Financial risk warning of listed real estate companies in China.

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วิธีหลักของการวิเคราะห์นี้รวมถึงการวิเคราะห์องค์ประกอบหลักและการถดถอยโลจิสติกแบบไบนารี และสาระสำคัญของการวิจัยคือการทำนายและค้นหาว่าปัจจัยทางการเงินใดที่จะนำไปสู่ความเสี่ยงทางการเงินและสินเชื่อของบริษัทอสังหาริมทรัพย์ บทความนี้กล่าวถึงบริษัทอสังหาริมทรัพย์ที่จดทะเบียนในกระดานหลักของจีนในตลาดหุ้น A และช่วงการวิเคราะห์ข้อมูลทางการเงินอยู่ระหว่างปี 2014 ถึง 2020 จากการวิเคราะห์เชิงประจักษ์จะพบว่าอัตรากำไรเงินสด อัตรากำไรจากการขาย อัตราเงินสดจากการขาย และอัตรากำไรจากการดำเนินงานมีผลกระทบมากที่สุดต่อความถูกต้องของการเตือนล่วงหน้าทางการเงิน สุดท้าย อัตราความแม่นยำของแบบจำลองการเตือนล่วงหน้าทางการเงินที่ได้จากการวิเคราะห์ตัวบ่งชี้ทั้งสองนี้ถึง 91.3% ซึ่งบ่งชี้ว่าแบบจำลองนี้เหมาะสำหรับการตรวจวัดการเตือนล่วงหน้าทางการเงินที่แม่นยำ

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The main methods of this analysis include principal component analysis and binary logistic regression, and the essence of the study is to predict and find out which financial factors will lead to the financial and credit risks of real estate companies. This paper examines the real estate companies listed on the main board of China in the A-share market, and the financial data analysis period is from 2014 to 2020. Through empirical analysis, it can be found that cash profit rate, sales profit rate, sales cash rate and operating profit rate have the greatest impact on the accuracy of financial early warning. Finally, the accuracy rate of the financial early warning model obtained by analyzing these two indicators reaches 91.3%, indicating that the model is suitable for accurate measurement of financial early warning.

Field of Study:	Business and Managerial Economics	Student's Signature ....
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1. Introduction

China's real estate market has experienced the "golden period" of rapid development in the past two decades and record high housing prices. Under the guidance of policies such as deleveraging at the national level and "housing to live without speculation" since the fourth quarter of 2016, financing channels such as development loans for real estate enterprises, corporate bonds and non-standard financing development loans have been tightened successively, and financing costs have continued to rise.

Based on the inherent operation mode of the real estate industry and the upcoming peak of credit debt repayment, the credit default risk of real estate enterprises, especially the short-term debt repayment risk, has become the focus of the real estate market, which is mainly reflected in the following aspects. Credit risk is used by investors and regulators to measure the development of the company. On the one hand, the regulator will judge whether it will have a greater impact on the real estate market through the company's credit risk status, and on the other hand, investors will judge whether it is suitable for investment and the strength of investment through credit risk judgment.

This paper summarizes the previous scholar's research, compares several different methods for financial early warning and the reasons for choosing binary logistic regression. Before the empirical analysis, data collection and the determination of indicators are carried out. In empirical analysis, principal component analysis is first used, and finally binary logistic regression is carried out. The main contribution of this paper is that through the combination of principal component analysis and binary logistic regression analysis, it is different from previous studies in the selection of financial indicators and the final influencing factors.

2. Credit Risk

2.1 Types and Concept Definition of Credit Risk

From the classification of credit risk, systematic risk and unsystematic risk are two common ways. Systemic risks cannot be transferred by the will of individuals or changed by the situation of individual companies. There are many types of systemic risks, including the need for external economic irresistible factors, as well as the impact of politics and economic cycles. For a single company, these risks always exist and are uncontrollable. Unsystematic risk refers to the losses and risks caused by the borrower's lack of willingness or ability to perform the contract due to industry or company factors. Politics and other factors affecting financial variables are irrelevant. This inherent uncertainty originates from the economic system and is caused by the subjective decision-making and information asymmetry of participants in the game. Whether listed real estate companies will default is closely related to their own management level, product competitiveness, capital structure rationality and other factors. This paper mainly studies the unsystematic credit risk of listed real estate companies. If there are major systemic risks such as war, the company's credit status is bound to be affected.

2.2 Characteristics of credit risk

The distribution of credit risk is asymmetric. Previous research has found that the return distribution curve of credit risk is not a normal distribution, and there is a relatively obvious thick-tailed feature on the left side, which is inconsistent with many other distribution curves. The reason for the thick-tailed feature on the left side of the curve may be that default events do not occur frequently and are low-probability events; therefore, credit risk does not necessarily show a normal distribution and tends to have a certain degree of skewness and left-sided fat tail phenomenon.

Credit risk is easily affected by the moral level. Since the debtor has a certain information advantage in lending, the loss of the creditor will be greatly affected by the debtor's moral level. For example, when small and medium-sized companies apply for loans from banks, they use the less risky scheme as an excuse, when in fact they implement another higher risk scheme. As far as real estate listed companies are concerned, not only do they need to be ethically restrained, but the China Securities Regulatory Commission will also closely supervise them. Before a listed real estate company obtains the required assets during the financing process, it must report to the local securities regulatory agency and obtain approval and need to make an announcement on the company's official website, the website of the China Securities Regulatory Commission and other important websites in a timely manner and explain in detail to the public and investors Changes in the use of funds in the next financing. Credit risk is somewhat predictable. A subject with a good credit status has a better credit rating in the future transaction process; conversely, a subject with a poor credit status is more inclined to default in future transactions. For listed real estate companies, banks also consider the company's previous credit status before approving medium and long-term loans. Therefore, fully understanding the characteristics of the credit risk of real estate enterprises is conducive to preventing the losses of investors and creditors in a timely manner.

