Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia Computer Science 17 (2013) 901 – 910
Procedia Computer Science

Information Technology and Quantitative Management (ITQM2013)

# Study on the Influence Factors of High-tech Enterprise Credit Risk: Empirical Evidence from China's Listed Companies

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**Abstract**

Taking 187 high-tech listed companies in China as samples, using the Cox model, an empirical test on the influence factors of high-tech enterprise credit risk is carried out. The empirical results show that, the financial situation has significant effect on credit risk of high-tech enterprise, especially the current ratio, accounts receivable turnover, total assets turnover ratio, return on equity, etc; and also the independent innovation capacity has significant effect on credit risk of high-tech enterprise, the stronger the independent innovation capacity is, the lower high-tech enterprise credit risk becomes. However, the influence of regional factor on credit risk of high-tech enterprise is relatively limited, the influence of growing factor is not obvious, as well as enterprise scale, and the influence of industry factor should be further examined. Particularly, this paper provides evidence that there is a significant negative correlation between independent innovation capacity and credit risk of high-tech enterprise; this will contribute to financial institutions to increase the credit support for independent innovation.


Selection and peer-review under responsibility of the organizers of the 2013 International Conference on Information Technology and Quantitative Management

*Keywords*: high-tech enterprise; credit risk; influence factors; independent innovation capacity; Cox model

## 1. Introduction

High-tech industry is the strategy leading for national economy. It is not only critical impetus of economic structure adjustment and development method change, but also the commanding heights of worldwide competition of overall national strength [1]. Since China entered into 11th Five-Year plan, its high-tech industry continues to maintain a rapid growth, leading the significant economic performance prosperity and speeding up the industrial restructure. The good momentum of the innovation and efficiency and self-development transition, enhances high-tech industry's leading role for national economy boost. According to the data released by National Bureau of Statistics, in 2010, China's high-tech industry output value (current price) reaches 7.615631 trillion Yuan, 79.08% increase compared to 2006, and an average annual growth rate of 19.77%. The high-tech industry output value accounted for GDP by 19.14 %. However, when the high-tech

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Selection and peer-review under responsibility of the organizers of the 2013 International Conference on Information Technology and Quantitative Management
doi:10.1016/j.procs.2013.05.115

enterprises make a significant contribution to economic growth, they have to facing the difficulties in financing for further development. On the one hand, the high-tech project technical confidentiality runs into conflict with partly public information in technical project financing, this information asymmetry caused the lack of funds support [2]. On the other hand, high-tech industry has characteristics of large capital investment and high-risk [3], compared with the traditional enterprise, when high-tech enterprises transfer technological research result into reliable products, high uncertainty will be exposed—high risk, high yield, and this uncertainty aggravate the impact of asymmetric information in turn, resulting in the high-tech enterprise financing obstacle. It can be said that the information asymmetry is main reason of financing obstacles when the high-tech enterprises transfer technological achievements into products [2]. One important measure to ease high-tech enterprise financing difficulties is to accelerate the construction of high-tech enterprise credit system, where the construction and consummation of credit evaluation index system is the key and basic work. Deep analysis on the credit risk affecting factors of the high-tech enterprises, and building a high-tech enterprise credit risk evaluation index system, will help improve the objectivity and accuracy of the credit evaluation, so as to reduce the transaction cost , lessen the information asymmetry, weakening credit risk. These efforts will greatly help reduce financing obstacle and increase the financing channels of high-tech enterprises, improve the transformation rate of technological achievements, and promote the sustainable development of the high-tech industry.

This article will draw experiences from research method invented by Narain (1992) [4], Xue-feng Song and Chao-Jun Yang (2006) [5], take a sample of high-tech listed companies and make empirical analysis on credit risk factors of China's high-tech enterprises. The rest part of this paper will be: the second part demonstrates the theory of the relevant articles, then combined with the characteristics of high-tech enterprises, gives a research hypothesis of factors affecting the high-tech enterprise credit risk; the third part will build Cox model to make a high-tech enterprise credit risk analysis; the fourth part takes a sample of 187 high-tech listed companies, and uses Cox model to empirically verify and analyze factors affecting high-tech enterprise credit risk; finally, conclusion will be drawn and policy implication will be carried out.

