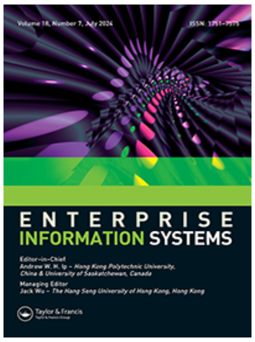

Enterprise Information Systems

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/teis20

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To cite this article: Victor Chang (22 Jul 2024): Credit risk evaluation on technological SMEs in China, Enterprise Information Systems, DOI: 10.1080/17517575.2024.2374741

To link to this article: https://doi.org/10.1080/17517575.2024.2374741

Published online: 22 Jul 2024.

ENTERPRISE INFORMATION SYSTEMS
https://doi.org/10.1080/17517575.2024.2374741

Credit risk evaluation on technological SMEs in China

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ABSTRACT
China's reform and opening-up policies have prioritized technological advancement, with technological SMEs driving employment and economic growth. Despite their significance, these SMEs face substantial financing and operational risks due to inadequate credit measurement tools. This study reviews the historical financing challenges of technological SMEs since the 1980s, summarizes their current credit risk status, and compares four modern credit risk models: Credit Metrics, Credit Risk+, Credit Portfolio View, and KMV. We propose a pioneering KMV Strategy for real-time risk analysis, contributing to accurate credit metrics for these SMEs. Finally, we suggest policies for managing their credit risks through prevention, control, and governance.

ARTICLE HISTORY
Received 3 January 2023
Accepted 27 June 2024

KEYWORDS
Technological SMEs in China; KMV model; risk management; credit system; risk analysis and SMEs; KMV strategy

1. Introduction and background

One of the most important factors in minimising SME development is credit risk (St-Pierre and Bahri 2011). With the financial crisis since 2008, it has been a major worldwide concern, including in emerging countries such as China, to strengthen financial monitoring and governance. Advanced techniques to evaluate credit risk and perform accurate analysis can be crucial for SMEs. Without stable and economic development, it will be challenging for the survival of SMEs and their subsequent contributions to risk analysis.

In the tide of China's market economy, small and medium-sized enterprises (SMEs) have become a crucial part of economic development. The number of SMEs accounts for 99% of the total number of enterprises in China. They guarantee about 75% of the employment ratio in cities and towns and create more than 60% of the country's gross product (Lyu 2015). Technological SMEs in China contribute to the main position of China's scientific and technological innovation by merging the advantages of high technology and SMEs. At present, the number of technological SMEs in China only accounts for 6.3% of small and medium-sized enterprises. Still, they contribute 74% of technological innovation, 65% of the patent invention and 82% of new product development to the country (Chen, Feng, and Peng 2012).

Technological SMEs have great potential for growth, but there are potential risks such as credit risk, market risk, technological risk and capital risk. Therefore, they are prone to

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encounter various difficulties and fade away (Eggers 2020). Due to the lack of default information, the loan thresholds for SMEs are getting higher, though mortgage guarantee systems are generally implemented (Berger and Udell 1995). Technological SMEs are no exception. In the case of asymmetric information, commercial banks impose uniformity during the loan process, which makes it difficult for technological SMEs with the development potential to obtain bank loans (Bates 1997). In such a grim financing environment, many technological SMEs in China collapsed. Therefore, both commercial banks and technological SMEs urgently need a fair and accurate technique that can effectively measure the true credit risk without hiding any sensitive data like some practices in China do. By doing so, they can evaluate their own financial performance and predict financial and market risk. This can reduce legal, and people disputes, as well as suppression of telling the truth that may face possible prosecution. Managing risk can help sustain the stability of SMEs and also the economy indirectly. Developing a fair and accurate technique for credit risk can help policy and decision-makers in the studies and practices of peacebuilders.

1.1. Research objectives

An effective credit grading system based on credit risk measurement can help SMEs and financial institutions develop each other and reduce risks (Altman and Sabato 2007) to achieve risk analysis for economic and SME development stability. The credit risk measurement model can transfer credit risk from qualitative to quantitative outputs, and engineering and digitalised measurement methods can more effectively evaluate the credit risk situation of technological SMEs. Therefore, using a suitable credit risk measurement model can effectively help technological SMEs solve their financing dilemma.

This paper aims to analyse the characteristics of technological SMEs in China based on credit status and their financing and study the advantages and disadvantages of the KMV model and its usage based on the comparative analysis of four kinds of credit risk measurement models. It is aimed that the empirical results can contribute to technological SMEs in China to get more efficient financing and also provide some references for the financial institutions to measure credit risk.

2. Literature review

2.1. Financing problems for technological SMEs

The financial problems of SMEs have attracted much attention from many scholars since the 1980s. Stiglitz and Weiss (1981) consider that the credit information collection mechanism and its evaluation system need to be established and improved because the problem of technological SMEs' financing is caused by information asymmetry. Banerjee, Besley, and Guinnane (1994) thought that developing small and medium-sized financial institutions may alleviate the financing difficulties of technological SMEs. In the meantime, Berger and Udell (1995) claimed that a long-term relational lending and trading system with centralised objects could help improve SMEs' loan conditions, which is in agreement with the opinion of Boot (2000) that SMEs should establish cooperation with banks for credit information sharing. As a result of the financial problems, SMEs need to be resolved. These may include the need for transformation in the use of ICTs. The success of technology giants has attracted the development of many technological SMEs, such as PayPal, WhatsApp, Instagram, acquired by eBay and Facebook, and new ones, such as Zoom and Tiptok, as they have developed extremely popular software since the late 2010s.

2.2. Evaluations of credit risk and limitations of risk analysis for SMEs in China

Credit risk (or default risk) generally refers to the risk that the debtor fails to fulfil the transaction contract on time, which leads to economic losses to creditors (Goodhart 2011). Beaver (1952) used univariate analysis to judge the business risk of enterprises by collecting their financial data. The Z-score credit risk model of Altman (1968) accelerated the development of credit risk quantitative analysis. Altman, Haldeman, and Narayanan (1977) also came out with ZETA Credit Risk Model based on the Z-Score Model. After that, Ohlson (1980) used the Logit model to analyse the credit risk of bankrupt and non-bankrupt companies. In the modern credit risk evaluation stage after the 1980s, this focus is the product development of modern capital market theory, information technology and portfolio theory, all of which can be integrated into the KMV model (Yeh, Lin, and Hus 2012). The benefits include reporting risk, receiving true information, and understanding the impacts on the survival of SMEs.

This is crucial for risk analysis to understand the current challenges and predict the future to avoid greater risk and reduce potential negative impacts. The outcomes of KMV analysis can identify why SMEs fail and under what circumstances.

Chinese tech SMEs have distinct characteristics including high growth volatility, intangible asset dominance, and dynamic policy environments that limit applicability of traditional credit modelling approaches (Ge et al. 2021). For example, accounting-based tools like Altman's Z-score overlook crucial market factors and technology risks (Tinoco and Wilson 2013). Assumptions from mature markets regarding default points or risk-free rates require localisation (Nowak and Romaniuk 2013). Hence this research tailors a specialised KMV model adapted to Chinese SME nuances, enabled by the mixture of quantitative calibration and qualitative strategy insights.

2.3. Technology integration matrix (TIM)

The Technology Integration Matrix (TIM) provides a framework to categorise technology usage in organisations across different dimensions from entry-level substitution to higher-order transformation (Harmes et al. 2016). For technological SMEs, TIM offers strategic archetypes corresponding to the firm's business and technology orientation. Prior research has applied TIM to segment SME technology adoption patterns (Sonmez Cakir and Adiguzel 2020).

For credit risk analysis, the TIM strategic classification provides a basis for segmenting Chinese tech SMEs. Nonetheless, the typology can be enhanced by adding more qualitative characteristics related to corporate governance frameworks, leadership dynamics, and organisational culture (Harmes et al. 2016; Sonmez Cakir and Adiguzel 2020; Azeem et al. 2021). Additionally, grouping SMEs according to their exposure to platform economics, IP portfolios, and level of industrial digitisation may help identify important trends regarding credit risk trajectories.