2.3 Information asymmetry theory

The theory of information asymmetry states that different market entities have different degrees of mastery of information, and the party with more information is in a more favorable position than the party with poor information. On the one hand, due to the separation of management rights and ownership, there is a difference in the sufficiency of information held by management and owners, resulting in information asymmetry between managers and owners. On the other hand, potential investors, creditors, and other stakeholders have very limited company information, and their investment decisions are often based on the company's public information, and the company's management is likely to provide false or watery information that tends to benefit the company. It is difficult for external users to distinguish between financial and non-financial information. Therefore, the problem of information asymmetry often makes investors or investment institutions make wrong investment decisions.

To reduce this problem of information asymmetry, the party with more information needs to actively transmit more information to external information users. The company can actively disclose audited accounting information, balance sheet, income statement, cash flow table and other related information, to send more signals to investors or investment institutions to enhance their understanding. In addition, external information users need to conduct a comprehensive analysis of financial information and non-financial information such as cash flow, financial risk, and operational risk, to judge the level of credit risk of an enterprise, and to improve the accuracy of investment decisions. Therefore, how to synthesize various information to judge the quality of financial information is very important for stakeholders and investors.

2.4 Research methods of credit risk

2.4.1 Qualitative research methods

The expert experience method is mainly used in qualitative analysis. Expert experience method experts are based on their own experience, combined with the enterprise's ability, quality and capital. It is a method of evaluating characteristics, among which the most common is 5C analysis method (5C are Company, Collaborators, Customers, Competitors, and Context.), which mainly qualitatively analyzes the credit status of borrowers to judge their willingness and ability to repay. 5C analysis method is also a standard to analyze customers' credit status from five perspectives: personal ability, capital status, assets that the company can use as collateral, economic environment, and personal quality. However, experts' judgments are highly subjective, so the evaluation results are often not convincing (Summers et al., 2004).

2.4.2 Quantitative research methods

There are many quantitative research methods. For example, American scholar Halligan (1966) is the first person to use it in the field of financial data and credit research. The OLS regression method has been used to study the correlation. The follow-up research methods are mainly divided into the following categories.

The first method is linear probability model. The use of this model is relatively simple, but in terms of fitting value, its value may not be between 0 and 1, which is contrary to the viewpoint put forward by probability theory (Loeve, 2017), which leads to subsequent scholars rarely using this model in the research process. Second, the Z model proposed by the British scholar Altman (1968) is another risk judgment method based on multilinear discriminant analysis. In his research, he finds that the liquidity and profitability of the financial sector directly affect whether the borrower will default. Third, Masood et al. (2012) has selected 148 bank managers as the respondents by using binary logistic regression analysis. These respondents are mainly engaged in credit risk work. Specific banks are divided into Islamic banks and non-Islamic banks. The study has found that the factors of people and experience will lead to the error of risk prediction.

The above methods inevitably have limitations, but from the perspective of predicting risk, they are applicable. Jayadevan (2006), a French scholar, has selected 112 companies to study the finance and financial field of defaulting companies. Through the research, it is found that the current ratio and operating profit ratio have an effective role in judging whether the company defaults. Giordano et al. (2014) mainly use spline function to analyze the relationship between corporate bankruptcy, corporate earnings, and liquidity of listed companies in the logistics industry. Through nonlinear relationship, it is found that the prediction of bankruptcy is greatly improved compared with the standard logical model.

In the analysis of this paper, the analysis is mainly based on binary logistic regression to predict credit risk, mainly based on the research of Ingrassia and Costanzo (2005).

2.5 Research on the credit risk of real estate companies

There are abundant research results on credit risk and financial early warning of listed real estate companies in both China and the West.

2.5.1 Researches

In China. Jin and Zeng (2007) studied the financial risk impact mechanism of listed real estate companies based on Cox survival model, comprehensively considering financial indicators and non-financial indicators, and dynamically considering the company's operating conditions. The empirical results show that the model has good applicability, and that interest income and real estate scale are two important impact indicators. Qiu Xiaolong and Ming (2010) analyzed the factors affecting the credit of real estate companies, established an index system on this basis, and used the back propagation neural network method to evaluate 10 listed real estate companies in Shanghai. There is little difference between the two methods. However, considering the small sample size of this study, it does not meet the sample size requirement of the back propagation neural network model. The selection of indicators is highly subjective, and statistical methods do not exclude the correlation between indicators, so it is difficult to ensure the independence and integrity of indicators.

Chen and Chu (2014). analyze Chinese listed companies from 2017 to 2012 and find that the asset liability ratio is an important factor that will lead to the increase of default risk, followed by the company size. Saunders (2014) has introduced foreign real estate credit risk management models and put forward innovative suggestions to improve the credit system of Chinese real estate companies. Antoniadis (2021) has chosen logistic regression model to conduct credit evaluation research on Chinese real estate enterprises, and found that indicators such as net profit rate, accounts receivable turnover rate, main business profit rate, land reserve and project market evaluation can effectively reflect the repayment ability and credit degree of enterprises and have a great impact on the probability of default of real estate enterprises. Zhou et al. (2021) analyze the subprime mortgage crisis in the United States and the current situation of China's real estate development. They find that at the macro level, preventing real estate financial risks needs to be carried out from two aspects: the monetary system and the financial system. From the perspective of monetary system, it is necessary to implement a relatively tight monetary policy. From the perspective of finance, it is necessary to pay attention to the main financial indicators of listed real estate companies, including asset liability ratio, earnings per share and growth rate.

2.5.2 Foreign researches

Western scholars have done a lot of research is on credit risk and financial early warning of listed real estate companies. American scholar Davis and Zhu (2009) evaluate the impact of changes in real estate prices on bank behavior and performance. The results show that real estate prices have a significant impact on bank behavior. With the rise of real estate prices, banks will issue more loans or relax loan conditions. The extent of this impact is related to the size of banks, the direction of real estate price trends and regional factors. These research conclusions have certain significance for risk managers, regulators, and monetary policy makers.

Akin et al. (2014) has proposed a real estate company lending credit evaluation index system including seven indicators: total asset profit margin, operating asset ratio, total asset turnover, asset liability ratio, main business clarity ratio, completed area ratio and sales area ratio, which considered the characteristics of the real estate industry, but relatively speaking, the number of indicators is too small to fully reflect the financial and credit status of enterprises.