## 2. Literature Review and Hypotheses

Credit risk is the possibility of loss owing to the default of the borrowers or market counterparties; more generally, the credit risk also includes possibility of loss resulted from the fluctuations of market value of debt caused by the changes of performance ability and the transformation of the borrower's credit rating. Therefore, in theory, all factors that affect performance capabilities and compliance intention should be classified to the ones affecting enterprise credit risk. The abroad researches about corporate bond credit risk influencing factor are mainly launched from three aspects: internal value of an enterprise, the uncertainty of the macroeconomic environment and the degree of information asymmetry [6]. (1) From the perspective of internal enterprise value, those researches come to almost the same conclusion that the enterprise management level and the maturity of the bonds will exert a significant impact on credit risk. For example, Ericsson, Jacobs and Oviedo (2005) [7] used the financial leverage of debt-issuing enterprise, risk-free rate and stock volatility as explanatory variables, while using credit risk premium as the explained variables to establish multiple regression model. The empirical results show that 1% increase of financial leverage ratio will leads to 5-10% increase of the credit risk premium. (2) From macroeconomic uncertainty perspective, studies focused on analyzing the impact from the risk-free interest rates, economic cycles, money supply, exchange rate, unemployment rate and other macroeconomic variables, on the credit risk of corporate bonds. For example, Avramov, Jostova and Philipov (2007) [8] constructed a structural model to explain corporate bond credit spreads. This model is able to explain 54% of the credit spreads change. Among all the factors, the five-year Treasury bill rate and the market value return (Measured by net assets) explain the credit spreads change for 28.63% and 18.25% respectively. (3) Those researches from information asymmetry perspective, analyze the impact of asymmetric information on the credit risk of corporate bonds in an indirect way. For instance, Yu (2003) [9] used AIMR disclosure level as a measure of financial information transparency, in this way, he studied the relationship between the term structure of the corporate bond credit spreads and the quality of financial information. He found that companies with higher financial transparency takes lower credit spreads, especially for short-term bonds.

Domestic research divided the factors affecting corporate credit risk into two major categories: financial factors and non-financial factors. (1) From those theoretical analysis, Gan Yuan and Yong-de Yuan (2002) [10] thinks that the non-financial factors analysis and financial analysis, provide mutual verification and complement to each other, with the introduction of industry risk factors, business risk factors, management risk factors, natural and social factors, non-financial factors such as the borrower's repayment intention to the credit market access analysis, the study can be more comprehensive and dynamic in the analysis of the risk level which decide loan amount. Ying Zhou and Ding-xiang Mao (2003) [11] consider that the traditional financial analysis will be hysteretic, short-term, grey to bank credit analysis, in order to prevent credit risk, bank should focus on implying non-financial research on enterprise loaner, including the analysis of the management environment, the core competitiveness of enterprises, enterprise management level, the development prospects analysis, and credibility analysis. (2) From the empirical analysis, Jiu-jie Ma (2004) [12] used the logit model to run empirical analysis on loan default factors of medium and small business in every county, and the conclusion comes that financial position, especially capital structure, asset turnover status, equity status have significant effect on enterprise credit risk; personal characteristics of entrepreneurs, especially age, education background and holdings corporate share or not have a greater impact on the company credit risk; the economic development level of where corporate located also have some impact on the corporate credit risk. Rong-guo Chou and Jian-hua Zhang (2010) [13] take capital structure, solvency, operating ability, profitability and cash flow as variables, use unbalanced panel data model to run empirical research on factors affecting credit default risk of small and medium-sized listed companies in China. The results showed that positive correlation between degree of stock concentration of the company's first shareholders and credit default risk while negative correlation exists between the proportion of tradable shares, corporate growth and the risk of credit default. Besides, education background of executives will have some negative impact on corporate credit default risk. Yu Zhang (2011) [14] conducted a survey on credit managers and show that: macroeconomic environment, macroeconomic policies, national industrial policy and industry development are the key consideration when credit managers run credit assessment, besides, the industry position, competitiveness in the market, the scale of capital, management capabilities of managers and the management of individual characteristics of managers will have a significant impact on credit assessment.