2.4. Studies of the KMV model

The KMV model is a credit risk measurement model developed by the KMV company to measure the default probability of enterprises. It is derived from the options pricing theory of Black Scholes (Black and Scholes 1973) and Merton (1974). The development of the model is divided into two stages. The first stage is to compare the prediction results of the KMV model with the actual default situation to verify the sensitivity of the model. McQuown (1993) study found that the simultaneous use of the company's financial statements and market prices can improve the accuracy of the KMV model's credit risk measurement. Kurbat and Korbalev (2002) used level validation and calibration methods to prove the validity of the KMV model. Crosbie and Bohn (2003) used the KMV model to detect the changes in the credit risk of financial companies. The results showed that the **Expected Default Frequency (EDF)** value could predict the change in the enterprise credit quality accurately in time before the default of the enterprise. Detail for EDF will be presented in Sections 4.4., 4.5, and 6. The second stage is to compare the validity of the KMV model with different methods in different periods and extend the use of the model. Dwyer (2007) compared the default rates of varying credit risk models through historical data from 1970 to 2005. The study showed that the KMV model could accurately measure the credit risk of different companies at different times and locations. Zhang et al. (2010) found that different industries, regions and some other factors can affect the accuracy of the KMV model. Camara, Popova and Simkins (2012) used the KMV model to predict the credit risk of Asian and European financial and non-financial enterprises before and after the financial crisis. The results showed that the model could predict the credit risk of the enterprise more accurately in a financial crisis, which is useful for risk analysis to identify risk and understand the extent of impacts.

3. Studies on technological SMEs in China as a case study

3.1. Definition of technological SMEs in China

Technological SMEs are SMEs focused on development of technological products and services. Due to the rapid economic growth and development, the case of China has been a popular subject, particularly the development of its SMEs and credit risk management. Generally speaking, SMEs are small businesses that have smaller assets scale, sales volume and number of workers than those of large enterprises. For China, the relevant departments of the Chinese government issued a '*Notice on the Printing and Issuing of the Criteria for the Classification of Small and Medium-sized Enterprises* (Table 1) in 2011 to adjust the previous definition of SMEs in 1988, such as reducing the standard of a number of workers, raising the upper limit of the standard of sales revenue and expanding the scope of industries. It is worth mentioning that micro-enterprises have also been added to the new division standards.

Technological SMEs are small and medium-sized enterprises engaged in the research and development of high-tech and new technology achievements and the production

Table 1. Definition standard for SMEs in various industries in China.

Serial number	Industries	Standard of definition
1	Agriculture, forestry, animal husbandry and fishery	Operating income of less than 200 million Yuan
2	Industrial	Less than 1,000 employees or an operating income of less than 400 million Yuan
3	Construction	Operating income of fewer than 800 million yuan or total assets of less than 800 million Yuan
4	Wholesale	Less than 200 employees or an operating income of less than 400 million Yuan
5	Retail	Less than 300 employees or an operating income of less than 200 million Yuan
6	Transportation	Less than 1,000 employees or an operating income of less than 300 million Yuan
7	Warehousing	Less than 200 employees or an operating income of less than 300 million Yuan
8	Post	Less than 1,000 employees or an operating income of less than 300 million Yuan
9	Lodging	Less than 300 employees or an operating income of less than 100 million Yuan
10	Catering	Less than 300 employees or an operating income of less than 100 million Yuan
11	Information Transmission	Less than 2,000 employees or an operating income of less than 1,000 million Yuan
12	Technology Services	Less than 300 employees or an operating income of less than 100 million Yuan
13	Real Estate Development	Operating income of less than 2,000 million Yuan or total assets of less than 800 million Yuan
14	Property Management	Less than 1,000 employees or an operating income of less than 50 million Yuan
15	Leasing and Business Services	Less than 1,000 employees or total assets of less than 1,200 million Yuan
16	Other not specified industries	Less than 300 employees

and operation of high-tech products. They are intellectual-intensive business organisations (You 2011). According to the '*Guiding Opinions on Further Increasing Credit Support to High-tech SMEs*' issued by the China Banking Regulatory Commission in 2009 and the '*Measures for the Administration of Science and Technology SMEs in Tianjin*' promulgated by the Tianjin Science and Technology Department in 2010, the definition of technological SMEs for China should be from five aspects which are the basic requirements, industrial scope, technical indicators, innovation and environmental requirements.

(1) **Basic requirements**. In terms of asset size, sales revenue and the number of hired staff in line with the definition of SME industry standards in China, with an independent legal personality
(2) **Industrial scope**. Technological SMEs in China need services in the following industries: electronics and information, earth and space marine engineering, biology and medicine, light mechanical and electrical integration, high-tech service industry, application of nuclear technology, new energy and energy-efficient, resources and environment, agriculture and rural areas, new materials, aerospace and aviation, etc.
(3) **Technical indicators**. The expenditure on science and technology accounts for at least 2% of the company's main business income; the income generated by intellectual property, proprietary technology, or advanced knowledge accounts

for at least 20% of the company's main business income. For technological SMEs in China, the proportion of staff with a college degree or above in the total number of employees is not less than 20%.

(4) **Innovation capacity**. Technological SMEs need to set up special scientific research institutions with the abilities of original innovation, integrated innovation and absorption and innovation of imported technology.
(5) **Environmental requirements**. According to state regulations, technological SMEs should have good measures and equipment to prevent pollution and waste emissions.

3.2. Characteristics of technological SMEs in China

According to the relevant literature, technological SMEs in China have the following characteristics:

(1) **High technology content and strong innovation ability**. Scientific and technological research and development and innovation ability are the souls of technological SMEs. Otherwise, they will lose their competitive advantage. Technological SMEs belong to intelligence-intensive enterprises with a large proportion of scientific and technical personnel with high degrees. The skeleton staffs have intellectual property, advanced knowledge and rich scientific research experience, and the research results of science and technology are more abundant than those of the global enterprises. At the same time, more than 2% of the enterprises' annual incomes are invested in the field of scientific and technological research and development, which increases their added value for them (Hsu 2010).
(2) **High profitability and growth potential**. At the beginning of the listing, technological SMEs tend to have a smaller scale and lower profit level but with obvious professional advantages. Once their scientific research achievements have been successfully transformed into new products that meet the requirements of the market, they can quickly occupy the market and even form a monopoly. In a few short years, many medium-sized technological enterprises have developed into large ones with better organisation and management. From January to June 2005, 18 technological SMEs on Shenzhen Stock Exchange issued prospectuses, while the total number of SMEs issuing prospectuses was only 20 (Wang, Yang, and Shen 2008).
(3) **High risk**. The future development of technological SMEs depends on the development of new products and the approval of consumers. Otherwise, enterprises will face severe pressure on survival and growth. The failure of enterprises' technology research and development will lead to technical risks. This will become the cause of failure to recover the investment cost and financing difficulties, resulting in financing risks. At the same time, if the new product cannot be recognised by the consumer, technological SMEs will face market risks. Relevant data show that the probability of survival of technological SMEs for more than ten years in America is less than 10%. In China, many technological SMEs appeared after the reform and opening up were only one-third left in the early twenty-first Century (, Zeng 2006).

(4) **Government –** The main difference is that the government has much greater power and control. Jack Ma was about to launch IPO for his Ant Financial Group but was stopped by the Chinese Communist Party due to breaches of monopoly and legal requirements. In the U.S.A., this can be possible for big financial groups to become well-established, leading to companies working with Wall Street. In China, the government has the absolute right to decide the future of any firm if its expansion may be in breach of its national development and interests.

3.3. Credit risk status of technological SMEs in China

3.3.1. The financial system is not sound and financial credit is missing

Most of the SMEs in China have been set up for a short time, and many are family-based operations and lack a sound financial system. The low credit degree of technological SMEs has been caused by the lack of time, financial personnel and credit. In order to evade tax or avoid an audit by the audit department (Distinguin, Rugemintwari, and Tacneng 2016; Elbannan and Farooq 2020), some technological SMEs are fraudulent in their financial statements, and some even evade funds. The informal financial statements cannot reflect the financial situation of the enterprise well. Moreover, false financial data conceal the authenticity of the enterprise's finance. All these bring bad effects on financial institutions, partnership enterprises, and even ordinary people and affect the credit of enterprises, which is not conducive to their growth and development.