Luqman (2017), a British scholar, has chosen companies listed on the Indonesian stock exchange from 2011 to 2015 to analyze the company's financial early warning. Through research, it is found that profitability and asset growth rate would play a significant role in the company's financial early warning. Sharma (2018) has chosen India's real estate market as the main research object and selected 125 companies listed on the Mumbai stock exchange (BSE) from 2009 to 2015. It is found that the profitability of listed companies, the size of the company, the time of establishment, and the strength of solvency are all important factors that determine the company's credit risk.

Rashidfarokhi et al. (2018) have selected Nordic companies when studying the sample of listed real estate companies. It is found that the reputation of enterprises is an important indicator that affects the credit risk of enterprises. Patel and Valdis (2006) study 112 real estate companies in the UK from 1980 to 2001 and find that high leverage and relatively high asset volatility are the two most important indicators of credit risk.

Nguyen a et al. (2019) have taken the real estate listed companies in Vietnam stock exchange to examine the impact of solvency on the bankruptcy risk of real estate companies. There are 45 listed companies selected, accounting for 81.82% of all listed companies. In their analysis, they use the logit model to find that the ratio of operating cash flow to average total liabilities and the ratio of net working capital to total assets affect a firm's bankruptcy risk. However, the influence of the other two factors in the study is not significant. The first is the ratio of owners' equity to long-term debt, and the second is the ratio of current assets to current liabilities. Anisa Dwiantari and Artini (2021) have found that liquidity and profitability are important factors affecting the financial distress of enterprises of listed companies in Indonesia. The results show that profitability would play an important role in the risk of enterprises, but the size of enterprises would not. Ashkin et al. (2021) use Eviews statistics and multiple regression analysis methods to analyze the impact of financial factors on the credit risk of real estate companies, selects 25 real estate and construction companies through purpose sampling, and finally finds that solvency and profitability have the greatest impact.

Therefore, after analyzing and comparing the above research methods, this analysis mainly uses principal component analysis and logistic regression to study the risks of Chinese real estate enterprises.

2.6 Research review

Domestic and foreign scholars' research is on credit risk and financial early warning evaluation are mainly achieved by designing the evaluation index system and improving the evaluation model. The research results are relatively rich, but there is still room for further improvement.

In the research of evaluation indicators, scholars have defined the credit risk of enterprises in many perspectives is from only considering the repayment ability of enterprises in the early stage to incorporating the repayment willingness of enterprises into the index system in the late stage, and from only considering financial indicators in the early stage to comprehensively considering financial and non-financial indicators in the late stage. Among them, financial indicators mainly focus on the dimensions of solvency, profitability, operating capacity and growth capacity, while non-financial indicators mainly include enterprise management level, macroeconomic environment, industry development, enterprise credit and personal credit of managers. However, most non-financial indicators are only at the level of normative analysis, and few scholars have conducted quantitative empirical analysis on them. In addition, some scholars believe that the financial crisis is one of the reasons for the increase of credit risk, and the corporate governance structure system is closely related to financial risk, but few studies have examined the impact of corporate governance factors on credit risk.

Regarding the logit model, many scholars have analyzed financial early warning and credit risk from the financial perspective and obtained a large number of research conclusions. However, there are still differences in these conclusions. The controversy of these conclusions lies in whether different financial indicators will have an impact on financial early warning and credit risk, and how the final impact effect will be. This is also the focus of this study and based about Chinese listed companies, we need to choose specific financial indicators from the perspectives of profitability, operating capacity, solvency and development capacity, and finally draw a conclusion.

3. Research Methods and Models

3.1 Data description

First, in terms of the use of the database, the WIND database is the main data source for this analysis and the period of study is from 2014 to 2020. In terms of the specific time for selecting research companies, combined with the amount of data, the difficulty of data collection, and the number of companies, some companies with incomplete data are excluded. Of course, companies that is first listed after 2014 are excluded. Therefore, there are 58 listed companies selected as sample.

Dependent variables are the standard for dividing risk and non-risk is mainly through ST and non-ST signs. For China's listed companies, ST (“Special Treatment”) refers to the policy of China's Shanghai and Shenzhen stock exchanges to warn that the stocks of listed companies have abnormal financial or other conditions. ST will be added before the stock name as a symbol to warn investors to invest cautiously in such stocks. Besides, if the following situations occur, the company will become an ST company and face the risk of delisting. First, if the net profit of the company's audit results in the last two fiscal years is negative. Second, from the perspective of shareholders' equity and registered capital, if the net asset per share is lower than the par value of the stock, ST is required. Third, in the audit report, the audit opinions issued by certified public accountants are unable to be issued or show negative opinions. Fourth, the financial situation is considered abnormal by the stock exchange or the China Securities Regulatory Commission. When these situations occur, the company will become an ST company. In this case, it can be considered that the company's financial situation is poor and faces credit risk.

SPSS is the main analysis software. For analysis software identification, ST companies are assigned values of 1 and non-ST companies are assigned values of 0, this is also more convenient for logit regression analysis.

This paper follows Roa et al (2019) research, for the selection of independent variables, there are 58 China's A-share market companies and each company observation for 7 years. The mainly financial indicators as follows Table 1.

Table1. Initial Financial Indicators

First-level indicator	**Secondary indicators**	**Three-level indicators**
Early warning indicators	Profitability	Return on equity
		Net asset interest rate
		Sales margin
		Gross profit margin
		Operating profit margin
		Cost profit margin
	Solvency	Current ratio
		Quick ratio
		Equity ratio
		Net gearing ratio
		Cash ratio
	Development ability	Operating income growth rate

		Net profit growth rate
		Net asset growth rate
		Total asset growth rate
	Operating capacity	Accounts receivable turnover
		Current asset turnover
		Fixed asset turnover
		Total asset turnover
	Cash flow capacity	Sales cash ratio
		Total asset cash recovery rate

3.2 Logistic regression model

The logistic regression model is a generalized linear regression analysis model, which can better overcome the requirement for the continuity of variables but may not satisfy the basic assumption of the normal distribution of the sample data. Using the Sigmoid function (a mathematical function which has a characteristic S-shaped curve), we can map any real value to a value between 0 and 1, and then use a threshold classifier to convert the value between 0 and 1 to 0 or 1, cleverly transforming the relationship between the dependent variable and the independent variable.