From the existing literature, scholars at home and abroad have carried out a series of theoretical and empirical research on the various factors affecting the corporate credit risk from different angles. However, existing researches are primarily for general corporate. Research on high-tech enterprise credit risk factors is rare. Based on existing literature, considering the characteristics of high-tech enterprises, we believe that enterprise financial position, growth potential, corporate size, region affection, industry affection, independent innovation ability are the main factors to affect the credit risk of the high-tech enterprises in China, therefore, with Cox model, we will verify following hypothesis:

Hypothesis 1: Financial position of the high-tech enterprises play a decisive role to default. Enterprise management level directly determines its operating profitability, and operating profitability will ensure the credit performance of enterprises. In a word, business management level is directly related to its credit risk. Enterprise management level is mainly reflected by the financial position. Indicators which reflect the enterprise financial flexibility, stability, profitability will directly predict the possibility of financial crisis and default [12]. An enterprise with more financial flexibility, high stability and good profitability, will less likely to default.

Hypothesis 2: Enterprise growth potential affects the possibility of default of the high-tech corporations. The high growth potential is an important feature of the high-tech enterprises, and high-tech products are so innovative and tech-leading to quickly take the market share, thus promoting the rapid growth of high-tech enterprises. Quick growth brings high-yield, thus affect the possibility of default of the high-tech enterprises. Generally speaking, the better growth of an enterprise is, the less its default probability will be.

Hypothesis 3: Corporate scale affects the possibility of default of the high-tech enterprises. In general, large-scale enterprises with abundant capital, has the strong ability to fight against market risk, and run its business carefully. At the same time, large-scale enterprises, with greater transparency of information, deserves the relatively low unit cost of supervision [12]. Therefore, the large-scale enterprises will less likely to default; conversely, the smaller ones will more likely to default.

Hypothesis 4: Region also influents the high-tech enterprises default possibility. China has a vast territory and different regions with different economic development. The diversity of the management capacity of local governments, financial market development level and social environment, generates different overall solvency and the paying debt intention of the debtor in various regions [15]. Economic development level, marketization degree, investment environment, industrial aggregation, and industrial supporting in one specific region where enterprise locates, will affect the operating conditions and performance capabilities. In general, the higher economic development level of one region is, the less default probability of enterprise will be.

Hypothesis 5: Industrial features influent the default of the high-tech enterprises. The borrowers in one industry face almost the same risk but different industries have different characteristics, appearance and risk level respectively [10]. The basic traits, industry cycles, industry prospects, will affect the possibility of corporate defaults. Generally speaking, the enterprise belongs to a sunrise industry, will less likely to default, while in a sunset industry, will more likely to default.

Hypothesis 6: Independent innovation ability also influent the default probability of high-tech enterprises. The high-tech enterprises are the ones which research, develop, produce and sell high-tech products or use high-tech widely; independent innovation is the prerequisite and basis of survival and development of those firms and is able to improve enterprise performance and core competitiveness [16-17]. High-tech enterprise produces multiple positive effects such as economic effects, technical effects and tissue effects [18], which affect default possibility of high-tech enterprises. In general, the stronger the independent innovation ability of enterprise is, the less its default probability will be.

## 3. Cox Model to Credit Risk Analysis

Cox model of a semi-parametric survival analysis of model [19], it has a big difference with the general model of multivariate statistical analysis. In this model, we can find that time series can be implied, no need for sample pairing, continuous prediction and high robustness [5]. Cox model, survival time can be broadly defined as: period starts from a specific time or a specific event, to another time or event [20]. The high-tech enterprise survival time defined in this paper is the period from the year that the high-tech enterprises run business to the year default occurred.