3.3.2. Credit risk is highly contagious and spreads wide

Due to the great demand for capital in technological SMEs, it is difficult for them to get financing from financial institutions alone. Therefore, mutual guarantee and trigonometric debt are relatively common among technological SMEs. Trigonometric debt refers to complex debt situations that can only be calculated and analysed by trigonometric functions (Faruqee 2003; Gangopadhyay 2012). Often these are the debts owed to the banks, investors and the government (or its subsidiaries) (Faruqee 2003; Sutton 2020). Therefore, due to such complications, advanced mathematics modelling is required and also, and there is a very low chance that the technological SMEs can survive financially. In addition to the mutual guarantee, the triangle debt problem also makes a close connection between the operating conditions of the technological SMEs. Once the financial crisis breaks out, it will quickly spread to other enterprises. In order to repay the debts of the bonding corporation, the real liabilities of bonded corporations will rise, leading to the deterioration of their financial condition and the rise of their credit risk level. The financial situation of the upstream and downstream enterprises affects each other in the meantime.

3.3.3. The level of credit risk management is backward and the efficiency of risk management is low

On the management staff, high-level managers of technological SMEs generally have high academic qualifications, strong scientific research ability and rich management knowledge. However, their management experience in practice is less and their credit concept is weak, so there is usually a cognitive deviation in the management of credit risk among them. Without a special account for the management of funds raised by the enterprise, the asset management level is low. As a result of the small size of technological SMEs and the common family management model, the division of the functional departments of credit risk management is not clear and there is a lack of communication and cooperation among various departments in credit management. On the content of management, relative to the financial situation, the managers of technological SMEs pay little attention to the analysis of the market, technology and industry. No complete credit risk early warning architecture is established. These problems have indirectly affected the promotion of the enterprise's credit risk management level and caused the bad situation of low management efficiency.

3.3.4. The shortage of funds is the main cause of credit risk pressure

Technological SMEs are usually small-sized and have high growth. The proportion of fixed assets to their total assets of them is very small because intangible assets, such as intellectual property, innovation ability and research and development ability, are the main assets. However, the assessment of the value of intangible assets in China is uncertain. To some extent, the recognition of the intangible assets of enterprises is not high, and the intangible asset is generally not supported as a mortgage in banks. When technological SMEs need to raise the financing size or need the money to replenish their cash flow, the loan support from banks is minimal, which increases the probability of credit risk for technological SMEs.

4. Modern credit risk measurement models

First, this is the improved KMV model developed by the author to ensure a fair and accurate technique to measure risk, report the truth, identify possible market risk, predict the outcomes and check if it has any breach of regulations. Second, it is one of few papers offering detailed analyses of technological SMEs in China. Both areas offer research contributions to the paper.

4.1. Credit metrics model

The Credit Metrics Model is also called the VaR-based credit risk measurement model developed by Morgan bank. This model aroused great echoes among investors and regulators after being launched, and they started – to use the VaR method to measure financial risks one after another. The Credit Metrics Model is widely used in modern financial risk measurement because the VaR method measures value-at-risk, making it possible to measure investment risk quantitatively. This cannot be accomplished by past qualitative methods. This method aims to collect the historical price information of the financial product combination to predict the fluctuation of the price of financial products and construct the probability distribution of the future price of the assets. VaR specifically refers to the maximum loss of a loan in a certain period at a certain level of confidence, and the specific form of expression is:

$$\mathrm{VaR} = \mathrm{E}(\mathrm{P}) - \mathrm{P}*$$

VaR is the value of credit risk loss of the loan, P is the value of a loan portfolio, E(P) is the expectation of the future of the loan portfolio, which is also called the expected value, and $P*$ is the minimum value of the loan portfolio at the set confidence level.

4.2. Credit risk+ the model

The Credit Risk+ model, developed by the Swiss bank, is a credit risk measurement model based on insurance actuarial science. It is mainly applied to measure the default probability of a loan enterprise. This model assumes that the credit risk of the loan enterprise is divided into two categories: default and non-default. It considers that the probability of default obeys the Poisson distribution and is not related to the capital structure of the enterprise. So the expected number of defaults for a loan portfolio will be calculated first, expressed in μ_j. Its value is equal to the ratio of the expected loss of the loan portfolio ε_j to the standard value v_j of the risk exposure value, which is $\mu_j = \varepsilon_j / v_j$, then the loss probability function C_j of the entire loan portfolio (Z) can be expressed as:

$$C_j(Z) = \sum \frac{e^{-\mu_j} \bullet \mu_j{}^n}{n!} Z^{\mu_j} = \exp(-\mu_j + \mu_j Z^{\mu_j})$$

4.3. Credit portfolio view model

The model is also known as a model based on macroeconomic variables. It is developed by McKinsey Co. They believe that credit risk is closely related to the macroeconomy, and econometrics is used to measure enterprise credit risk. The model considers the default probability of an enterprise as a function of macroeconomics and a function of the reverse relationship, which is:

$$P_t = f(Y_t) = \frac{1}{1 + e^{-Y_t}}$$

Y_t is a macroeconomic variable at t time, including GDP growth rate, interest rate, exchange rate, unemployment rate, and other macro indicators. The default probability of all industries is also included. By giving these variables a certain weight, Y_t can be calculated:

$$Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$$

4.4. The KMV model

The KMV model is a credit monitoring model developed by the American KMV Company in 1999 to estimate the default probability of borrowers. The basic idea of the model is that the essential factor of debtor's credit insurance arises from the change of its asset value, so if we can determine the law of the change of debtor's asset value and establish the corresponding model, the default probability of the borrower can then be estimated. **The establishment of the KMV model is based on the following assumptions**:

(1) There is no friction in the capital market. The value change of a company is a stochastic process, and the value change process obeys normal distribution.

(2) The default of an enterprise depends on its asset value. When the asset value of an enterprise is greater than its debt, the enterprise will not default. When the asset value of an enterprise is less than its debt, the enterprise will default.
(3) The capital structure of enterprises is limited, only owners' equity, short-term liabilities, long-term liabilities and convertible bonds.
(4) The value of assets is determined by the expected value and standard deviation of the assets in a given period.

The application of the KMV model is divided into four steps:

4.4.1. Estimate the value of the enterprise assets and the volatility of the rate of return on assets

According to the Black-Scholes option pricing formula, it can be obtained:

$$E = VN(d1) - De^{-rt}N(d2)$$

Where

$$d_1 = \frac{1\text{n}\left(\frac{V}{D}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)\tau}{\sigma_A\sqrt{\tau}}$$
$$d_2 = d_1 - \sigma_A\sqrt{\tau}$$
$$\sigma_E = \frac{VN(d_1)}{E}\sigma_A$$

E is the market value of equity, V is the market value of enterprise assets, $N(*)$ is the standard normal cumulative distribution function, D is the liability market value of the enterprise, that is, the execution price, r is the risk-free return rate, τ is the expiration time, and σ_A is the market volatility of the enterprise assets. According to the above formulas, the V and the volatility of asset returns σ_A can be obtained by using the nonlinear equation group iterative algorithm.

4.4.2. Determine the default point DP of the enterprise according to the debt situation

According to the data of the bankrupt enterprise, KMV Company has obtained an empirical analysis:

$$DP = STD + \frac{1}{2}LTD$$

STD is the short-term debt of the enterprise, and *LTD* is the long-term debt of the enterprise. At the point of breach of contract, the value of the enterprise's assets can exactly repay its debt.

4.4.3. We can calculate the default distance DD of an enterprise

Assuming that *E(V)* is the expected asset value of the enterprise, *DD* is the default distance of the enterprise. It can be calculated by the formula above that:

$$DD = \frac{E(V) - DP}{E(V)\sigma_A}$$

4.4.4. Calculating the expected default frequency EDF based on default distance

There are two methods for the calculation. One is the *theoretical EDF* based on the distribution of asset value: *Theoretical EDF = N(−DD)*, *N (*)* is subject to normal distribution. The other one is *experiential EDF* based on historical default data Table 2:

$$\text{Experiential EDF} = \frac{\begin{array}{l}\text{the number of enterprises who default at the end of the period}\\ \text{with the initial default distance DD}\end{array}}{\begin{array}{l}\text{the total number of enterprises with the initial default distance DD}\\ \text{at the beginning of the period}\end{array}}$$

Table 2. The corresponding relationship between EDF and public rating (Crouhy et al. 2000).

