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Research on Credit Risk Assessment of Sci - tech Enterprises Based on Logistic Model

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Abstract: ***Credit risk is the most important financing risk to sci-tech enterprises, which causes financing difficulty. In view of this deficiency, this paper firstly analyzes the reasons for financing difficulties of sci-tech enterprises, then combined with the characteristics of sci-tech enterprises focus on innovation and R&D to select the index of credit risk. Finally, the logistic model is used to construct the credit risk evaluation model of sci-tech enterprises. The data of 111 science and technology listed companies were used as samples to carry on the empirical analysis and the test results show that the model has high accuracy and stability.***

Keywords: sci-tech enterprises, credit risk, logistic model, empirical analysis

1. Introduction

In the 21st century, where knowledge economy became the mainstream economy, the development of science and technology enterprises was one of the most striking events. Science and technology industry as the core of all industries, based on knowledge-intensive technology, is the main motive force for a country to gain long-term competitive advantage, and is an important driver of sustainable socio-economic growth. However, in the process of continuous development and expansion of scientific and technological enterprises, the difficulty of credit financing has affected and restricted their healthy development to a certain extent. This dilemma, partly because the investment risk is generally higher than that of the traditional enterprise, the specific performance: long R & D cycle, light asset operations, lack of collateral, credit records less, and there is a lot of uncertainty about the market's acceptance of newly developed technologies and products. This is contrary to the principle of prudent banking management, reducing the enthusiasm of financial institutions to provide loans for them.On the other hand, because the development of China's science and technology finance started late, the credit approval procedures of financial institutions are too cumbersome, too many credit indicators are investigated, and the efficiency of credit is very low. And in the risk identification, measurement and so on is still based on empirical analysis, can not objectively reflect the true credit status of science and technology enterprises (Angelini and Salvo,1999). Therefore, financial institutions are difficult to screen out the high quality and credit better technology companies to provide credit support, leading to its lack of research and development funds, financing costs remain high. This not only increased the burden on enterprises, hindering the transformation of scientific and technological achievements into realistic productivity, but also affected the fairness of the capital market, it is difficult to stimulate the enthusiasm of young people entrepreneurship.In view of this problem, this paper analyzes the reasons for the financing difficulty of science and technology enterprises, constructs a set of credit risk evaluation system according to the characteristics of science and technology enterprises, and expounds how to use logistic regression to measure and evaluate the risk of science and technology financial credit to improve the credit efficiency of financial institutions, and accelerate the development of science and technology finance industry.

2. Literature Review

In economically developed countries, some credit risk measurement models have been recognized by governments, large enterprises and the Bank for International Settlements, and are widely used in many large financial institutions and multinational enterprises. Such as the credit metrics model of the VAR-based credit measure established by JPMorgan in 1997, the KMV model established by the KMV firm based on the option theory and so on.

Looking at the whole process of credit risk measurement, we can see that with the development of credit rating, it has experienced the development of roughly three generations: classical credit analysis, multivariate statistical analysis and modern credit risk model.

Classical credit analysis is qualitative analysis, is the bank's most basic credit risk measurement method, it relies on well-trained experts subjective judgments, credit analysis is that they rely on personal knowledge to judge the process. Banking in the development process for the control of credit risk has already formed some useful credit risk management techniques, such as the common 5C method and 5P method. Beaver (1966) of accounting department of University of Chicago put forward a single variable decision model.

In 1968 the American scholar Altman proposed a predictive discriminant model: the Z scoring model. The model indicates that the credit risk measure has entered the multivariate linear statistical analysis phase. Altman and Haldeman (1977) extended the Z-score model to establish the second-generation model, the ZETA model. The Z-score model and the ZETA model are typical representations of the multivariate linear discriminant model and have a great impact on the credit risk measure until now people are still using it.In the article "Early warning of bank failure: a logistic regression Approach" published in 1977, Martin first used the Logistic regression model to predict firm's bankruptcy and default probability. He chooses eight financial ratios from 25 financial indicators to predict the bankruptcy and default probability of the firm, establishes the Logistic model, sets the risk police line for risk positioning, and the accuracy rate of the judgment is more than 90%. Ohlson (1980) established a multivariate logistic model to predict the company's ruin probability, and he proposed to use the data modeling of the previous two years to avoid the problem of over-estimating the model's ability to predict. Cramer (2004) proposed a boundary Logistic model and pointed out that the model can overcome the shortcomings of difficult to test by goodness. At present, this kind of multivariate nonlinear regression model is the most widely used, and is regarded as the mainstream method by the international financial industry and the academic circles.