The survival time was considered a continuous random variable $T$, let's assume $T$ has continuous survival function $S(t) = P(T > t)$ and distribution function $F(t) = P(T \le t)$, and the density function of $F(t)$ is

$$f(t) = \lim_{\Delta t \to 0} \frac{P(t < T < t + \Delta t)}{\Delta t} \tag{1}$$

Hazard rate function [19] is the default contingent probability in $(t, t + \Delta t)$, when the high-tech enterprise stay at the normal state in the time t. The expression will be:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t < T < t + \Delta t \mid T > t)}{\Delta t} \tag{2}$$

where $h(t) \ge 0$.

Cox model uses hazard rate function as the main form to observe when so many relevant factors has influence on survival time, which of them play key role in this process, then analyze the hazard rate after prediction. $h(t)$ is usually considered relevant to some concomitant variable of high-tech enterprises (We assume these concomitant variables are some financial factors and non-financial factors of high-tech enterprise), therefore $h(t)$ can be interpreted as:

$$h(t) = h_0(t)\exp(\beta' X) \tag{3}$$

where $X$ is covariance matrix, $\beta$ is regression coefficients of Cox model, $h_0(t)$ is reference hazard rate which is a hazard rate when all covariance stay 0 or standard state, it is a random nonnegative function only related to $t$, and no any limit to its function form. When we can not make a specific hypothesis to the distribution form of $h_0(t)$, the coefficient $\beta$ will be estimated by partial likelihood function method [21].

Let's observe the survival time of many high-tech companies (The number will be $n$), covariance of Ith company is $X_i$, survival time is $t_i$. When $t_i$ is complete data (Sample company default in the observation period), censoring indicator variable $\delta_i = 1$; when $t_i$ is censoring data (Because of some reason, we cannot know the exact survival time of the corporate), censoring indicator variable $\delta_i = 0$, then the observed data of the $n$th corporate will be:

$$(t_i, \delta_i, X_i) \quad i = 1, 2, \cdots, n \tag{4}$$

Sort the different survival time by size: $t_{(1)} < t_{(2)} < \cdots < t_{(\tau)}$. Let $D_j = \left\{ i : \delta_i = 1, and\, t_i = t_{(j)} \right\}$, $C_j = \left\{ i : \delta_i = 0, t_i \in \left[ t_{(j)}, t_{(j+1)} \right) \right\}$, while $R_j = \left\{ i : t_i \ge t_{(j)} \right\}$ can be defined as risk set at time $t_{(j)}$, that's a set composed of those companies which do not default before $t_{(j)}$.

In general, if a corporate doesn't default at $t_{(i)}$, then there is no information about $\beta$ at $t_{(i)}$. Actually, in any period, we cannot get the information of $\beta$ if there is no corporate default. If $t_{(i)}$ represents real default, then

$$P\left\{ one\, default\, occur\, in \left[ t_{(i)}, t_{(i)} + \Delta \right) \middle| R_i \right\} \approx \sum_{j \in R_i} h_0(t_{(i)}) \exp(\beta' X_j) \Delta \tag{5}$$

where $\triangle$ means a tiny time increment. While

$$P\left\{ company\,(i)\, default\, at\, t_{(i)} \middle| one\, of\; R_i\; default\, at\, t_{(i)} \right\} = \frac{\exp(\beta' X_{(i)})}{\sum_{j \in R_i} \exp(\beta' X_j)} \tag{6}$$

After we deal with all the time point of default for all high-tech companies, we multiple all the time point and get so called partial likelihood function:

$$L_C(\beta) = \prod_X \frac{\exp(\beta' X_i)}{\sum_{j \in R_i} \exp(\beta' X_j)} \tag{7}$$

In the above formula, multiple process $\prod_X$ will be implemented on all time point of default.

Cox model conveys such opinion: constructing formula (7) and calculating MLE based on formula (7), we can get the estimated value of $\beta$. After the value of $\beta$ is known, we can determine the influence level and influence direction of all covariance implied on high-tech enterprise credit risk. In general, it is assumed covariance will not change over time in the process of estimating $\beta$, once we allow covariance $X$ change over time, we can construct Cox model of time dependent covariant by replacing $X$ by $X(t)$, this is what we said Cox can use time series sample to make multiple period estimation.