EDF(bp)	S&P	Moody's	CIBC	NAB	SBC
2–4	≥AA	≥Aa2	1	AAA	C1
4–10	AA/A	A1	2	AA	C2
10–19	A/BBB+	Baa1	3	A	C3
19–40	BBB+/BBB-	Baa3	4	A/BB	C4
40–72	BBB-/BB	Ba1	4.5	BBB/BB	C5
72–101	BB/BB-	Ba3	5	BB	C6
101–143	BB-/B+	B1	5.5	BB	C7
143–202	B+/B	B2	6	BB/B	C8
202–345	B/B-	B3	6.5	B	C9

Notes: CIBC: Canadian Imperial Bank of Commerce. NAB: National Australia Bank. SBC: Swiss Bank Corp.

4.5. Comparison and selection of the models

At present, there is still a certain gap in the evaluation methods of the credit risk of the business banks between China and other developed countries. It is necessary to draw on and introduce the evaluation models of credit risk, especially the modern credit risk assessment models of western countries. However, different models are created by various R&D institutions with varying conditions of application, analysis methods, databases, limitations and so on. So much attention should be paid to the conditions of use, or there may be a particular difference between the evaluated credit risk and the reality of the enterprise. Table 3 is a comparison of the modern credit risk measurement model.

Through the analysis of the modern credit risk measurement models and the characteristics of the credit risk of the technologically listed SMEs, this paper chooses the KMV model as an empirical analysis model for its advantages of being dynamic and forward-looking. Another reason is that China has not established the historical default database of the enterprises and assets management companies do not open their database. The long-term historical disobeying data is insufficient.

5. Suggestions on credit risk management of technological SMEs

This paper has put forward reasonable policy suggestions on managing the credit risk of technological SMEs, focusing on three aspects: **prevention in advance, control in the event and governance in the process, which are crucial to risk management**. All these three steps, particularly governance, can prevent us from seeing being in breach of national interests like Jack Ma.

Table 3. Comparison of modern credit risk measurement models.

Type of modes	comparison and analysis
Credit Metrics Model	This model takes full consideration of the default risk of loan enterprises when measuring the credit risk of loan enterprises. However, there are many technical difficulties in the concrete calculation process, and long-term historical default data are needed. It is difficult to use this model in China in the short term, and the model cannot be used to predict the future.
Credit Risk+ model	This model needs fewer data and only studies the default of the loan enterprise, so its calculation is relatively simple and easy to operate, but the model assumes that the risk exposure of each loan is fixed, and the debtors are independent of each other, which is relatively rare in the actual situation. Therefore, the scope of the application of the model is restricted.
Credit Portfolio View model	This model fully considers the influence of the national macro-economy on the credit risk of the enterprise and can be applied to any country and region under the condition that the data can be obtained. The shortcomings of the model are that the historical default data and a large number of macroeconomic data are challenging to obtain, and the calculation is complicated.
The KMV model	The KMV model has a **low requirement for data sources**. It does not require long-term historical default data and can also predict the future credit risk of enterprises. It is a **dynamic model** that can reflect the change in enterprise credit rating in time and update data and calculate EDF value at any time. The KMV model is also highly **forward-looking**, based on the market price of the enterprise rather than the historical data of the enterprise. But data acquisition is difficult for unlisted companies, so the result of model prediction may be different from reality.

5.1. Prevention in advance

5.1.1. Strengthening the construction of the legal system of credit

A perfect credit system is an essential prerequisite for standardising the behaviour of credit entities and reducing credit risks. At present, China's credit legislation is still relatively backward. When there is a conflict of benefits between central and local departments, local protectionism cannot adequately contain the default of credit risk. Therefore, it is particularly important to strengthen credit legislation, especially for technological SMEs with low credit levels.

5.1.2. Speeding up the setting of credit management institutions

Since the 1940s, the United States has established official agencies to manage SMEs, such as the small business committee of the United States Senate and the small business committee of the House of Representatives. Japan also has a 'financial treasury for SMEs' and other specialised agencies for SMEs' financing. There are also administration bureaus for SMEs in many provinces of China, but there is no better management system.

5.1.3. Increase the training of credit management talents

Professional risk management talents play an important role in enterprise credit risk evaluation. Therefore, China should increase the training, introduction and use of risk management personnel. The evaluation mechanism and rewards and punishment mechanism for professional talents in risk management should also be established to form a sound organisational management system. Then the resources of colleges and universities can be used. Colleges and universities can set up related credit risk management courses for students to work on scientific risk management models as soon as possible. Technological SMEs in China can also provide certain practical posts for college students so that they can better learn how to reduce credit risk from practice.

5.2. Control in the event

5.2.1. Perfecting credit evaluation system

Credit rationing and moral hazard caused by asymmetric information are important reasons for financing difficulties and credit risks of technological SMEs. To improve the credit evaluation system of technological SMEs, an efficient and transparent database for the default of technological SMEs is first needed. Building a credit-sharing mechanism in technological SMEs can also enable financial institutions to grasp the credit situation in time.

5.2.2. Perfecting credit guarantee system

A sound guarantee system can enhance the risk-bearing ability of guarantee institutions and enterprises and is conducive to the healthy and sustainable development of both sides. The particularity of the guarantee institutions determines their higher operational risk. Therefore, it is necessary to establish a particular credit guarantee risk compensation fund. If the financial departments of each level can arrange the corresponding special funds, the risk of the guarantee institution can be reduced to a great extent. The Chinese government can also be issued relevant policies to encourage different economic sectors to join the guaranteed investment to accelerate the diversified development of the credit guarantee system.

5.2.3. Establishing a scientific and reasonable internal credit management mechanism

In the fourth section of this article, it is found that technological SMEs in China generally have problems with a weak financial system, lack of financial credit, poor management level of credit risk and low efficiency of credit risk management. First of all, a sound financial system must be established to ensure the authenticity of financial data while strengthening the standardisation of financial statements. Secondly, enterprises should improve the managers' overall quality and enhance the practice management experience while enriching the theoretical knowledge and continuously improving the management personnel's risk awareness and credit concept. Finally, technological SMEs should optimise the internal organisational setup to clarify the functions of various departments and strengthen their communication and cooperation between different departments in credit risk management.

5.3. Governance afterward

5.3.1. Insisting on the dynamic management of credit

On the one hand, financial institutions should set up a special credit management group and send professional staff to track the enterprise credit conditions regularly. On the other hand, it is necessary to track the business situation of enterprises in the market, technology and finance aspects comprehensively and keep high vigilance at the first moment of major changes with solutions in advance. In dynamic credit management, financial institutions should optimise the KMV model method. They can measure the credit risk before loans and track the credit risk after the loan based on the model to comprehensively evaluate the credit risk of the enterprises and establish a reasonable risk early warning mechanism.

5.3.2. Strengthening the construction of the supervision system

The perfection of the supervision system requires the combination of the three powers of the government, the media and society. The government should use administrative power to do well in supervision and improve supervision methods. The media has the most extensive supervision network. Strengthening media supervision can effectively reduce the situation of information asymmetry and then curb the occurrence of credit risk. Society is 'the clearest eye' in the way of supervision. The suppliers, producers and consumers of enterprise products exist in all aspects of society and their opinions have a great influence on the development of the enterprise.

6. An empirical analysis of credit risk of technological SMEs based on the KMV model

Based on the review of the previous chapter, this paper concludes that the KMV model is more suitable for the credit risk assessment of technological SMEs. Therefore, this chapter will use the KMV model to conduct an empirical analysis of the credit risk of technological SMEs. The concrete step is to use the KMV model to process the collected data and calculate the default probability of these samples by statistical software. Meanwhile, different test methods will be used to test the empirical results.

