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An Empirical Study of Financial Early Warning in the Real Estate Industry

-- Based on the Principal Component Logistic Regression Model

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Abstract

This article selects 9 real estate companies that were roughly the same in ST time in 2021 and another 31 real estate companies with good financial conditions. Select the financial indicators from T-3 to T-1 as the sample data (the time for selecting the financial indicators of non-ST companies is the same). Use SPSS 26.0 to analyze the significance of the selected financial indicators, and then use principal component analysis and Logistic regression to establish two types of models: one, financial variable early warning model, second, comprehensive early warning model. The research conclusions show that the accuracy of the early warning model is improved after the addition of non-financial indicators. The introduction of non-financial indicators can increase the ability of the financial early warning model to discriminate future conditions.

Keywords

Financial early warning; Logistic model; Estate enterprise; Principal component analysis.

1. INTRODUCTION

As a high-liability and high-asset industry, real estate companies have the characteristics of long payback periods, high investment costs, high risks and high returns, and susceptibility to government guidance. Therefore, a high-leverage development model has become the core of real estate companies. In the process from the purchase of the land to the preparation of the project and the sale of the real estate, the time limit is as long as several years. However, the entire project requires a large amount of capital investment, so the asset-liability ratio is in the process of rising, and the hidden dangers of the capital chain will also be exposed. If there is a problem in the capital chain in a certain link, then the entire project The process will be affected. In severe cases, the capital chain may be broken, which will lead to the failure of the project. Coupled with the unscientific internal organizational structure of most companies and the poor awareness of capital chain risk prevention, it will also bring certain risks to the corporate capital chain. Therefore, the security of the capital chain is closely related to the healthy development of enterprises, and avoiding risks in the capital chain is a challenge that most real estate companies need to face. Based on this, this article uses principal component analysis and Logistic regression model to establish financial early warning models for 40 real estate companies, and build appropriate financial early warning models to assist the healthy development of the real estate industry.

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2. LITERATURE REVIEW

Financial risk prediction was first proposed by Fitzpatrick (1932) in the univariate analysis method to discriminate bankruptcy research. The research method is mainly to compare financial ratios between financially healthy enterprises and financial risky enterprises [1], so it is used the limitations are greater. After that, Beaver proposed a single ratio model in 1966, and pointed out that the best discriminant is to analyze specific indicators in working capital: cash flow/debt and net profit/total assets. The success rate of discrimination is as high as 90% and 88% [2]. However, the use of the two fractions has greater limitations and cannot give guiding suggestions for the real estate industry, so this article does not take this method into consideration. Ohlson (1980) believes that the former's univariate discriminant method has not considered the characteristics of each industry and has not considered comprehensively. Therefore, it uses the Logistic method to analyze bankrupt companies and non-bankrupt companies, and increases the size of assets on the original basis. The results show that: capital structure, return on assets, and short-term liquidity have significant effects on financial forecasts, and the accuracy rate is as high as 92% [3]. Liu Yanhong (2007), Caggiano, etc. (2016) use Logistic logistic regression model for early warning, and analyze logistic regression The more the model considers the more factors, the higher the accuracy rate [4-5]. Compared with the discriminant analysis method, the use of logistic regression model is more suitable for the researcher's use purpose and the research object to give targeted judgments.

3. EMPIRICAL RESEARCH

3.1. Sample Selection and Index Selection

3.1.1. Sample Selection

In order to ensure the reliability of the data source, this article takes listed real estate companies as the research object. Whether the company has a financial crisis is distinguished by whether the company is labeled ST. To ensure data comparability, the selected company will be ST in approximately 2021. Between month and June, the time range selected for financial indicators is the first three years of ST, which corresponds to 2018-2020. A total of 40 listed real estate companies are selected as shown in Table 1, of which 9 are ST companies and 31 are non-ST companies. The source of the sample data is the financial report and the CMSAR database.

3.1.2. Index selection

Based on previous studies [6-8], the selection of bids follows the requirements of comprehensiveness, objectivity, and accessibility, and combines them with the characteristics of my country's real estate industry. 21 financial indicators and one non-financial indicator are selected from the six dimensions of development capability, per share indicator, and relative indicator.