## 4. Empirical Analysis

### *4.1. Sample selection*

In this paper, we take the high-tech listed companies in China as samples; imply the empirical verification and analysis on factors affecting the credit risk of the high-tech enterprises with Cox model. Occurrence of financial crisis of a loan company has direct relation with recoverable ability of the commercial banks credit asset [22]. Therefore, this paper defined that the special treatment (ST) of listed companies by abnormal financial position as an event of default, and abnormal financial position consist primarily of two situations: (1) The listed company's continuous two year audited net profit is negative. (2) Audited net asset per share of listed companies in recent one fiscal year is less than the par value of shares.

The sample period is from 2003 to 2007, and 2003 has been selected as the starting point for the survival time. When the listed companies is special treated for the first time in 2003, the survival time is 0 year; when the first time in 2004, the survival time is 1 year; when the first time in 2005, the survival time is 2 years; and so on. In particular, if the listed company is specially treated before 2003, then the survival time will be left censored data, if the listed company is not specially treated during the sample period, then the survival time will be right censored data. After considering survival time, and excluding abnormal data samples, this paper has received a total of 187 enterprise samples consisting of 35 ST companies and 152 non-ST companies. The sample industries involved from pharmaceutical manufacturing, aerospace manufacturing, electronics and telecommunications equipment manufacturing, computer and office equipment manufacturing, medical equipment and instrument manufacturing, and so on.

### *4.2. Variance selection and data resource*

According to the assumption given in second part of this paper, this paper has selected 17 factors as covariates for constructing Cox model from following 6 aspects, and these factors may have important affection on high-tech listed companies. (1) Financial position: Refer to enterprise performance evaluation index system released by the Statistics Evaluation Division of the Ministry of Finance and enterprise credit evaluation index system created by ICBC, we selected 12 indicators, such as current ratio, quick ratio, asset-liability ratio, interest protection multiples, inventory turnover, accounts receivable turnover, total asset turnover, fixed asset turnover, ROA, return on net asset, net profit margin, ROE, to reflect the financial position of the high-tech listed companies. The sample data come from the GTA database. By the way, in order to analyze easily, fixed type indicators (such as the current ratio, quick ratio, etc.) will be extreme-normalized. Refer to algorithm in article [23]. (2) Growth potential: Select the capital increment rate to reflect the growth potential of high-tech listed companies. The sample data is from the GTA database. (3) Enterprise size: Select the asset size to reflect the firm size of high-tech listed companies. The sample data is from the GTA database. (4) Regional factor: The literature [24] points out the three-year credit transformation matrix of the high-tech enterprises for China's eastern, central and western regions, this article adapted three-year, five-grade default possibility of high-tech enterprises in east, center and west of China to reflect regional factor of survival time of high-tech listed companies. (5) Industrial factor: The literature [25] gives three-year credit transformation matrix of high-tech industry, so this paper adapted three-year, five-grade default possibility of high-tech enterprises in east, center and west of China to reflect industrial factor of survival time of high-tech listed companies. (6) Independent innovation ability: Due to the difficulties of data acquisition, this paper adapted the dynamic evaluation values of independent innovation ability of China's high-tech industries from 2003 to 2007 provided by literature [26], approximately to represent the independent innovation ability of high-tech listed companies.

### *4.3. Significance test*

For above 17 variables, with the help of SPSS 16 [27], using Mann-Whitney U non-parametric test to decide whether there is significant difference on these variables between ST companies and non-ST companies. Those variables which will not bring significant difference will be discarded. Mann-Whitney U non-parametric test results are listed in table 1.