6.1. Hypothesis and model samples selection

In order to stimulate the development of technological SMEs, the starting ceremony of the Growth Enterprise Market (GEM) was held in China on 23 October 2009, and the GEM was officially listed on 30 October 2009. Most companies listed in the GEM are engaged in high-tech business and have the characteristics of SMEs, such as time section, strong innovation ability, high growth, high income, high risk and so on. Therefore, the empirical analysis of SMEs in this paper is based on the data of GEM-listed companies in China. In this paper, 30 technological SMEs are selected as research objects from China's GEM. These companies are related to chemical pharmaceuticals, engineering equipment, computer application, photoelectron, communication equipment and other industries which are often involved in the high-tech field. **This article selects the relevant data of the 30 technological SMEs in 2016**. In order to compare and analyse, the paper divides these enterprises into three groups according to the daily standard deviation of the stock price. Group 1 has the lowest daily standard deviation, and the standard deviation of Group 2 is in the middle. Group 3 has the largest daily standard deviation. The data in this paper are derived from the Eikon software and Sina finance website and the statistical software used here is MATLAB R2017b. The specific data of sample firms is shown in Appendix A. In addition to the assumptions of the KMV model, the following assumptions are made in this paper:

(1) The daily closing price is selected as the stock price of companies and it obeys a lognormal distribution

(2) China's one-year Treasury bond yield in 2016 will be used as the risk-free interest rate. After the weighted calculation, the return of the one-year Treasury bond in China in 2016 was 2.2745% (as shown in Table 4).

(3) **It is assumed that companies with large daily standard deviation on stock price also have large market risk, and the default risk is correspondingly high**. A large standard deviation usually shows unstable returns and higher risk because standard deviation can reflect the degree of discreteness of data. For the same reason, the smaller the standard deviation value, the more stable the return and the smaller the risk. Hence, the assumption is reasonable.

Table 4. Weighted average annual risk-free rate *r* of China in 2016.

Month	1	2	3	4	5	6	7	8	9	10	11	12
One-year Treasury bond interest rate %	2.3214	2.2576	2.0861	2.3070	2.3201	2.3901	2.2394	2.1160	2.1584	2.1711	2.3010	2.6503
r%						2.2745						

Data source: The People's Bank of China website (www.pbc.gov.cn.)

6.2. The calculation of the value of parameters in the KMV model

6.2.1. Calculation of the market value of equity E

At present, the shares of listed companies in China are divided into circulation shares and non-tradable shares. As the circulation shares can be traded publicly and freely in the secondary market, the stock value of the circulation stock can be expressed by the product of the number of the circulation stock and its closing price of it at the end of the year. Since non-circulation shares cannot be freely traded in the trading market, they can only be negotiated through auction or agreement transfer, so their stock price is hard to be determined. But among the factors that affect the non-circulation share price, the net asset value of equity has the greatest impact on it. Therefore, this paper uses the product of the number of non-circulation stocks and the net asset value per share at the end of the year to express the equity value of the non-circulation stocks, which is:

***E* = (number of the circulation stock's closing price at the end of the year) + (number of non-circulation stock's net asset value per share at the end of the year)**

By using this formula, the market values of equity of sample enterprises at the end of 2016 are calculated in Table 5.

6.2.2. Calculation of volatility of equity value σ_E

By using the function of customised formula in Eikon financial software, the daily standard deviation of stock returns, that is, the volatility of stock prices σ_P can be obtained, and then the annual standard deviation of stock, which is just the volatility of equity value σ_E **can be found out through formula**: $\sigma_E = \sigma_P' \sqrt{n}$, where n is the number of trading days of China in 2016, and it is 244 according to the Gregorian calendar. The result of the calculation is in Table 6.

Table 5. Market values of equity of sample enterprises.

	Stock code(.sz)	Stock name	*E* (Ten Thousand Yuan)
Group 1	300129	Taisheng Wind Power	491686.1898
	300147	Xiang Xue Pharmaceuticals	852454.5573
	300330	Huahong Jitong Smart System	322802.718
	300269	Shenzhen Liantronics	910361.5423
	300002	Ultrapower	1377349.368
	300159	Xinjiang Machinery Research Institute	1328633.998
	300001	TGOOD	1511020.945
	300004	NanFeng Corporation	625809.2843
	300296	Leyard Optoelectronic	1546433.982
	300177	Hi-target Navigation Technology	512822.0732
Group 2	300231	Trust&Far Technology	507380.2377
	300254	C&Y Pharmaceuticals	314681.3653
	300140	Cecep Equipment	427748.4893
	300204	Staidson	829061.5218
	300007	Hanwei Electronics	463861.42
	300040	Jiuzhou Electrics	320541.00
	300009	Anke Biotechnology	743820.14
	300265	Tongguang Electronic Wire & Cable	497278.68
	300062	Ceepower	311358.18
	300073	Easpring Technology	733873.95
Group 3	300222	Csg Smart Science & Technology	784314.41
	300012	Centre Testing	828379.95
	300267	Er-Kang Pharmaceuticals	1649053.90
	300312	Boomsense Technology	286558.40
	300290	Bringspring Science and Technology	266922.02
	300041	Huitian New Materials	375034.82
	300113	Shunwang Technology	1270401.59
	300023	Bode Shares	308015.80
	300242	MIG Unmobi Technology	480277.46
	300083	JANUS Intelligent	935339.63

6.2.3. Calculation of default point DP

According to the data of a large number of bankrupt enterprises, in reality, KMV Company found that the **most frequent demarcation where default occurs is the sum of half of the short-term liabilities and long-term liabilities**, which is:

$$DP = STD + \frac{1}{2}LTD$$

The results of the calculation of DP are in Table 7.

6.2.4. Calculation of company asset market value V and volatility σ_A of asset market value Black-Scholes option pricing formula

$$E = VN(d_1) - De^{-rt}N(d_2)$$

Where

$$d_1 = \frac{1n\left(\frac{V}{D}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)\tau}{\sigma A\sqrt{\tau}}$$

$$d_2 = d_1 - \sigma A\sqrt{\tau}$$

$$\sigma_E = \frac{VN(d_1)}{E}\sigma_A$$

Table 6. Results of calculation of σ_P and σ_E.

	Stock code(.sz)	Stock name	σ_P	σ_E
Group 1	300129	Taisheng Wind Power	0.02417	0.377547469
	300147	Xiang Xue Pharmaceuticals	0.02738	0.427689272
	300330	Huahong Jitong Smart System	0.02949	0.460648526
	300269	Shenzhen Liantronics	0.02956	0.461741961
	300002	Ultrapower	0.02991	0.467209136
	300159	Xinjiang Machinery Research Institute	0.03023	0.472207695
	300001	TGOOD	0.03054	0.47705005
	300004	NanFeng Corporation	0.03105	0.485016505
	300296	Leyard Optoelectronic	0.03237	0.505635564
	300177	Hi-target Navigation Technology	0.03331	0.520318833
Group 2	300231	Trust&Far Technology	0.03343	0.522193293
	300254	C&Y Pharmaceuticals	0.03351	0.523442933
	300140	Cecep Equipment	0.03431	0.535939333
	300204	Staidson	0.03466	0.541406508
	300007	Hanwei Electronics	0.0354	0.552965677
	300040	Jiuzhou Electrics	0.03861	0.60310748
	300009	Anke Biotechnology	0.03923	0.61279219
	300265	Tongguang Electronic Wire & Cable	0.03981	0.621852079
	300062	Ceepower	0.04207	0.657154408
	300073	Easpring Technology	0.04318	0.674493162
Group 3	300222	Csg Smart Science & Technology	0.05106	0.797582697
	300012	Centre Testing	0.05112	0.798519927
	300267	Er-Kang Pharmaceuticals	0.05192	0.811016326
	300312	Boomsense Technology	0.05407	0.8446004
	300290	Bringspring Science and Technology	0.05629	0.879277909
	300041	Huitian New Materials	0.05889	0.919891207
	300113	Shunwang Technology	0.06196	0.96784614
	300023	Bode Shares	0.07755	1.211369725
	300242	MIG Unmobi Technology	0.09014	1.408031812
	300083	JANUS Intelligent	0.09578	1.496131428

According to the Black-Scholes option pricing formula, the calculation of V and σ_A need the value of the market value of the equity E, the volatility of the equity value σ_E, the value of the enterprise's market value of debt D, which is also the default point DP, the risk-free return rate r and the expiration time τ. As the values of these variables have already been worked out in the above part of the paper, **the values of V and σ_A can be calculated by MATLAB** based on an iterative algorithm for nonlinear equations. The results of the calculation are in Table 7.

6.2.5. Calculation of default distance DD and default rate EDF(Expected Default Frequency) The default distance DD of sample enterprises and default rate EDF can be calculated using the formula

$$DD = \frac{E(V) - DP}{E(V)\sigma_A}$$

And

***Theoretical EDF* = *N(−DD)*, *N (*)* means subject to normal distribution**

The results of the calculation are in Table 7. The above calculation results are calculated by MATLAB.