To find the probability of an event, the dependent variable of the research problem is the credit risk status of listed real estate companies and the value of risky (ST) companies is set to 1 and non-risky (non-ST) companies is set to 2. Logistic regression model can be either binary or multi-category. For the binary logistic regression model, it is assumed that p is the probability of the occurrence of credit risk of listed real estate companies, and its value range is (0, 1), and X is the influencing factors of the company's credit level, the relationship between p and x is:

$$\mathrm{p} = \frac{e^{a+\beta x+e}}{1+ e^{a+\beta x+e}}$$

The function formula of Logistic is:

$$\ln\frac{p}{1-p} = \alpha + \sum_{i=1}^{n} \beta_1 X_1 + e$$

where β is the regression coefficient of the variable, α is the intercept term, and e is the residual term.

3.3 Significant difference test

This test is mainly carried out by Kolmogorov-Smirnov test (K-S test) and Mann-Whitney U test. The purpose of the test is to test whether a group of samples come from a certain probability distribution.

3.3.1 Kolmogorov-Smirnov Test

Kolmogorov Smirnov test (K-S test) can be used to test whether the distribution of a single population obeys the distribution of a certain theory. It can also test between the distribution of the two populations. The original assumption is that there is no significant difference in the distribution of the two populations from which the two groups of independent samples came.

It can be found from Table 2 that all 21 financial indicators obey the normal distribution and do not need to be eliminated.

Table 2. Kolmogorov-Smirnov Test Result

	Normal parameters [a, b]		Most extreme difference			Test statistics	Asymptotic significance (Two-tailed)
	Average value	Standard deviation	Absolute	Just	Burden		
Equity ratio	326.31	307.44	0.157	0.120	-0.157	0.157	0.000-
Cost profit margin	21.45	42.42	0.264	0.174	-0.264	0.264	0.000-
Inventory							

turnover	0.74	4.65	0.444	0.444	-0.438	0.444	0.000-
Fixed asset turnover	64.13	146.24	0.331	0.309	-0.331	0.331	0.000-
Net profit growth rate	24.87	312.65	0.313	0.296	-0.313	0.313	0.000-
Net gearing ratio	349.72	1130.95	0.375	0.239	-0.375	0.375	0.000-
Return on equity	7.87	24.23	0.320	0.201	-0.320	0.320	0.000-
Net asset growth rate	11.02	69.14	0.321	0.286	-0.321	0.321	0.000-
Current ratio	1.88	0.87	0.174	0.174	-0.116	0.174	0.000-
Current asset turnover	0.30	0.22	0.177	0.177	-0.140	0.177	0.000-
Quick ratio	0.66	0.56	0.222	0.222	-0.179	0.222	0.000-
Cash ratio	41.01	53.28	0.246	0.246	-0.238	0.246	0.000-
Sales margin	-4.31	158.77	0.455	0.352	-.455	0.455	0.000-
Gross profit margin	33.61	12.60	0.092	0.092	-.036	0.092	0.000-
Sales cash ratio	-12.39	111.77	0.241	0.174	-0.241	0.241	0.000-
Accounts receivable turnover	15161.89	287.35	0.502	0.502	-0.478	0.502	0.000-
Operating profit margin	1.36	152.30	0.420	0.341	-0.420	0.420	0.000-
Operating income growth rate	25.59	101.74	0.236	0.236	-0.196	0.236	0.000-
Net asset interest rate	2.50	4.55	0.251	0.148	-0.251	0.251	0.000-
Total asset cash recovery rate	1.06	10.83	0.079	0.071	-0.079	0.079	0.000-
Total asset growth rate	16.09	24.89	0.104	0.104	-0.069	0.104	0.000-
Total asset turnover	0.23	0.11	0.074	0.074	-0.040	0.074	0.000-

3.3.2 Mann-Whitney U Test

Mann-Whitney U test is a t-test method for independent samples, which does not require the data to conform to the normal distribution. It is mainly used to test whether there is a significant difference between two populations with the same population mean. The original assumption is that there is no significant difference between the two independent samples.

From the output results of Table 3, there are 5 financial indicators (operating profit rate, operating income growth rate, inventory turnover rate, accounts receivable turnover rate and fixed asset turnover rate) whose p-value is greater than 0.05, they are eliminated, and 18 financial indicators are finally retained.

Table 3. Mann-Whitney U Test Result

Original hypothesis	Significance	Result
In ST category or not, the distribution of equity ratio is the same	0.033	Reject the original hypothesis
In ST category or not, the distribution of cost rate is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of inventory turnover rate is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of fixed asset turnover is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of net profit growth rate is the same	0.068	Keep the original hypothesis
In ST category or not, the distribution of net asset liability ratio is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of return on net assets is the same	0.000	Reject the original hypothesis

In ST category or not, the distribution of net asset growth rate is the same	0.000	Reject the original hypothesis
In ST category or not, the current ratio distribution is the same	0.081	Keep the original hypothesis
In ST category or not, the distribution of current asset turnover is the same	0.000	Reject the original hypothesis
In ST category or not, the quick ratio distribution is the same	0.003	Reject the original hypothesis
In ST category or not, the distribution of cash ratio is the same	0.502	Keep the original hypothesis
In ST category or not, the distribution of net profit margin of sales is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of gross profit margin of sales is the same	0.042	Reject the original hypothesis
In ST category or not, the distribution of sales cash ratio is the same	0.021	Reject the original hypothesis
In ST category or not, the distribution of accounts receivable turnover is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of operating profit margin is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of operating revenue growth rate is the same	0.001	Reject the original hypothesis
In ST category or not, the distribution of net interest rate of assets is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of total asset cash recovery rate is the same	0.069	Keep the original hypothesis

