. 100756. https://doi.org/10.1016/j.measen.2023.100756

30. *Conte D., Bussoli C., Hemmings D.* Responsible risk-taking and the CSP-financial performance relation in the banking sector: A mediation analysis // Research in International Business and Finance. 2024. Vol. 69. 102293. https://doi.org/10.1016/j.ribaf.2024.102293

31. *Rahman M. J., Zhu H.* Predicting financial distress using machine learning approaches: Evidence China // Journal of Contemporary Accounting & Economics. 2024. Vol. 20, Issue 1. 100403. https://doi.org/10.1016/j.jcae.2024.100403

32. *Yu H., Su T.* ESG performance and corporate solvency // Finance Research Letters. 2024. Vol. 59. 104799. https://doi.org/10.1016/j.frl.2023.104799

33. *Prol J. L., Paul A.* Profitability landscapes for competitive photovoltaic self-consumption // Energy Policy. 2024. Vol. 188. 114084. https://doi.org/10.1016/j.enpol.2024.114084

34. *Chiaramonte L., Dreassi A., Pisera S., Khan A.* Mergers and acquisitions in the financial industry: A bibliometric review and future research directions // Research in International Business and Finance. 2023. Vol. 64. 101837. https://doi.org/10.1016/j.ribaf.2022.101837

35. *Zhu W., Zhang T., Wu Y., Li S., Li Z.* Research on optimization of an enterprise financial risk early warning method based on the DS-RF model // International Review of Financial Analysis. 2022. Vol. 81. 102140. https://doi.org/10.1016/j.irfa.2022.102140

36. *Chen L., Zhang C.* The impact of financial agglomeration on corporate financialization: The moderating role of financial risk in Chinese listed manufacturing enterprises // Finance Research Letters. 2023. Vol. 58. 104655. https://doi.org/10.1016/j.frl.2023.104655

37. *Afshan S., Leong K. Y., Najmi A., Razi U., Lelchumanan B., Cheong C. W.H.* Fintech advancements for financial resilience: Analysing exchange rates and digital currencies during oil and financial risk // Resources Policy. 2024. Vol. 88. 104432. https://doi.org/10.1016/j.resourpol.2023.104432

38. *Saputra W. H., Prastyo D. D., Kuswanto H.* Machine Learning Modeling on Mixed-frequency Data for Financial Growth at Risk // Procedia Computer Science. 2024. Vol. 234. Pp. 397–403. https://doi.org/10.1016/j.procs.2024.03.020

39. *Tian S., Li S., Gu Q.* Measurement and contagion modelling of systemic risk in China's financial sectors: Evidence for functional data analysis and complex network // International Review of Financial Analysis. 2023. Vol. 90. 102913. https://doi.org/10.1016/j.irfa.2023.102913

40. *Kandpal B., Backe S., del Granado P. S.* Power purchase agreements for plus energy neighbourhoods: Financial risk mitigation through predictive modelling and bargaining theory // Applied Energy. 2024. Vol. 358. 122589. https://doi.org/10.1016/j.apenergy.2023.122589

41. *Cafferata A., Casellina S., Landini S., Uberti M.* Financial fragility and credit risk: A simulation model // Communications in Nonlinear Science and Numerical Simulation. 2023. Vol. 116. 106879. https://doi.org/10.1016/j.cnsns.2022.106879

42. *Yang L., Cui X., Hamori S., Cai X.* Risk spillover from international financial markets and China's macro-economy: A MIDAS-CoVaR-QR model // International Review of Economics & Finance. 2023. Vol. 84. Pp. 55–69. https://doi.org/10.1016/j.iref.2022.11.006

ИНФОРМАЦИЯ ОБ АВТОРАХ

Ин Ван

Аспирант кафедры финансового и налогового менеджмента Уральского федерального университета имени первого Президента России Б. Н. Ельцина, г. Екатеринбург, Россия (620002, г. Екатеринбург, ул. Мира, 19); ORCID https://orcid.org/0009-0007-8225-028X e-mail: 1127486294@qq.com

Майбуров Игорь Анатольевич

Доктор экономических наук, профессор, заведующий кафедрой финансового и налогового менеджмента Уральского федерального университета имени первого Президента России Б. Н. Ельцина, г. Екатеринбург, Россия (620002, г. Екатеринбург, ул. Мира, 19); ORCID https://orcid.org/0000-0001-8791-665X e-mail: mayburov.home@gmail.com

Леонтьева Юлия Владимировна

Кандидат экономических наук, доцент кафедры финансового и налогового менеджмента Уральского федерального университета имени первого Президента России Б. Н. Ельцина, г. Екатеринбург, Россия (620002, г. Екатеринбург, ул. Мира, 19); ORCID https://orcid.org/0000-0003-4676-9926 e-mail: uv.leonteva@mail.ru

ДЛЯ ЦИТИРОВАНИЯ

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