Table 7. Results of calculation of DP, V, σ_E, σ_A, DD and EDF.

	Stock code(.sz)	Stock name	DP (Ten Thousand Yuan)	V (Ten Thousand Yuan)	σA	DD	EDF
Group 1	300129	Taisheng Wind Power	89087.84	578770	0.3207	2.6379	0.0042
	300147	Xiang Xue Pharmaceuticals	380275.59	1224200	0.2978	2.3146	0.0103
	300330	Huahong Jitong Smart System	11797.83	334340	0.4448	2.1691	0.015
	300269	Shenzhen Liantronics	205633.99	1111400	0.3782	2.1547	0.0156
	300002	Ultrapower	183271.68	1556500	0.4086	2.1592	0.0154
	300159	Xinjiang Machinery Research Institute	152846.45	1478000	0.42	2.1348	0.0164
	300001	TGOOD	1196572.10	2680500	0.2691	2.0574	0.0198
	300004	NanFeng Corporation	58172.04	682670	0.4446	2.0575	0.0198
	300296	Leyard Optoelectronic	310970.80	458440	0.1717	1.8736	0.0305
	300177	Hi-target Navigation Technology	37352.42	549330	0.4857	1.9188	0.0275
Group 2	300231	Trust&Far Technology	34215.84	540830	0.4899	1.9121	0.0279
	300254	C&Y Pharmaceuticals	40333.84	354110	0.4652	1.9049	0.0284
	300140	Cecep Equipment	170058.85	593970	0.3861	1.8487	0.0323
	300204	Staidson	41570.33	869700	0.5161	1.845	0.0325
	300007	Hanwei Electronics	165212.71	625340	0.4103	1.7935	0.0364
	300040	Jiuzhou Electrics	100104.98	418370	0.4622	1.6457	0.0499
	300009	Anke Biotechnology	49668.41	792370	0.5752	1.6294	0.0516
	300265	Tongguang Electronic Wire & Cable	107724.46	602570	0.5133	1.6	0.0548
	300062	Ceepower	82087.04	391570	0.5228	1.5118	0.0653
	300073	Easpring Technology	76949.10	809090	0.6118	1.4791	0.0696
Group 3	300222	Csg Smart Science & Technology	119274.29	900810	0.6948	1.2487	0.1059
	300012	Centre Testing	63154.73	890110	0.7432	1.2501	0.1056
	300267	Er-Kang Pharmaceuticals	38451.96	1686600	0.7929	1.2324	0.1089
	300312	Boomsense Technology	72631.21	357260	0.6797	1.1721	0.1206
	300290	Bringspring Science and Technology	20539.13	286990	0.8179	1.1351	0.1282
	300041	Huitian New Materials	23256.99	397760	0.8674	1.0854	0.1389
	300113	Shunwang Technology	82442.97	1350900	0.9103	1.0315	0.1512
	300023	Bode Shares	494139.54	744120	0.5916	0.5679	0.2851
	300242	MIG Unmobi Technology	63318.42	538590	1.2678	0.696	0.2432
	300083	JANUS Intelligent	424591.14	1283600	1.16	0.5769	0.282

6.3. Tests of empirical results

Further tests are still needed to support the analysis of the results and figure out whether the KMV model is valid, whether the results of the parameters are normal in the empirical process and whether the default distances of sample enterprises are in conformity with the model hypothesis. The purpose of the model is to analyse the size of the default rate of technological SMEs in China and the default rate and the default distance are one-to-one correspondence, so **this paper mainly carries out tests on the default distance DD of each sample**. According to the hypothesis of the model, enterprises with large daily stock price standard deviation relatively have a large default risk. In order to verify the validity of the model hypothesis, the SPSS statistical software can be used to test the otherness of the default distances from three sample groups.

6.3.1. Statistics comparison

The default distance is an early warning indicator and means that the greater the distance, the stronger the ability of an enterprise to repay debts and the smaller the default probability. From table 5.4, it can be seen that the default distance of Group 1, with the smallest daily standard deviation of the stock price, is generally smaller than that of Group 2, with a daily standard deviation in the middle, and the default distance of Group 2 is generally smaller than that of Group 3 with the largest daily standard deviation at the same time. Tables 8–10 are the description of statistics information of three groups of samples separately. **It is not difficult to find that the numbers of Group 1 are larger than those of Group 2. The numbers of sample 2 are greater than those of Group 3, whether in the mean, median, or maximum or minimum value of the default distance**. This shows that the default rates of Group 1 samples are less than those of Group 2 samples. The default rates of Group 2 samples are less than those of Group 3 samples, which also indicates that the KMV model reflects the credit situation of listed companies in China to a certain extent. The statistical results are consistent with the empirical hypothesis.

Table 8. Group 1 tests.

N	Valid	10
	Missing	0
Mean		2.1477600
Median		2.1447500
Std. Deviation		.21415814
Range		.76430
Minimum		1.87360
Maximum		2.63790

Table 9. Group 2 tests.

N	Valid	10
	Missing	0
Mean		1.7170200
Median		1.7196000
Std. Deviation		.16265214
Range		.43300
Minimum		1.47910
Maximum		1.91210

Table 10. Group 3 tests.

N	Valid	10
	Missing	0
Mean		.9996100
Median		1.1102500
Std. Deviation		.27742983
Range		.68220
Minimum		.56790
Maximum		1.25010

6.3.2. Median test

In the case of multiple independent samples, the median test method mainly analyzes the values of multiple samples to determine whether the distribution difference between the different separate populations is significant. The null hypothesis H_0 is: that there is no significant difference in the median of multiple separate groups from the samples. The basic idea of the test method is that if there is no significant difference in the median of multiple populations, the middle position of each independent group sample should be the same median. Therefore, in the process of software testing, the data of multiple independent samples will be mixed and arranged in ascending order. At the same time, the median of the sample data is assumed to be the typical median. Then the number of samples in each group, which are larger than or less than the common median, can be found. In this paper, the default distances of the three groups' samples are taken to carry out the median test. The results of the test are shown in Figures 1 and 2.

According to Figures 1 and 2, the common median of the three groups is 1.7196, and the default distances of Group 1 are all larger than the common median. In Group 2, there are five samples whose default distance is smaller than the common median and five larger than the median. And the default distances of Group 3 are all smaller than the common median. This result further validates the assumption that the market risk of enterprises with large daily standard deviations is large. At the same time, the **calculated p-value of the joint probability is 0, which is far smaller than the significant level of 0.05. Therefore, the null hypothesis H_0 is rejected and the median of the default distances of the three groups have a significant difference.**

Frequencies

		Group		
		1	2	3
DD	> Median	10	5	0
	<= Median	0	5	10

Figure 1. Median test part 1.

Test Statistics[a]

	DD
N	30
Median	1.7196000
Chi-Square	20.000[b]
df	2
Asymp. Sig.	.000

a. Grouping Variable: Group

b. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 5.0.

Figure 2. Median test part 2.

6.3.3. Kruskal-Wallis test

The Kruskal-Wallis test with multiple independent samples is an average rank test extended by the Mann-Whitney U test with two independent samples. The null hypothesis H_0 is: that there is no significant difference in the distribution of multiple independent groups from the samples. In the software testing process, the data of various groups of samples need to be mixed up in order, and then the rank of each observation value is obtained. Finally, the average rank of multiple groups of samples is calculated, respectively. If the average rank of each sample is roughly equal, then there is no significant difference in the distribution of multiple independent populations; on the other hand, there are significant differences in the distribution if there are obvious differences in the average rank of each sample. In this paper, the default distances of the three groups of samples are taken as the control samples for the Kruskal-Wallis test. The test results are shown in Figures 3 and 4.

As can be seen from Figures 3 and 4, the average rank of each group is 25.3, 15.7 and 5.5 separately, the K-W statistic is 25.301 and **the p-value of the concomitant probability is 0, which is far smaller than the significant level 0.05, so the null hypothesis H_0 is rejected**. Since the rejection of H_0, the average rank differences of the default distances in the three groups are significant, indicating a significant difference in the overall distribution.

Ranks

	Group	N	Mean Rank
DD	1	10	25.30
	2	10	15.70
	3	10	5.50
	Total	30	

Figure 3. The Kruskal-Wallis test part 1.