In ST category or not, the distribution of total asset growth rate is the same	0.000	Reject the original hypothesis
In ST category or not, the distribution of total asset turnover is the same	0.000	Reject the original hypothesis

3.4 The principal component analysis

3.4.1 The Kaiser-Meyer-Olkin (KMO) test and Bartlett test

After standardizing the original financial indicator data, the first thing to do is the Kaiser-Meyer-Olkin (KMO) test and Bartlett test. The value of Kaiser-Meyer-Olkin (KMO) mainly reflects the correlation between various financial indicators. The closer the value of KMO is to 1, the more suitable it is for factor analysis. When the value is less than 0.5, it is not suitable for factor analysis. In other words, 0.5 is the critical value of whether it is suitable for factor analysis. When the value of KMO is less than 0.5 or even a non-positive definite matrix appears, it means that it is not suitable for factor analysis. In addition to the requirements for the size of the KMO value, there are also strict requirements for the significance in the Bartlett test. That is, the required value is less than 0.05.

Specifically, it can be found from the Table 4 that the value of KMO is equal to 0.629, and the value is significantly greater than 0.5. In terms of significance, the value is equal to 0.000 (less than 0.05), which also meets the requirements, so factor analysis is suitable for this analysis.

Table 4. The Kaiser-Meyer-Olkin (KMO) and Bartlett's Test Result

KMO Sampling Suitability Quantity.		0.629
Bartlett 's sphericity test	Chi-square last read	3992.712
	Degrees of freedom	153
	Significance	0.000

3.4.2 Determination of main factors

After KMO and Bartlett tests and common factor variance tests, we know that the method of factor analysis is suitable for this analysis, but we cannot determine how many common factors the original financial indicators should be divided into. In this case, it is necessary to determine how many classes of the original financial indicators can be divided into by extracting principal components. Since there may be correlations between the data, they may express the same meaning. It is necessary to reduce the dimensionality of these related data and to use fewer variables to explain most of the variables in the original sample data, these variables are either independent variables or irrelevant variable.

There are two main criteria for the division. In the first aspect, the initial eigenvalues need to be greater than 1, which is the default value of the system and is the most widely used in division criterion. When the value is large, it means that the explanatory power of the factor is also larger, and the smaller the value, the weaker the explanatory power. The second aspect is the requirement for the cumulative contribution rate, and the maximum value of the cumulative contribution rate is also 1, so the requirement for the cumulative contribution rate should be as far as possible, close to 1 (close to or greater than 80%). For both the eigenvalue and the cumulative value, the requirement needs to be met at the same time, which is reasonable in this case. Finally, the 18 financial factors are transformed into 6 new variables to explain the comprehensive indicators. That is, a given set of correlated variables is transformed into another set of uncorrelated variables through linear transformation, and these new variables are arranged in the order of decreasing variance.

The results are shown in Table 5. From the perspective of eigenvalues, all values greater than 1 have 6 components. Judging from the final cumulative contribution rate, the value is 67.135%. Both the eigenvalues and the cumulative contribution rate meet the requirements.

Table 5. Total variance explained

Components	Initial eigenvalues			Extract the load sum of squares			Rotational load sum of squares		
	Total	Percent variance	Cumulative %	Total	Percent variance	Cumulative %	Total	Percent variance	Cumulative %
F1	4.203	23.352	23.352	4.203	23.352	23.352	2.977	16.537	16.537
F2	2.032	11.290	34.642	2.032	11.290	34.642	2.640	14.669	31.206
F3	1.862	10.343	44.985	1.862	10.343	44.985	2.165	12.030	43.235
F4	1.630	9.056	54.041	1.630	9.056	54.041	1.460	8.111	51.347
F5	1.233	6.848	60.888	1.233	6.848	60.888	1.422	7.900	59.246
F6	1.124	6.247	67.135	1.124	6.247	67.135	1.420	7.889	67.135

3.4.3 Factor loading matrix

In the previous analysis, it has been clarified that all financial indicators need to be divided into 6 categories, but it is not clear which financial indicators are included in which category. So we need to classify these financial indicators by factor loading matrix. Component matrix analysis is used to discriminate. The principal component matrix mainly reflects the load values of all the original financial indicators on the six common factors, the results are shown in Table 6.

It should be noted that the specific value of the load can be less than 0, so it is necessary to determine which specific financial indicators belong to. Under the common factor of, it is mainly judged by the size of the absolute value, not the size of the value. The standard for the size of the absolute value is generally considered to be 0.4. When the absolute value is greater than 0.4, it can be classified under the factor of this column. However, when the value of the entire row is less than 0.4, it is necessary to delete the financial indicator where the value of the row is located and restart the factor analysis until each row contains at least one value whose absolute value is greater than 0.4.

Table 6. The rotated component matrix [a]

	Components					
	F1	F2	F3	F4	F5	F6
Equity ratio	-0.655	0.120	-0.091	-0.062	0.130	0.511
Cost profit margin	0.593	0.611	-0.018	0.032	0.425	-0.060
Inventory turnover	-0.050	-0.059	0.549	-0.064	0.017	-0.085
Fixed asset turnover	0.040	0.075	0.038	0.830	-0.065	-0.021
Net gearing ratio	0.528	0.008	-0.080	-0.036	-0.654	0.079
Return on equity	0.849	0.200	0.072	0.028	-0.119	0.050
Net asset growth rate	0.657	0.021	0.022	-0.020	0.124	0.126
Current asset turnover	0.072	0.105	0.903	0.011	-0.038	-0.047
Quick ratio	0.124	-0.076	0.029	0.039	0.201	-0.717
Sales margin	0.171	0.926	0.002	0.045	0.100	0.047
Gross profit margin	0.197	0.144	-0.073	-0.065	0.695	-0.003
Sales cash ratio	-0.110	0.510	0.324	-0.103	-0.106	0.019
Accounts receivable turnover	-0.008	-0.053	-0.015	0.817	0.032	0.127
Operating profit margin	0.156	0.910	-0.014	0.048	0.104	0.027
Operating income growth rate	0.143	-0.062	0.419	0.091	0.219	0.297
Net asset interest rate	0.708	0.406	0.199	0.081	0.365	-0.018
Total asset growth rate	0.297	-0.043	-0.034	0.218	0.126	0.707
Total asset turnover	0.154	0.216	0.835	0.096	-0.091	0.011

Because there is often a certain correlation between variables, the information reflected by all financial factors will overlap. Therefore, to find some uncorrelated comprehensive variables that reflect most of the information contained in the original data and to make these correlation coefficients more significant, the factor loading matrix can be rotated to make the relationship between the original variable and the factor more prominent, thus making the interpretation of the factor easier. The rotation method generally adopts the maximum variance method, which can make each variable have a high load on one factor as much as possible, and a small load on the other factors, to facilitate the classification and interpretation of financial factors.