Multivariate statistical analysis has been further expanded in the past more than 20 years, the modern credit risk measurement model based on neural network, genetic algorithm and linear programming is formed by applying nonlinear discriminant analysis, neural network method, genetic algorithm, linear programming and nonparametric statistical method.

As China's risk management research started late and most of the focus on the introduction and comparison of foreign credit risk management methods, the establishment of a real fit and measure the default rate of science and technology enterprises in China credit risk model is not much, it is necessary to carry out in-depth study.In recent years, Logistic regression model has a certain guiding significance for the development of scientific and technological enterprises, which is based on the advantages of predicting the probability of credit default probability and expanding the practicality. Based on the above situation, combining with the characteristics of innovation and R & D of science and technology enterprises, this paper aims to apply logistic model to establish a set of credit evaluation index system suitable for technology-based enterprises.Enhance the ability of financial institutions to finance the risk management of science and technology enterprises, and realize the efficiency and foresight of the economic development of science and technology enterprises.

3. Analysis on the Causes of Financing Difficulties of Science and Technology Enterprises

After the investigation of science and technology enterprises themselves and the reality of capital demand and supply of technology enterprises, it is clear that the financing problems these enterprises facing are still grim.To fundamentally ease the financing problems, we must explore its causes in depth, and take the appropriate measures.In this section we will analyze the causes of enterprise financing difficulties from four aspects of science and technology enterprises themselves, financial institutions, guarantees and venture capital.

3.1 The Defects of Science and Technology Enterprises

3.1.1 Science and technology enterprises operating a higher risk

High-Tech companies have a characteristics of high risk and high yield. From the new product development to production, there are many unknown factors. No matter which part of the problem may cause business difficulties.As a result, financial institutions are generally reluctant to take such a high risk of lending for technology-based enterprises.

3.1.2 Scientific and technological enterprises have less real estate collateral

In order to reduce their own credit risk, when loan is issued, the banks usually require the relevant enterprises to give real estate collateral.Technology-based enterprises have less fixed assets as collateral, so it is difficult to obtain loans from financial institutions.

3.2 Financial institutions are reluctant to lend money

Financial institutions and other companies are the same, whose main purpose is to profit, however, credit risk is an important factor in the loss of its loans. At present, financial institutions still refer to the traditional enterprise credit risk assessment standards to carry out high-tech companies'loan review, which cannot be objective and impartial response to science and technology enterprises real credit status. Therefore, it is difficult for banks to screen out the quality, credit better technology enterprises to provide credit support.

3.3 The guarantee system is not perfect

The guarantee of corporate credit, to a certain extent, directly affects whether the credit can be successfully achieved. Because, through mortgage and pledge, banks and other financial institutions will ease the worries that the financing enterprises can repay the loans on time and reduce the degree of information asymmetry between the banks and the enterprises. However, China has not yet exist sound science and technology enterprises credit risk data for archives, and enterprise security law system is still not perfect. Banking institutions for financing to repay the loan on time the situation can not be determined, so it is difficult to smooth for the science and technology enterprises to provide financial support.

3.4 Venture capital and listing financing costs are high

In addition to bank loans, science and technology enterprises can also use venture capital and listing to ease the plight of its funds. The institutional defects of the domestic capital market lead to a higher cost and strict audit when enterprises obtain funds through the listing and other means. At the same time, the capital market supporting the scientific and technological enterprises is still imperfect, and there is a big obstacle for venture capital exiting which leads to few fund investment institutions getting involved.

To sum up, there are two reasons for the financing difficulties of science and technology enterprises: the enterprise's own limitations and the external environment.

As a financial institution, it should focus on the problem of financing for science and technology enterprises and carry out business innovation, actively introduce program and products adapt to science and technology enterprises. From the perspective of science and technology financial institutions, next section will better screen the science and technology enterprises through the construction of evaluation index system and evaluation model, thus alleviating the financing problem of science and technology enterprises.

4. Logistic model method description

In practice, in addition to the case of credit defaults, the so-called "normal" companies do not represent 100% of the safety, and there is still a possibility of default. It is difficult to categorically designated a specific company "Will not" bankruptcy or breach of contract, the key point is the probability of a corporate credit default, logistic model was used to solve this problem.