Table 1. Mann-Whitney U non-parametric test results

| Variables | 1 year ahead | | 2 years ahead | | 3 years ahead | |
|---|---|---|---|---|---|---|
| | Mann-Whitney U | Exact Sig. (1-tailed) | Mann-Whitney U | Exact Sig. (1-tailed) | Mann-Whitney U | Exact Sig. (1-tailed) |
| Current Ratio | 1.299E3 | 0.046 | 943.500 | 0.034 | 307.000 | 0.008 |
| Quick Ratio | 1.437E3 | 0.145 | 1.125E3 | 0.194 | 429.000 | 0.083 |
| Asset-liability Ratio | 1481.500 | 0.196 | 1071.000 | 0.126 | 513.000 | 0.233 |
| Interest Protection Multiples | 842.000 | 0.000 | 644.000 | 0.000 | 341.000 | 0.018 |
| Inventory Turnover | 1557.000 | 0.303 | 1191.000 | 0.301 | 548.000 | 0.324 |
| Accounts Receivable Turnover | 958.000 | 0.000 | 650.000 | 0.000 | 346.000 | 0.019 |
| Total Asset Turnover | 833.000 | 0.000 | 667.000 | 0.000 | 207.000 | 0.000 |
| Fixed Asset Turnover | 1123.000 | 0.006 | 921.000 | 0.026 | 298.000 | 0.007 |
| Return on Net Asset | 1044.000 | 0.002 | 878.000 | 0.015 | 365.000 | 0.028 |
| ROA | 910.500 | 0.000 | 813.500 | 0.006 | 378.000 | 0.036 |
| Net Profit Margin | 1293.500 | 0.043 | 980.000 | 0.052 | 608.000 | 0.501 |
| ROE | 924.000 | 0.000 | 777.500 | 0.003 | 326.000 | 0.013 |
| Capital Increment Rate | 801.000 | 0.000 | 1116.500 | 0.181 | 408.500 | 0.060 |
| Total Asset | 1.010E3 | 0.001 | 835.000 | 0.008 | 429.000 | 0.083 |
| Regional Factor | 856.500 | 0.000 | 842.500 | 0.008 | 171.500 | 0.000 |
| Industrial Factor | 735.500 | 0.000 | 780.000 | 0.003 | 152.500 | 0.000 |
| Independent Innovation Ability | 1.157E3 | 0.007 | 961.000 | 0.033 | 306.000 | 0.005 |

PS: Exact Sig.(1-tailed)< 0.05 means the variables will be significant at the 95% confidence interval.

From table 1, variables with significance during the 3 years before default occurs for both ST companies and non-ST companies include: current ratio, interest protection multiples, inventory turnover, total asset turnover, fixed asset turnover, ROA, return on net asset, ROE, regional factor, industrial factor and independent innovation ability, and so on.

### *4.4. Correlation test*

Because of the high colinearity may exist during the above 11 variables, and colinearity is the important factor to affect the Cox model to predict the performance, therefore, it is necessary to implement colinearity test on these variables, to exclude those variables having strong colinearity [5]. With the help of SPSS16.0, we run Pearson correlation test, under the 1% level of significance, excluding some high correlation variables, then we can get that current ratio, interest protection multiples, accounts receivable turnover, total asset turnover, return on net asset, ROE, regional factor and independent innovation ability may be suitable for constructing a Cox model covariates.

### *4.5. Empirical result and analysis*

This paper uses backward stepwise regression to run the model estimation and analysis in the process of constructing the Cox model. The significance level of variable reserved by model is set to 0.05, and the CI of relative risk is set to 95%. Regression result of Cox model is shown in table 2.

Table 2. Regression result of Cox model

| Variable | B | SE | Wald | df | Sig. | Exp(B) | 95.0% CI for Exp(B) | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | Lower | Upper |
| Current Ratio | -0.641 | 0.144 | 19.846 | 1 | 0.000 | 0.527 | 0.397 | 0.698 |
| Accounts Receivable Turnover | -0.192 | 0.093 | 4.253 | 1 | 0.039 | 0.825 | 0.687 | 0.991 |
| Total Asset Turnover | -4.466 | 1.178 | 14.378 | 1 | 0.000 | 0.011 | 0.001 | 0.116 |
| ROE | -2.154 | 0.676 | 10.142 | 1 | 0.001 | 0.116 | 0.031 | 0.437 |
| Independent Innovation Ability | -6.366 | 2.831 | 5.056 | 1 | 0.025 | 0.002 | 0.000 | 0.442 |

PS: Sig < 0.05 means the variables will be significant at the 95% CI.