The results are shown in the Table 7, the 18 financial factors finally can be divided into 6 categories, which are represented by F1, F2, F3, F4, F5, F6, respectively.

Table 7. Classification Result

Factor 1 (F1)	Factor 2 (F2)	Factor 3 (F3)	Factor 4 (F4)	Factor 5 (F5)	Factor 6 (F6)
Equity ratio	Cost profit margin	Inventory turnover	Fixed asset turnover	Net gearing ratio	Quick ratio
Return on equity	Sales margin	Current asset turnover	Accounts receivable turnover	Gross profit margin	Total asset growth rate
Net asset growth rate	Sales cash ratio	Operating income growth rate			
Net asset interest rate	Operating profit margin	Total asset turnover			

3.4.4 Component score coefficient matrix

After knowing that the original independent variable is classified as F1-F6, the specific value of F1-F6 needs to be calculated through a specific formula, so that regression analysis can be carried out with y (the explained variable). The specific formula calculation needs to be obtained through the component score coefficient matrix. The specific results are as shown in Table 8.

Table 8. Component Score Coefficient Matrix

	Components					
	F1	F2	F3	F4	F5	F6
Equity ratio(X1)	-0.261	0.116	-0.008	-0.058	0.103	0.351
Cost profit margin(X2)	0.133	0.146	-0.063	-0.006	0.212	-0.052
Inventory turnover(X3)	-0.033	-0.060	0.273	-0.049	0.045	-0.040
Fixed asset turnover(X4)	-0.044	0.046	-0.014	0.591	-0.072	-0.106
Net gearing ratio(X5)	0.238	0.034	-0.082	-0.056	-0.525	0.070
Return on equity (X6)	0.312	-0.015	-0.017	-0.035	-0.146	0.051
Net asset growth rate(X7)	0.261	-0.113	-0.009	-0.069	0.075	0.114
Current asset turnover(X8)	-0.024	-0.017	0.425	-0.014	-0.015	-0.016
Quick ratio(X9)	0.029	-0.058	0.004	0.093	0.158	-0.514
Sales margin(X10)	-0.070	0.405	-0.069	0.023	-0.076	-0.005
Gross profit margin(X11)	0.044	-0.065	-0.026	-0.063	0.506	0.009
Sales cash ratio(X12)	-0.121	0.255	0.124	-0.072	-0.147	0.006
Accounts receivable turnover(x13)	-0.041	-0.027	-0.021	0.568	0.024	0.006
Operating profit margin(x14)	-0.074	0.401	-0.076	0.028	-0.070	-0.020
Operating income growth rate(x15)	0.047	-0.128	0.215	0.010	0.192	0.224
Net asset interest rate(x16)	0.201	0.022	0.050	0.011	0.203	-0.010
Total asset growth rate(x17)	0.132	-0.110	-0.009	0.060	0.098	0.500

Total asset turnover(x18)	-0.006	0.037	0.378	0.039	-0.079	0.012

The specific formulas are as follows:

$$F1 = -0.261 * X1 + 0.133 * X2 - 0.033 * X3 - 0.044 * X4 + 0.243 * X5 + 0.313 * X6 + 0.260 * X7 - 0.023 * X8 + 0.028 * X9 - 0.070 * X10 + 0.039 * X11 - 0.120 * X12 - 0.041 * X13 - 0.074 * X14 + 0.045 * X15 + 0.199 * X16 + 0.130 * X17 - 0.008 * X18$$

$$F2 = 0.116 * X1 + 0.146 * X2 - 0.060 * X3 + 0.046 * X4 + 0.034 * X5 - 0.014 * X6 - 0.112 * X7 - 0.017 * X8 - 0.058 * X9 + 0.405 * X10 - 0.065 * X11 + 0.255 * X12 - 0.027 * X13 + 0.401 * X14 - 0.128 * X15 + 0.023 * X16 - 0.110 * X17 + 0.037 * X18$$

$$F3 = -0.008 * X1 - 0.063 * X2 + 0.273 * X3 - 0.014 * X4 - 0.083 * X5 - 0.017 * X6 - 0.009 * X7 + 0.425 * X8 + 0.004 * X9 - 0.069 * X10 - 0.025 * X11 + 0.124 * X12 - 0.021 * X13 - 0.076 * X14 + 0.215 * X15 + 0.050 * X16 - 0.009 * X17 + 0.378 * X18$$

$$F4 = -0.058 * X1 - 0.006 * X2 - 0.049 * X3 + 0.591 * X4 - 0.056 * X5 - 0.035 * X6 - 0.069 * X7 - 0.014 * X8 + 0.093 * X9 + 0.023 * X10 - 0.063 * X11 - 0.072 * X12 + 0.568 * X13 + 0.028 * X14 + 0.010 * X15 + 0.011 * X16 + 0.060 * X17 + 0.039 * X18$$

$$F5 = 0.100 * X1 + 0.214 * X2 + 0.044 * X3 - 0.073 * X4 - 0.522 * X5 - 0.143 * X6 + 0.078 * X7 - 0.016 * X8 + 0.158 * X9 - 0.076 * X10 + 0.507 * X11 - 0.148 * X12 + 0.024 * X13 - 0.071 * X14 + 0.193 * X15 + 0.205 * X16 + 0.099 * X17 - 0.080 * X18$$

$$F6 = 0.350 * X1 - 0.052 * X2 - 0.040 * X3 - 0.106 * X4 + 0.071 * X5 + 0.052 * X6 + 0.115 * X7 - 0.017 * X8 - 0.514 * X9 - 0.005 * X10 + 0.009 * X11 + 0.006 * X12 + 0.006 * X13 - 0.020 * X14 + 0.224 * X15 - 0.010 * X16 + 0.500 * X17 + 0.012 * X18$$