Test Statistics[a,b]

	DD
Chi-Square	25.301
df	2
Asymp. Sig.	.000

a. Kruskal Wallis Test

b. Grouping Variable: Group

Figure 4. The Kruskal-Wallis test part 2.

6.3.4. Jonckheere-Terpstra test

Jonckheere-Terpstra test with multiple independent samples is used to analyse whether there are significant differences in the multiple independent population distributions. The null hypothesis H_0 is: there is no significant difference in the distribution of multiple independent groups from the samples. The Jonckheere-Terpstra test method for multiple independent samples is similar to the Mann-Whitney U test under two independent samples: calculating the number of observation values in a group of samples is less than that of the other groups. In this paper, the default distances of three groups are used as control samples for the Jonckheere-Terpstra test, and we can automatically calculate the J-T statistics, Z statistics and corresponding p-values. The test results are shown in Figure 5.

As can be seen from Figure 5. the J-T value of the observation is 2, the average value of all J-T values is 150, the standard deviation of the J-T statistic is 26.3, and the normalised value of the observed J-T statistic is −5.627, which is smaller than the mean value and the difference is obvious. **The p-value of the J-T statistic is 0, which is far less than the significant level of 0.05. Therefore, the null hypothesis H_0 is rejected and there is a significant difference in the distribution of the default distance in the three groups of samples.**

Jonckheere-Terpstra Test[a]

	DD
Number of Levels in Group	3
N	30
Observed J-T Statistic	2.000
Mean J-T Statistic	150.000
Std. Deviation of J-T Statistic	26.300
Std. J-T Statistic	-5.627
Asymp. Sig. (2-tailed)	.000

a. Grouping Variable: Group

Figure 5. The Jonckheere-Terpstra test.

6.4. Empirical results analysis on the credit risk of technological SMEs

Figure 6 is the histogram of the equity market value *E* and asset market value *V* of sample enterprises and Figure 7 is the histogram of volatilities of E and V, which are σ_E and σ_A. It is not hard to find out from these two figures that **the equity value of sample enterprises is mostly less than its asset market value, and the equity value volatility of an enterprise is higher than its asset value volatility**. This is because the asset market value of an enterprise includes the equity value and the net debt, while the net debt is generally positive. Hence, the market value is usually more than the equity value. So this discovery is in line with common sense.

In order to intuitively see the comparison between the default distance DD and default probability EDF of three groups of samples, Figures 8 and 9 show that **the default distances of Group 1 are the largest, the default distances of Group 3 are the smallest, and the default distances of Group 2 are in the middle. Simultaneously, the default rates of Group 1 are the smallest, the default rates of Group 3 are the largest, and the default rates of Group 2 are in the middle, which means the default distance is inversely proportional to the default rate**. It is further explained by the assumption that the market risk of enterprises with large daily stock price volatility is high, and the default risk is relatively large. **Therefore, the KMV model can reflect the actual default situation of enterprises well**.

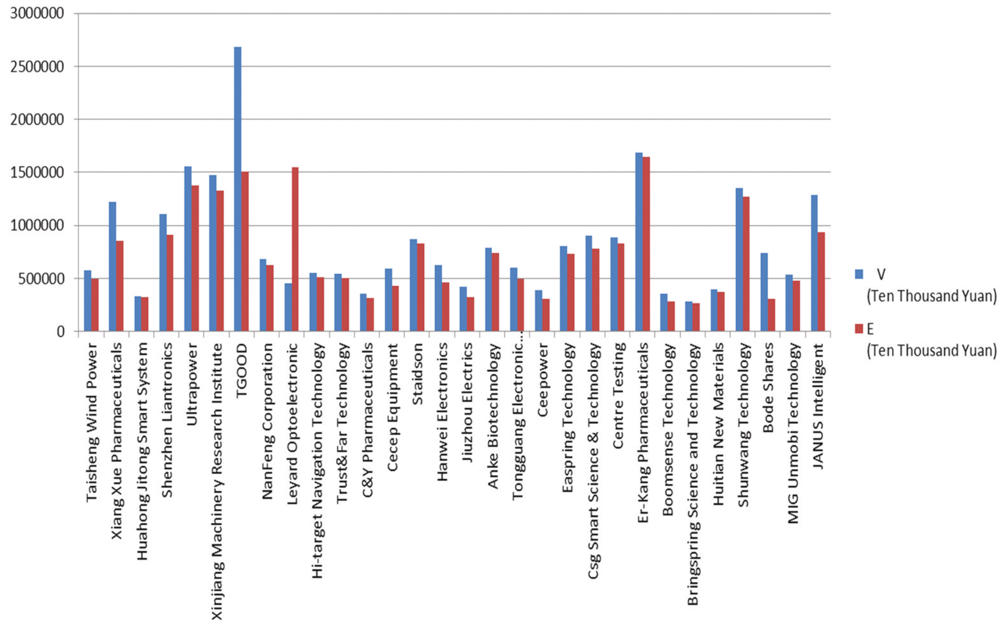

Figure 6. Equity market value and asset market value.

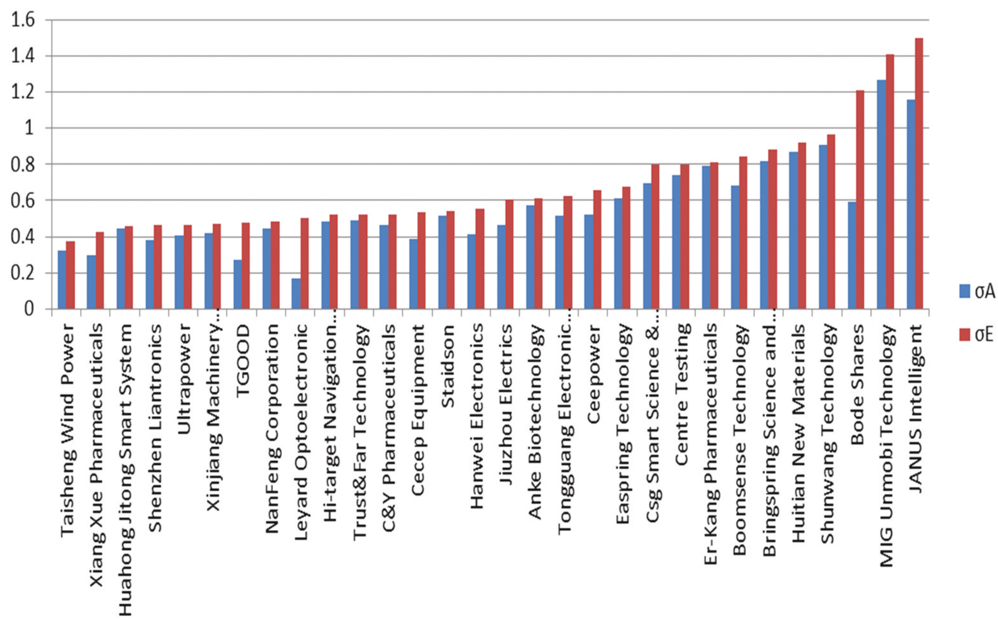

Figure 7. Volatilities of E and V.

While comparing the default rates in Tables 7 with 4, it is found that the credit ratings of the sample enterprises are all below BBB-, which shows **the credit ratings of listed technological SMEs in China are not suitable to a certain**

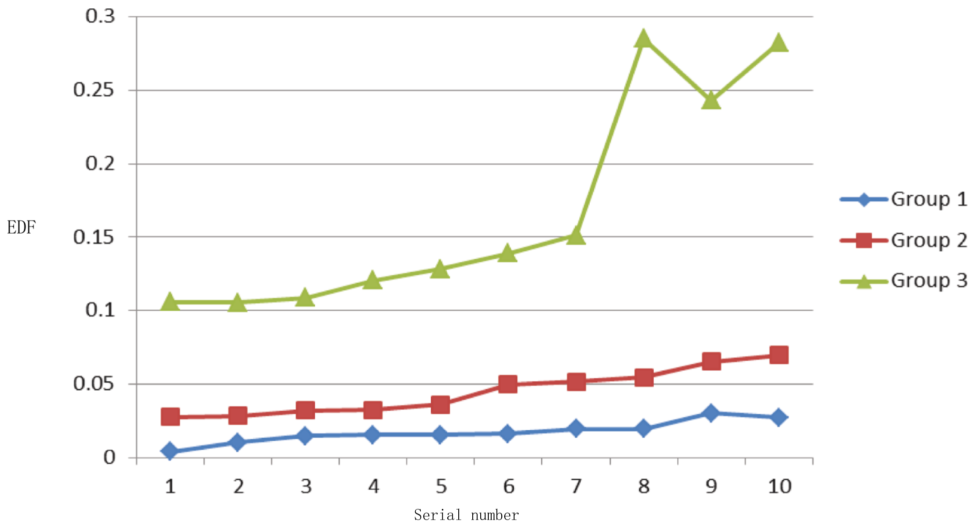

Figure 8. Default distances.