Table 2 is an estimate of the various parameters in the regression equation. B stands for partial regression coefficient; SE is standard error of partial regression coefficient; Wald statistic is used to test whether there is significant difference between overall partial regression coefficient and 0, it subject to $\chi^2$ distribution. When df (degree of freedom) is 1, Wald statistic is the square of the quotient of partial regression coefficient and standard error. Sig presents significance level; Exp (B) is relevant risk, CI for Exp (B) presents confidence interval of relevant risk [27]. From table 2, we can know that the model excludes interest protection multiples, return of net asset and regional factor, so the following Cox model expression can be obtained:

$$h(t) = h_0(t)\exp(-0.641X_1 - 0.192X_2 - 4.466X_3 - 2.154X_4 - 6.366X_5) \tag{8}$$

In the above formula, $X_1, X_2, \cdots, X_5$ respectively represents the five variables, including current ratio, accounts receivable turnover, total asset turnover, ROE, independent innovation capability, and so on.

Judge from the partial regression coefficient and degree of relative risk, at the 5% significance level, hypothesis 1 is valid, which means financial position has significant influence on possibility of high-tech listed company default, especially current ratio, accounts receivable turnover, total asset turnover and ROE, these four indicators has significant affection. The more close current ratio is to premium stable value (Normally the value is 2), the less default probability of high-tech listed company will be; the higher accounts receivable turnover, total asset turnover or ROE is, the less default probability of high-tech listed company will be. At the 5% significance level, hypothesis 6 is valid, which means the significant negative correlation exists between the independent innovation ability and the default probability of high-tech listed company. The stronger independent innovation ability is, the less default probability of high-tech listed company will be. This conclusion also reflects that since the implementation of the national strategy of independent innovation, the independent innovation ability of China's high-tech enterprises gradually is enhanced and the influence brought by independent innovation become increasingly prominent, which brings significant reversed influence on credit risk. At the 5% significance level, hypothesis 4 is not proved; there is no significant correlation between the regional factor and the default probability of high-tech listed company, that's to say that regional factor impose the relatively limited impact on the credit risk of high-tech enterprises.

Hypothesis 2 doesn't pass the significance testing, which tells there is no significant correlation between the growth potential and the default probability of high-tech listed company. Maybe because of high-tech listed companies are in mature stage of industry cycle, compared with the growing stage, the growth speed slows down and affection on credit risk is relatively small. Hypothesis 3 doesn't pass the significance testing, which tells there is no significant correlation between the corporate scale and the default probability of high-tech listed company. Maybe because of the scale of high-tech listed companies is not large, affection on credit risk from corporate scale is not obvious. In addition, the industry factor has pass the test of significance, but were excluded in the correlation test, therefore, we can only made the initial determination that hypothesis 5 may be correct, the final determination needs to be validated later.

## 5. Conclusions and Policy Implication

In this paper, we take the listed companies in high-tech industries as a sample to analyze the factors affecting the credit risk of the high-tech enterprises in China with the Cox model, and the results show that: the financial position, in particular, the current ratio, accounts receivable turnover ratio, total asset turnover, ROE, have a significant impact on credit risk of high-tech enterprise; as well as the independent innovation ability, the stronger independent innovation ability is, the lower credit risk of high-tech enterprises will be; the regional factor imposed the relatively limited impact on the credit risk of high-tech enterprises. But the influence from growth potential and enterprise-scale is not yet clear and the industrial factor needs to be validated later. Its policy implication includes: (1) Current ratio, accounts receivable turnover ratio, total asset turnover, return on equity, independent innovation ability should be taken into consideration for constructing a high-tech enterprise credit risk evaluation index system, even for the entire high-tech enterprise credit system. (2) The strength of independent innovation should be taken into count when commercial banks or other financial institutions made loaning decision for high-tech enterprises. Premium credit policy imposed on the high-tech enterprises will be good for optimizing the credit structure, strengthen the credit support for the independent innovation. Also, this policy will be good for allocating financial resources to technical industry, which boosts the integration of technology and finance, thus provide an important guarantee for the further implementation of independent innovation strategy.

## Acknowledgements

This work was financially supported by National Natural Science Foundation of China (71263011) and Humanity and Social Science Planning Foundation of Ministry of Education of China (11YJA630196).

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