4. Research results

4.1 Likelihood ratio test

Through the above Component score coefficient matrix analysis, the relationship between the specific values of F1-F6 and independent variables and dependent variables is calculated, so that y (explained variable) can be used for regression analysis. Likelihood ratio test is used to verify whether the model is applicable. Its essence is to compare the maximum value of likelihood function under constrained conditions with the maximum value of unconstrained likelihood function. Among the main indicators to measure whether the model is applicable, we mainly look at the p-value. The results are shown in Table 9, the p-value is less than 0.05, it can be considered that the logit model is effective.

Table 9. Likelihood Ratio Test

Model	-2x log-likelihood	Chi-square value	df	P-value	AIC value	BIC value
Intercept only	325.766					
Final model	220.564	105.202	6	0.000	234.564	262.609

4.2 Regression results

It can be seen from the table 10: ln (p/1-p) =2.266 + 0.580*F6-0.401*F5 + 1.745*F4 + 0.253*F3 + 2.053*F2 + 1.919*F1 (where p is the probability that the company is ST and 1-p is the probability that the company is non-ST). It can be found from the table that F3 (inventory turnover, current asset turnover, operating income growth rate, total asset turnover), F4 (fixed asset turnover, net gearing ratio), and F5 (accounts receivable turnover, gross profit margin) have no significant effect on the dependent variable. However, F1 (equity ratio, return on equity, net asset growth rate, net asset interest rate) has a positive effect on the dependent variable with a coefficient of 1.919, and F2 (cost profit margin, sales margin, sales cash ratio, operating profit margin) has a positive effect on the dependent variable with a coefficient of 2.053. Moreover, the effect of F6 (quick ratio, total asset growth rate) on the dependent variable is positive with a coefficient value of 0.58. The dependent variable means the credit risk.

Table 10. Regression results

	Regression coefficients	Standard error	Z-value	Wald χ^2	P-value	OR value	OR value 95% CI
Intercept	2.266	0.269	8.42	70.903	0	9.64	5.689 ~ 16.336
F1	1.919	0.581	3.302	10.901	0.001	6.816	2.181 ~ 21.297
F2	2.053	0.505	4.062	16.498	0	7.788	2.893 ~ 20.970
F3	0.253	0.181	1.397	1.951	0.162	1.288	0.903 ~ 1.836
F4	1.745	0.978	1.784	3.182	0.074	5.725	0.842 ~ 38.944
F5	-0.401	0.367	-1.091	1.19	0.275	0.67	0.326 ~ 1.376
F6	0.58	0.212	2.73	7.45	0.006	1.786	1.178 ~ 2.709
McFadden R square: 0.323							
Cox & Snell R-square: 0.228							
Nagelkerke R square: 0.414							

4.3 Forecast results

The fit quality of the model is judged by the model prediction accuracy. As can be seen from the Table 11, the overall prediction accuracy of the research model is 91.13%, which is relatively high. Therefore, it can be shown that the regression model is a more accurate means to measure the financial crisis early warning of real estate enterprises. That is, the overall prediction accuracy rate reached 91.13%, and the prediction error rate just reached 8.87%.

Table 11. Forecast result

		Predictive value		Prediction accuracy	Prediction error rate
		0	1		
Actual value	0	22	34	39.29%	60.71%
	1	2	348	99.43%	0.57%
Summary				91.13%	8.87%

5. Research Implications

This analysis mainly selects Chinese listed real estate companies for research and with more and more Chinese real estate listed companies experiencing financial crisis, it is important to study which factors will affect the financial early warning and credit risk of Chinese real estate listed companies. In the specific analysis, this paper finally selected 18 financial indicators, classified these 18 financial indicators by using the principal component analysis method and then through logistic regression analysis, it find that the regression coefficient of cash profit rate, sales profit rate, sales cash rate and operating profit rate reached 2.053, so the prediction of financial early warning and credit risk contributed more than other indicators. It also can be seen from Table 11 that the overall prediction accuracy of the research model is 91.13%, it means that the regression model is a more accurate means of measuring the financial crisis early warning of real estate companies.

Although this paper chooses the real estate industry to design the indicators of the credit evaluation system, some indicators in the evaluation system may be extended to other industries, which can provide some reference ideas for the credit evaluation of enterprises in other industries. For example, the mismatch between income and cash flow usually exists in the construction industry and other industries. In the financial indicator system, EBIT margin and cash return on equity after deducting non-recurring gains and losses are also suitable for capital-intensive industries to check their profitability. At the same time, quantitative and empirical research on non-financial indicators such as company size and corporate governance structure, which reflect the soft power of enterprises, can provide ideas for the credit evaluation research of listed companies in other industries. Therefore, the executives of Chinese listed real estate companies need to focus on these financial indicators when reducing the financial and credit risks of enterprises. The first financial indicator is the sales cash ratio. As an industry with a long cash recovery cycle, when the sales cash ratio is low, enterprises need to pay attention and improve the sales cash ratio. Of course, this index should not be too high, otherwise it means that the current assets of enterprises have not been used reasonably. The second financial indicator is the operating profit margin. Firstly, it can increase the sales revenue of the enterprise. Secondly, it can also increase the profit margin of a single product by reducing production costs. Finally, in developing new customers, it can explore new customer groups and new markets.

REFERENCES

Antoniades, A. (2021). Commercial bank failures during the Great Recession: The real (estate) story. *Available at SSRN 2325261.*

Altman, EI (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance, 23* (4), 589-609.

Akin, O., Montalvo, JG, García Villar, J., Peydró, JL, & Raya, JM (2014). The real estate and credit bubble: evidence from Spain. *SERIEs, 5* (2), 223-243.