3.1.3. Introduction to the model

Logistic regression is a multivariate analysis method. Logistic model is often used to solve 0-1 regression problems. It is mainly used to distinguish the relationship between research results and research factors. Its prediction accuracy in the early warning model is high, which is more in line with the research. Therefore, this paper chooses Logistic regression model to predict whether a real estate company will experience a financial crisis. The Logistic model can be explained as: the conditional probability P (P = 1) in the event of an event, the probability of its observation relative to the occurrence of changes, the formula is:

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Table 1. Research sample

Stock code	Securities abbreviation	Stock code	Securities abbreviation
000002	China Vanke Co.,Ltd	600383	Gemdale Corporation
000006	SHENZHEN ZHENYE(GROUP) CO.,Ltd	600641	Shanghai Wanye Enterprises Co.,Ltd
000031	Grandjoy Holdings Group Co.,Ltd	600649	Shanghai Chengtou Holding Co.,Ltd
600606	Greenland Holdings Corporation Limited	600665	Tande Co.,Ltd
000517	Rongan Property CO.,Ltd	600376	Beijing Capital Development, Co.,Ltd
000537	Tianjin Guangyu Development Co.,Ltd	600823	Shanghai Shimao Co.,Ltd
600466	Sichuan Languang Development Co., Ltd	600848	Shanghai Lingang Holdings Co.,Ltd
000628	ChengDu Hi-Tech Development Co.,Ltd	600266	Beijing Urban Construction Investment & Development Co.,Ltd.
600510	Black Peony(Group)Co.,Ltd	601155	Seazen Holdings Co.,Ltd
000671	Yango Group Co.,Ltd	601992	Bbmg Corporation
000886	Hainan Expressway Co.,Ltd	600185	Gree Real Estate Co.,Ltd
000926	Hubei Fuxing Science And Technology Co.,Ltd	600239	*ST Yunnan Metropolitan Realestate Development Co.Ltd
001914	China Merchants Property Operation & Service Co.,Ltd	600890	*ST Cred Holding Co.,Ltd
001979	China Merchants Shekou Industrial Zone Holdings Co., Ltd	600275	*ST Hubei Wuchangyu Co.,Ltd
002077	Jiangsu Dagang Co.,Ltd	600766	*ST Yantai Yuancheng Gold Co.,Ltd
002305	Langold Real Estate Co.,Ltd	600615	Shanghai Fenghwa Group Co.,Ltd
002314	Shenzhen New Nanshan Holding (Group) Co.,Ltd	000609	Beijing Zodi Investment Co.,Ltd
002968	New Dazheng Property Group Co., Ltd	000638	*ST Vanfund Urban Investment And Development Co., Ltd
600048	Poly Developments And Holdings Group Co.,Ltd	600515	*ST Hna Infrastructure Investment Group Co.,Ltd
600053	Kunwu Jiuding Investment Holdings Co.,Ltd	000502	*ST Lvjing Holding Co.,Ltd

$$\ln \frac{P}{1-P} = X_0 + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + \ldots + X_n\beta_n$$

Table 2. Early warning indicators

Latitude	Indicator name	Latitude	Indicator name
Financial Crisis	Whether there is a financial crisis.Y	Profitability	Net profit margin of total assets. C1
Solvency	Current ratio .X1		Operating gross profit margin. C2
	Quick ratio .X2		Operating cost ratio. C3
	Cash ratio. X3		Operating net profit margin. C4
	Assets and liabilities. X4	Development ability .	Capital preservation and appreciation rate. D1
	Interest coverage ratio. X5		Capital accumulation rate. D2
	Long-term gearing ratio. X6		Growth rate of total assets D3
Operating capacity	Accounts receivable turnover rate. B1		Net profit growth rate. D4
	Liquid assets turnover rate. B2		Operating income growth rate. D5
	Turnover rate of total assets. B3	Earnings per share indicator	Total operating income per share. E1
	Capital intensity. B4		Free cash flow per share E2
		Relative index	Tobin's Q. F1
		Non-financial indicators	Audit opinions. J1

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3.2. Model Data Verification