Logistic regression is a statistical method of non-linear classification, logistic function is:

$$f(x)=\frac{1}{1+e^{-\left(\beta_0+\sum_{i=1}^{n}\beta_i x_i\right)}}.$$

Where x_i is the impact variable of the default, ie the default measure;

β_i is the regression coefficient, obtained by regression or maximum likelihood estimation;

$\beta_0+\sum_{i=1}^{n}\beta_i x_i$ is a measure of the financial indicators that affect an enterprise's default;

$f(x)\in[0,1]$, represents the default probability of an enterprise.

We also call $f(x)/(1-f(x))$ the rate of occurrence, also known as relative risk.

Logistic regression applies to the problem that the dependent variable is a two-state categorical variable, that is, the value of the variable is 0 or 1. Such questions can be expressed as follows:

$$Y=\begin{cases}0, & f(x)\le \text{Critical value}\\ 1, & f(x)>\text{Critical value}\end{cases}.$$

The practical significance of the results of logistic regression:

For two valued dependent variables, it is generally assumed that when the value of $f(x)$ is greater than a critical value, the dependent variable is 1, otherwise the dependent variable is 0. The regression coefficient β_i is no longer the marginal contribution of the independent variable x_i to the variation of the default probability P, but the marginal contribution of the independent variable x_i to the $In\left(p/(1-p)\right)$ of the $p.e^{\beta_i}$ is the marginal contribution of the independent variable to the ratio of x_i. That is, when the independent variable x_i increases by one unit, the $In\left(p/(1-p)\right)$ will increase to the original β_i times, and the ratio will increase by e^{β_i} times.

The main advantage of the logistic regression is that it does not require restrictive statistical assumptions about variables. In addition, if the dependent variable is two, or even only qualitative variables, or whether the pros and cons of the two types, then logistic regression analysis can well handle the explanatory variables and the relationship between variables. This paper assumes that the dependent variable value of the default enterprise is 1, and the dependent variable value of the normal enterprise is 0, which belongs to the dependent variable of the two state. Therefore, logistic regression applies to the study of this thesis.

5. Science and Technology Financial Credit Risk Evaluation System Establishment, Sample Description and Evaluation Index Screening

5.1 Construction of credit risk evaluation index system

With reference to the existing research results, after investigation and analysis, this paper initially established the financial indicators and non-financial indicators of scientific and technological enterprises credit risk evaluation index system, as shown in Table 1.

Table 1: Scientific and technological enterprises credit risk evaluation index system

Level 1 indicators	Level 2 indicators	Grade
Solvency	Flow ratio	X1
	Quick ratio	X2
	Property ratio	X3
Profitability	Basic earnings per share	X4
	Net assets per share	X5
	Roe	X6
	Sales gross margin	X7
Operation capability	Business cycle	X8
	Inventory turnover days	X9
	Accounts receivable turnover days	X10
Growth	Year-on-year growth rate of EPS	X11

ability	Year-on-year growth rate of operating income	X12
	Year-on-year growth rate of net profit	X13
	Year on year growth rate of return on assets	X14
R&D capability	Total R&D expenditure	X15
	R&D expenditure as a proportion of net assets	X16
	R&D expenditure as a percentage of operating revenue	X17
Non-financial indicators	Enterprise scale	X18
	Enterprise management level	X19
	Advanced technology	X20
	Commercial credit	X21
	Industry development prospect	X22

5.2 Sample description

Because of the general science and technology enterprise data acquisition is not easy, but the financial data of listed companies are easy to obtain, so this paper only focuses on the 17 financial indicators for empirical analysis, according to the SME and gem select some listed science and technology enterprises as samples. The data were derived from data from 111 scientific and technological enterprises in the CCER and were divided into two groups, one as test samples, and one group as validation samples.

In order to make the selected data meet the validity of the above indexes, and can distinguish the credit risk of the enterprise is normal, this article selects the sample data are divided into two groups: (1) from 2016 to 2017 because of abnormal financial condition and special treatment (ST) of the 28 science and technology enterprises for credit risk samples;(2) from 2016 to 2017 of the 83 normal financial enterprise of science and technology as a non credit risk sample. For the index data, since ST was announced in t and T-1 announced that the annual report of credit risk is basically the same thing, it is likely to overestimate the accuracy of the model.