Asikin, B., Afifah, E. S. N., Albida, H., Kania, N. A. N., & Firdaus, R. A. A. A. R. (2021). The Effect of Liquidity, Solvency, And Profitability on Stock Return (Empirical Study on Property, Real Estate, And Building Construction Companies Listed on The Indonesia Stock Exchange for the 2014-2017 Period). *Review of International Geographical Education Online*, *11*(5), 872-885.

Chen, Y., & Chu, G. (2014). Estimation of default risk based on KMV model—An empirical study for Chinese real estate companies. *Journal of Financial Risk Management, 2014.*

Davis, EP, & Zhu, H. (2009). Commercial property prices and bank performance. *The Quarterly Review of Economics and Finance, 49* (4), 1341-1359.

Dwiantari, R. A., & Artini, L. G. S. (2021). The Effect of Liquidity, Leverage, and Profitability on Financial Distress (Case Study of Property and Real Estate Companies on the IDX 2017-2019). *American Journal of Humanities and Social Sciences Research (AJHSSR)*, *5*(1), 367-373.

Giordani, P., Jacobson, T., Von Schedvin, E., & Villani, M. (2014). Taking the twists into account: Predicting firm bankruptcy risk with splines of financial ratios. Journal of Financial and Quantitative Analysis, 49(4), 1071-1099.

Gu, Y., & Yuan, F. (2020, August). Internal Control, Financial Flexibility and Corporate Performance–Based on empirical analysis of listed companies in information Technology industry. In *Journal of Physics: Conference Series* (Vol. 1607, No. 1, p. 012118). IOP Publishing.

Horrigan, JO (1966). The determination of long-term credit standing with financial ratios. *Journal of Accounting Research,* 44-62.

Ingrassia, S., & Costanzo, G. D. (2005). Functional principal component analysis of financial time series. In New developments in classification and data analysis (pp. 351-358). Springer, Berlin, Heidelberg.

Jayadev, M. (2006). Predictive power of financial risk factors: An empirical analysis of default companies. Vikalpa, 31(3), 45-56.

Jin, Y., & Zeng, Z. (2007). Real estate and optimal public policy in a credit-constrained economy. *Journal of Housing Economics, 16* (2), 143-166.

Kuttner, K., & Shim, I. (2012). Taming the Real Estate Beast: The Effects of Monetary and Macroprudential Policies on Housing Prices and Credit Conference–2012.

Kwilinski, A., Shteingauz, D., & Maslov , V. (2020). Financial and credit instruments for ensuring effective functioning of the residential real estate market. *Financial and Credit Activities: Problems of Theory and Practice, 3* (34), 133-140.

Kapopoulos *, P., & Siokis, F. (2005). Stock and real estate prices in Greece: wealth versus 'credit -price ' effect. *Applied Economics Letters, 12* (2), 125-128.

Loeve, M. (2017). *Probability theory.* Courier Dover Publications.

Lee, WC (2011). Redefinition of the KMV model's optimal default point based on genetic algorithms – Evidence from Taiwan. *Expert Systems with Applications, 38* (8), 10107-10113.

Luqman Hakim, L. (2017). Determinant Of Leverage and It's Implication on Company Value of Real Estate and Property Sector Listing In IDX Period Of 2011-2015. *Man in India*, *97*(24), 131-148.

Masood, O., Al Suwaidi, H., & Thapa, PDP (2012). Credit risk management: a case differentiating Islamic and non-Islamic banks in UAE. *Qualitative Research in Financial Markets.*

Nguyena, T., Nguyen, N., & Nguyen, V. (2019). A study on the impact of the factors reflect solvency to the bankruptcy risk of real estate companies: Evidence from Vietnam stock exchange. *Management Science Letters*, *9*(11), 1773-1782.

Patel, K., & Vlamis, P. (2006). An empirical estimation of default risk of the UK real estate companies. *The Journal of Real Estate Finance and Economics*, *32*(1), 21-40.

Rashidfarokhi, A., Toivonen, S., & Viitanen, K. (2018). Sustainability reporting in the Nordic real estate companies: empirical evidence from Finland. *International Journal of Strategic Property Management*, *22*(1), 51-63.

Renaud, B. (1997). The 1985 to 1994 global real estate cycle: an overview. *Journal of Real Estate Literature, 5* (1), 13-44.

Roa, MJ, Garrón, I., & Barboza, J. (2019). Financial decisions and financial capabilities in the Andean region. *Journal of Consumer Affairs, 53* (2), 296-323.

Saunders, A. (2014). *Financial institutions management.* Macmillan Press.

Sharma, R. K. (2018). Factors affecting financial leveraging for BSE listed real estate development companies in India. *Journal of Financial Management of Property and Construction*.

Summers, B., Williamson, T., & Read, D. (2004). Does method of acquisition affect the quality of expert judgment? A comparison of education with on - the - job learning. *Journal of Occupational and Organizational Psychology, 77* (2), 237-258.

Valášková, K., Gavláková, P., & Dengov, V. (2014). Assessing credit risk by Moody's KMV model. In *2nd International Conference on Economics and Social Science (ICESS 2014), Information Engineering Research Institute, Advances in Education Research* (Vol. 61, pp. 40-44).

Wiginton, JC (1980). A note on the comparison of logit and discriminant models of consumer credit behavior. *Journal of Financial and Quantitative Analysis, 15* (3), 757-770.

Widiatmoko, J., & Indarti, M. K. (2018). The Determinants of Earnings Response Coefficient: An Empirical Study for The Real Estate and Property Companies Listed On The Indonesia Stock Exchange. *Accounting Analysis Journal*, *7*(2), 135-143.

Xia long, H., & Ming, Z. (2010, July). Applied research on real estate price prediction by the neural network. In *2010 The 2nd Conference on Environmental Science and Information Application Technology* (Vol. 2, pp. 384- 386). IEEE.

Zhou, W., Chen, M., Yang, Z., & Song, X. (2021). Real estate risk measurement and early warning based on PSO-SVM. *Socio-Economic Planning Sciences, 77,* 101001.

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