3.2.1. Significance Test

Significance test is performed on the initially screened indicators to find out the financial indicators that can significantly distinguish ST companies from non-ST companies. The first choice of this article is the KS test, and the significance level is set to 0.05 to find out whether the distribution of each indicator satisfies normality, and in the following steps, the independent sample T test is performed on the indicators that meet the normal distribution. The Mann-Whitney test is performed on the indicators that meet the normal distribution. The final result shows that the asset-liability ratio X4, the accounts receivable turnover ratio B1, and the free cash flow per share E2 are normally distributed when the significance is greater than 0.05. After the independent sample T test is performed, the significance level is greater than 0.05. The three indicators did not have significant differences in the sample, so they were excluded. The Mann-Whitney test is performed on the data that is not normally distributed, and the significance level of 0.05 is set. From the test results, it is known that the interest protection multiple X5, the long-term gearing ratio X6, the capital intensity B4, the total asset turnover rate B3, Operating net profit margin C4, capital accumulation rate D2, total asset growth rate D3, net profit growth rate D4, total operating income per share E1, Tobin's Q value F1, and audit opinion J1 are significantly less than 0.05, which are shown in the two sets of samples Significant difference.

3.2.2. Principal Component Extraction

In order to avoid errors in the establishment of the subsequent regression equations, the multivariate financial data is processed by "dimensionality reduction" through factor analysis to show the differences of individual indicators in the principal components. Because non-financial indicators are not suitable for factor analysis, this article intends to test the 10 financial indicators after screening. Before doing principal component analysis, KMO and Bartlett sphere test need to be used to verify the correlation between the indicators. It can be seen from Table 3 that the KMO value is 0.629>0.5, which is greater than the metric 0.5. In the experiment, the KMO value is 0-1, and the closer to 1 the better the correlation between the indicators.

Table 3. KMO and Bartlett sphere test

KMO sampling appropriateness number		0.629
Bartlett sphericity test	Approximate chi-square	222.529
	Degree of freedom	45
	Significance	0

Table 4. Principal component information extraction

Element	Initial eigenvalue	Variance%	accumulation%	Extract the sum of squares of the load	Variance%	accumulation%
1	2.892	28.919	28.919	2.892	28.919	28.919
2	1.703	17.028	45.947	1.703	17.028	45.947
3	1.453	14.531	60.478	1.453	14.531	60.478
4	1.044	10.438	70.916	1.044	10.438	70.916
5	0.822	8.221	79.137			
6	0.621	6.211	85.348			
7	0.519	5.187	90.534			
8	0.454	4.543	95.077			
9	0.307	3.07	98.147			
10	0.185	1.853	100			

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In the process of principal component extraction, principal components with eigenvalues greater than 1 are generally used. As shown in Table 4.5, the initial eigenvalues of the first four principal components are all greater than 1, and their contribution rates are 28.919%, 17.028%, 14.531%, 10.438% and the cumulative contribution rate reaches 70.915%. It is generally believed that when the cumulative contribution rate is above 70%, the original data information can be well reflected.

Therefore, the four are named F1, F2, F3, and F4 respectively. From Table 5, it can be seen that the four principal components have a high degree of correlation with some financial indicators, and they represent the company's indicator types. Principal component 1 is highly correlated with capital accumulation rate and total asset growth rate, which represents the company's development capability. Principal component 2 has a high degree of correlation with the total asset turnover rate, which represents the company's operating capacity, principal component 3 has a high degree of correlation with interest coverage multiples, represents the company's solvency, and principal component 4 is related to Tobin's Q value and capital intensity. High degree, representing the value of the enterprise itself. Afterwards, through orthogonal rotation, the predicted index coefficients between 10 financial early warning indicators and 4 principal components are obtained, as shown in Table 6.