5.3 The selection of evaluation indicators

The first step, t test. Screening out the significant differences in the two groups of data indicators, the difference is not significant that can not be clearly different from ST and non-ST companies to remove the indicators. Where the 0.05 is bounded, the Levene test Sig. Greater than 0.05, does not overthrow the original hypothesis, that is, the variance is equal, and then see the mean value of the t test Sig. (Bilateral), if more than 0.05, do not overturn the original hypothesis that there is no significant difference between the two sets of data variance, where we choose to give up this indicator, and vice versa. Finally, in accordance with the above rules, the following six indicators are excluded: property ratio, net assets per share, business cycle, inventory turnover days, accounts receivable turnover days and total R & D expenditure.

The second step, factor analysis dimensionality. The principle of factor analysis is to group the variables according to the correlation, that is, in the case of preserving the information as much as possible, the common factor is extracted from the variable group, the correlation between the variables within the group was higher, and the correlation between the variables was low, so as to achieve the purpose of reducing dimension.

Table 2: Applicability test of factor analysis

Samples are sufficient to measure the Kaiser-Meyer-Olkin metric		0.747
Bartlett's Spherical Test	Approximate card side	683.464
	df	100
	Sig.	0.000

According to the test results in Table 2, KMO statistic = 0.747>0.5, indicating that the overlap between the variables is not high. In addition, the significance level P is less than 0.05, we can see that these financial indicators with factor analysis method to reduce the dimension is appropriate. With the eigen value of more than 1 as the standard, the index variable corresponding to each sample is simplified to three, that is, one enterprise corresponds to three main factors that represent it. According to the three principal components of the factor load and the economic implications, respectively, named: growth factor, R & D and profitability factor and solvency factor, as shown in Table 3.

Table 3: Rotation Factor Load Matrix

	Factor		
	F1	F2	F3
Year-on-year growth rate of net profit	.974	.037	.091
Year-on-year growth rate of EPS	.894	.058	.083
Year on year growth rate of return on assets	.763	.275	.065
Year-on-year growth rate of operating income	.463	.143	-.231
Roe	.219	.871	.109
R&D expenditure as a proportion of net assets	-.043	-.796	-.152
Basic earnings per share	.536	.741	.164
R&D expenditure as a percentage of operating revenue	-.169	.667	.175
Quick ratio	.045	.043	.965
Flow ratio	.048	.072	.964
Sales gross margin	.174	.316	.476
Eigenvalues	3.684	1.891	1.640
Cumulative contribution rate%	28.796	56.238	75.685
Factor name	growth factor	R & D and profitability factor	solvency factor

6. Logistic Regression Analysis Results

On the basis of the above factor analysis, logistic regression analysis of each extraction factor was carried out. In the regression analysis, the variable selection adopts Enter method (all variable forced entry) .When the model predicts the probability of the demarcation point is 0.5, that is, the probability P is greater than 0.5 for ST enterprise; less than 0.5 is not ST enterprise. The extraction of the common factor into the regression analysis, the output of the results shown in the following table, which Table 4 for the regression model of the overall significance of the test results. As can be seen from the table, the model of the chi-square statistic test observations 43.121, the probability p value of 0, if the significance level is 0.05, then the probability p value is less than the significance of 0.05 level, the original assumption that all regression coefficients are equal to zero should be rejected, and the overall model is considered to be significant.

Table 4: Simulates the overall significance test

	Chi-square	df	Sig.
Step	43.121	3	0.000
Piece	43.121	3	0.000
Model	43.121	3	0.000

Table 5 gives the evaluation model goodness test. -2 logarithmic likelihood is -2 times the logarithmic likelihood function, and the smaller the numerical value, the higher the goodness of the regression model, the closer the Nagelkerke R is to 1 and the higher the goodness of fit. From the analysis results, it is shown that the -2 logarithmic likelihood is very small and the Nagelkerke R is 0.872, which indicates that the model has good good fit.

Table 5: Model goodness of fit test

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
13.051	0.562	0.872

Table 6 shows the values of the regression coefficients in the regression model. B corresponds to the final model parameter estimate. The constant is -3.992, the coefficient of f1 is -10.992, the coefficient of f2 is -9.161, and the coefficient of f3 is -3.186.

Table 6: Statistical regression results

	B	S.E	Wals	df	Sig.	Exp(B)
F1	-10.992	7.294	2.271	1	0.032	0.000
F2	-9.161	6.403	2.047	1	0.043	0.000
F3	-3.186	2.500	1.624	1	0.021	0.041
constant	-3.992	2.476	2.598	1	0.007	0.018

Write the Logistic model expression from the statistical results as follows:

$$\lambda_1 = -3.992 - 10.992 f_1 - 9.161 f_2 - 3.186 f_3 \quad (1)$$

$$p_1 = 1/(1+e^{-\lambda_1}) \quad (2)$$

After the expression is determined, training samples can be used to verify the accuracy of expressions. The specific method is to bring the concrete data of f1, f2 and f3 of the 66 scientific and technological enterprises into the formula (1), Obtain each enterprise's λ_1, and then bring λ_1 into equation (2), get p_1 of these 66 science and technology enterprises. Then, it can be seen from Table 7, two of the 66 companies were misjudged, and the overall prediction accuracy of the model was 97%, the model's prediction was ideal.

Then, the model is tested. Using the same method as above, 45 scientific and technological enterprises with inspection samples were used to validate the model and calculate the probability of enterprise default p. The model test results are shown in Table 7:

As can be seen from Table 7, seven of the test samples were misjudged and the correctness of the assessment was 84.4%. The correct rate of the total sample is 91.9%. Therefore, the logistic regression model constructed in this paper is ideal for the classification of enterprises in the sample.

Table 7: Test results of logistic model

Sample	N	Percentage	Observed	Predicted		
				0	1	Correct percentage
Training sample	66	59.5%	0	52	0	100.0%
			1	2	12	85.7%
			Total percentage	81.8%	18.2%	97.0%
Test sample	45	40.5%	0	27	4	87.1%
			1	3	11	78.6%
			Total percentage	66.7%	33.3%	84.4%
Total sample	111	100.0%	0	79	4	95.2%
			1	5	23	82.1%
			Total percentage	75.7%	24.3%	91.9%

7. Suggestions on Preventing the Financial Credit Risk of Science and Technology

7.1 Establishment of specialized institutions of science and Technology Finance

Science and technology financial franchise refers to the scientific and technological enterprises as the main target, and the implementation of specialized management and evaluation mechanism of financial institutions. Science and technology financial franchise institutions can be branches of banks, securities institutions, insurance companies.It could also be a technology bank, a technology guarantee company, a technology microloan company, and so on to adapt to the development of science and technology finance (Xiao K and Xie Y, 2016). The establishment of technology financial franchise is conducive to the implementation of risk aversion, that is, on the basis of risk identification and measurement, through specialized enterprises and project screening, effectively avoid some exposure to credit risk.

7.2 Develop adaptive financial products

In addition to the characteristics of technology enterprises, adaptive financial product development requires the principle of revenue coverage risk. The overall credit risk of scientific and technological enterprises is relatively large, but the enterprises that successfully realize the transformation of scientific research achievements can also grow rapidly, thus bringing substantial returns for investors.Because of the uncertainty of scientific and technological innovation activities, some of the financial and social capital of scientific and technological enterprises will be damaged and some will be successful, if the higher return on investment from a successful firm can partially or completely cover investment losses to a failed business, science and technology financial activities has business sustainability.

7.3 Development Performance Guarantee Insurance and Technology Guarantee Loans

Scientific and technological enterprises, especially those in the seed period and start-up stage, are difficult to finance because of their short establishment time, less tangible assets and low credit rating. The performance guarantee insurance and credit guarantee service for the technology oriented enterprises, as the traditional means of credit enhancement, are also the methods of risk transfer. Combining science and technology credit with science and technology insurance, and by introducing insurance company's insurance mechanism, it can solve the problem of light assets and guarantee difficulty faced by science and technology enterprises.

8. Conclusion

This paper in science and technology financial services institutions to credit risk evaluation of enterprise of science and technology has made a useful exploration, presents a quantitative analysis method and introduces the sample data for empirical analysis and verification.The result shows that the overall prediction rate of the evaluation index system is 91.9%, and the evaluation effect is better.The construction of the credit evaluation model can help the scientific and technological financial institutions to screen and supervise the science and technology enterprises, reduce the transaction costs, broaden the investment channels, effectively avoid the occurrence of science and technology financial credit risk; on the other hand, it has eased the difficulty of obtaining credit support for technology-based companies that are largely intangible, make it pay more attention to the credit status, found deficiencies in the process of credit evaluation, and actively adjust business strategy, competitive advantage. The deficiency is that the selected samples are small, and only empirical analysis of financial indicators. In the future, we can use large data and other technologies to develop a faster and more accurate processing of a larger sample size.

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