Table 5. Component matrix information table

	Element			
	1	2	3	4
Interest coverage ratio. X5	0.123	-0.018	0.841	0.14
Long-term gearing ratio. X6	0.381	-0.776	-0.035	-0.253
Turnover rate of total assets. B3	0.504	0.615	0.275	-0.013
Capital intensity. B4	-0.03	-0.391	-0.173	0.819
Operating net profit margin. C4	0.615	-0.057	-0.096	0.074
Capital accumulation rate. D2	0.782	0.402	-0.044	0.205
Growth rate of total assets D3	0.807	0.076	-0.161	0.275
Net profit growth rate. D4	0.355	0.208	-0.689	-0.27
Total operating income per share. E1	0.566	-0.135	0.351	-0.293
Tobin's Q. F1	-0.622	0.581	-0.058	0.089

Table 6. Early warning index coefficient

	Element			
	1	2	3	4
Interest coverage ratio. X5	0.066	0.018	0.591	-0.034
Long-term gearing ratio. X6	-0.162	0.503	-0.061	-0.037
Turnover rate of total assets. B3	0.303	-0.185	0.148	-0.222
Capital intensity. B4	0.123	-0.056	0.1	0.808
Operating net profit margin. C4	0.186	0.115	-0.053	0.071
Capital accumulation rate. D2	0.392	-0.106	-0.006	0.058
Growth rate of total assets D3	0.335	0.028	-0.055	0.214
Net profit growth rate. D4	0.086	0.02	-0.537	-0.163
Total operating income per share. E1	0.045	0.259	0.158	-0.296
Tobin's Q. F1	-0.005	-0.412	-0.029	-0.029

According to the predicted index coefficients in Figure 6, the score coefficient models of F1-F4 can be obtained:

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F1=0.066X5-0.162X6+0.303B3+0.123B4+0.186C4+0.392D2+0.335D3+0.086D4+0.045E1-0.005F1

F2=0.018X5+0.503X6-0.185B3-0.056B4+0.115C4-0.106D2+0.028D3+0.02D4+0.259E1-0.412F1

F3=0.591X5-0.061X6+0.148B3+0.1B4-0.053C4-0.006D2-0.055D3-0.537D4+0.158E1-0.029F1

F4=-0.034X5-0.037X6-0.222B3+0.808B4+0.071C4+0.058D2+0.214D3-0.163D4-0.296E1-0.029F1

3.2.3. Logistic Model of Financial Variables

Using SPSS 26.0 software to analyze and forecast, define the corporate financial crisis as Y, Y=0 represents the financial health of the enterprise, and Y=1 represents the financial risk of the enterprise. The split point of the model is positioned at 0.5-if the model calculates the result probability value P≥0.5, it means that the company has the possibility of financial risks, and if P<0.5, it means that the company's financial status is good. Take the previously selected 40 listed real estate companies as model samples, and bring the principal components F1, F2, F3, and F4 into the model. After 9 iterations, the model is represented by F1, F2, F3, and F4 through calculations , And its coefficients are shown in Table 7. In the process of model building, the SPSS test result of the goodness of fit of the model is: the likelihood of regression model-2 is 20.222a. The relatively small parameter indicates that the goodness of the model combination is better. It is 0.823, which shows that when the model uses F1, F2, F3, and F4 as parameters, the explanation of whether the company has a financial crisis is 82.3%, and the accuracy is high.

Table 7. Financial Variable Logistic Model Estimated Results

	B	Standard error	Wald	Degree of freedom	Significance	Exp(B)
F2	-2.813	1.042	7.292	1	0.007	0.06
F3	0.229	0.088	6.721	1	0.01	1.258
F4	-0.034	0.044	0.616	1	0.432	0.966
F1	-1.229	0.557	4.877	1	0.027	0.293
Constant	-2.2	0.827	7.08	1	0.008	0.111

Combined with the parameters, the expression of the financial variable logistic model is:

$$\ln\frac{P}{1-P} = -2.2 - 1.229F1 - 2.813F2 + 0.229F3 - 0.034F4$$

3.2.4. Comprehensive Logistic Model

A comprehensive model is established when non-financial indicator audit opinions are added on the original basis. As shown in Table 8, the likelihood value of this model-2 is 14.410a, which is lower than the logistic model of financial variables, indicating that the combination of the model is excellent The degree is better, and its R2 is equal to 0.896, indicating that after the audit opinion is added, the existing indicators can explain whether the company has a financial crisis as high as 89%, and the accuracy of the model has been improved.

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Table 8. Comprehensive Logistic model estimation results

	B	Standard error	Wald	Degree of freedom	Significance	Exp(B)
F2	-3.075	1.317	5.447	1	0.02	0.046
F3	0.23	0.123	3.465	1	0.063	1.258
F4	-0.099	0.076	1.681	1	0.195	0.906
F1	-0.91	0.713	1.63	1	0.202	0.403
Audit opinion type	21.599	9316.286	0	1	0.998	2400756335
Constant	-3.343	1.321	6.407	1	0.011	0.035

Combined with the parameters, the expression of the financial variable logistic model is:

$$\ln\frac{P}{1-P} = -3.343 - 0.91F1 - 3.075F2 + 0.23F3 - 0.099F4 + 21.599J1$$

3.2.5. Result Analysis

Table 9. Forecast result

		Prediction group	
		Financial Logistic model	Comprehensive Logistic model
Number of samples	31 ST	29	30
	9 ST	6	8
Prediction rate		87.5%	95%

It can be seen from Table 9 that if the financial early warning model is only established from the perspective of financial indicators, its forecast accuracy is about 87.5%. When non-financial indicators such as the audit opinions in this article are added, its accuracy is increased to 95%. It was increased by 7.5%. Therefore, this model can play an early warning role for real estate companies.

4. CONCLUSION

By collecting the financial indicators of listed real estate companies in Shanghai and Shenzhen, a total of 21 financial indicators and 1 non-financial as the sample data of this article, and using principal component analysis, the financial early-warning models are made for financial early-warning models that only target financial variables. And a comprehensive early warning model. Through empirical analysis: (1) Interest protection multiple, long-term debt to capital ratio, capital intensity, total asset turnover rate, operating net interest rate, capital accumulation rate, total asset growth rate, net profit growth rate, total operating income per share , Tobin's Q value, and audit opinions can well distinguish the financial status of enterprises in the real estate industry, and the solvency, development ability, operating capacity, and corporate value are also the most significant factors affecting real estate enterprises. (2) After adding non-financial indicators to the model, the prediction accuracy has been improved. Therefore, it can be considered that when non-financial variables are added to the financial early warning model, it can increase its ability to discern whether the company will have a financial crisis in the future. In addition, the shortcomings of this article are that the company's internal governance and macro-environment changes are not considered, and due to the selection of years, the selected ST companies are limited, and the results may still have certain errors with the actual situation, and there are more studies. It shows that the effect of the neural network model in forecasting will be better than the logistic regression model. It is hoped that

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the above shortcomings can be made up in the later learning, and a more accurate real estate financial early warning model can be constructed.

REFERENCES.

[1] P.J Fitzpatrick.A Comparison of Ratio of Successful Industrial Enterprises with those Failed Firms[J]. Certified Public Accountant, 1932:598-605

[2] Beaver. Financial Rations as Predictors of Failure [J]. Supplement to Journal Accounting Research, 1966, (1):71-111.

[3] Ohlson, J.S.Financial Ratios and the Probabilistic Prediction of Bankruptcy [J]. Journal of Accounting Research, 1980, (19):109-131.

[4] Yanwen Liu, Hongjun Dai.An Empirical Study on the Early Warning Model of Financial Distress Based on Three-dimensional Logistic[J]. Journal of Dalian University of Technology (Social Science Edition), 2007(02):60-66

[5] Caggiano.G, CaliceP, Leonida L,etc. Comparing Logistic-based early warning systems: Does the duration of systemic banking crises matter?[J]. Journal of Empirical Finance, 2016, 37(6):104-116.

[6] Xiaoyun Zheng, Jianhua Li. An Empirical Study on Financial Early Warning of Listed Real Estate Companies [J]. Friends of Accounting, 2015(09):72-76.

[7] Xudong Deng, Yu Zhang, Wenping Xu. Research on Financial Early Warning Model Based on the Perspective of Cash Flow——Taking the Real Estate Industry as an Example[J]. Accounting Friends, 2018(23):89-93.

[8] Kun Tian,Wen xi Chen.Research on Financial Early Warning of Real Estate Delisting Risky Enterprises——Based on the Comparison of Principal Component Analysis and Logistic Model[J]. Journal of Shenyang Jianzhu University (Social Science Edition), 2019, 21(04):376-381.

[9] Qing Cheng: Research on Financial Early Warning of Pharmaceutical Industry Based on Principal Component-Logistic Model(MS., East China Jiaotong University, China 2020).