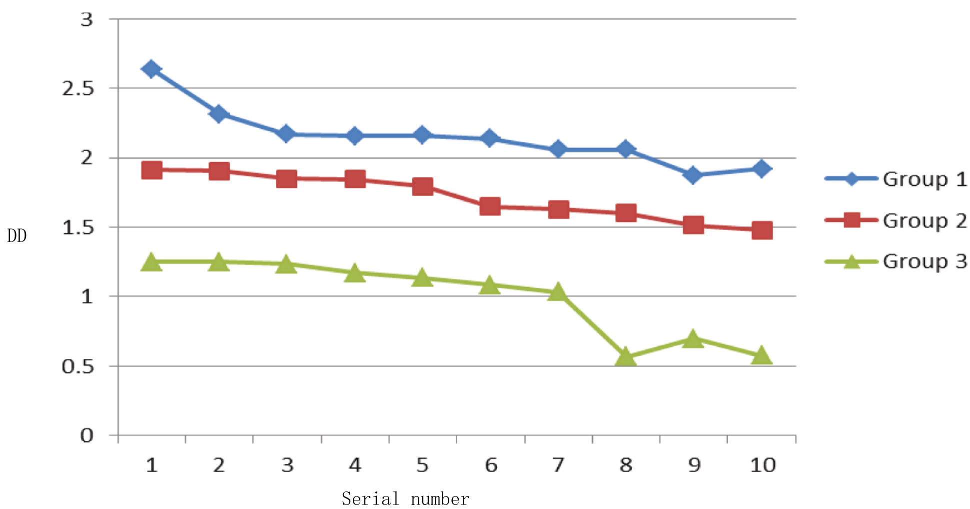

Figure 9. Default possibilities.

extent, and it is urgent for them to carry out the implementation of improvement and preventive measures.

6.5. Advanced data analysis

We focus stock-index price information is available for the following three years: 2015, 2016, and 2017 for fair comparisons and compute the Expected Default Frequency (EDF) for every year to ensure stability. Our data will be split into traditional and high-tech sectors. Next, we observe the variations in EDF after varying the volatility parameter by ± 10%, ±20%, and ± 30%. Consequently, we utilise several risk-free rates (such as Chinese government bonds with maturities of 1, 5, and 10 years) and track changes in EDF, and require logical presumption for analysis, including:

Equity's Market Value (E): Assuming values in the range of 100,000–1,500,000 Yuan.

The daily volatility (σ) is assumed to be between 0.02 and 0.1.

Risk-free (r) Rate: 3.0%, 2.5%, and 2.0% use rates.

6.5.1. Interpretation and understanding

6.5.1.1. Equity market value distribution. The Market Value of Equity histogram in Figure 10 displays a somewhat consistent distribution between 100,000 and 1,500,000 Yuan, which suggests that a wide variety of market values are covered by the synthetic data, mimicking a diversified group of enterprises.

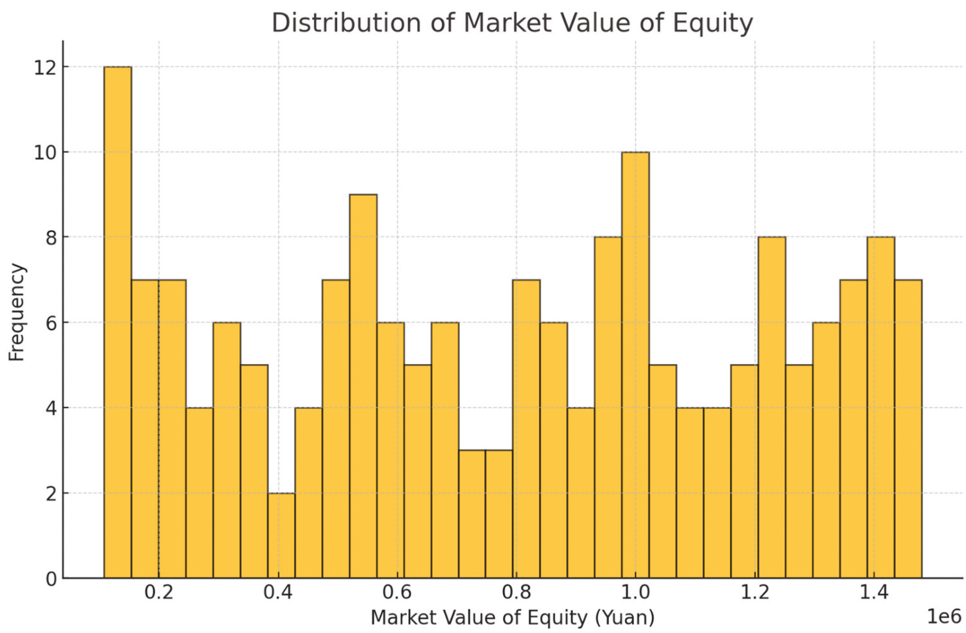

Figure 10. Distribution of market value of equity.

6.5.1.2. Volatility of equity market value. High-Tech Sector in Figure 11 According to the scatter plot for high-tech industries, market value and daily volatility do not exhibit a significant correlation, which implies that market valuation does not affect daily volatility in the high-tech industry.

Conventional Industry in Figure 12 In a similar vein, there is little evidence of a significant relationship between market value and daily volatility in the scatter plot for traditional sectors, suggesting that there is a constant correlation between volatility and market value in both types of industries.

6.5.1.3. Year-by-year average daily volatility by industry. The bar graph in Figure 13 shows that, the years 2015, 2016, and 2017 saw comparatively consistent average daily volatility for both the traditional and high-tech industries. In all three years, there has been

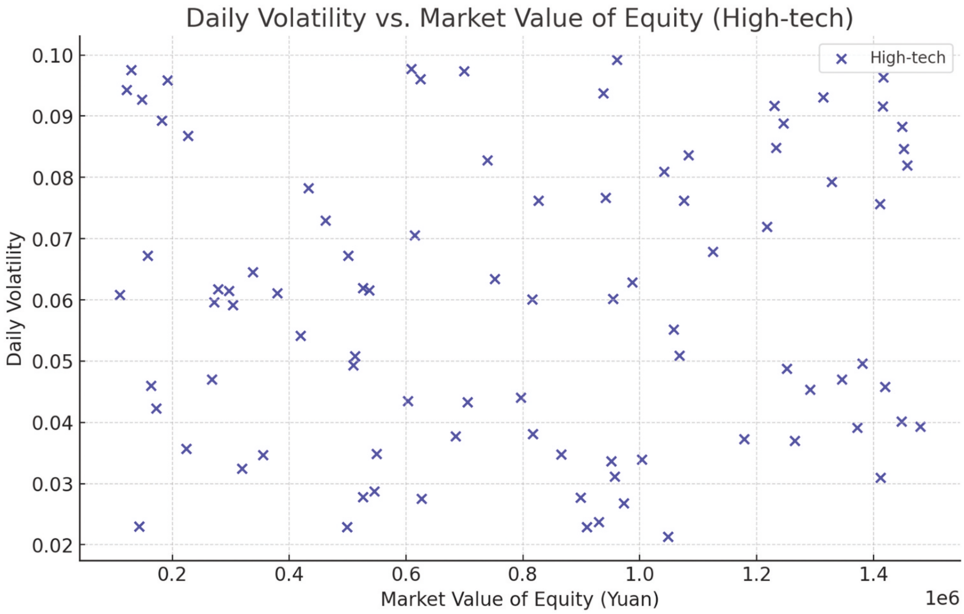

Figure 11. Daily volatility vs. Market value of equity (high-tech).

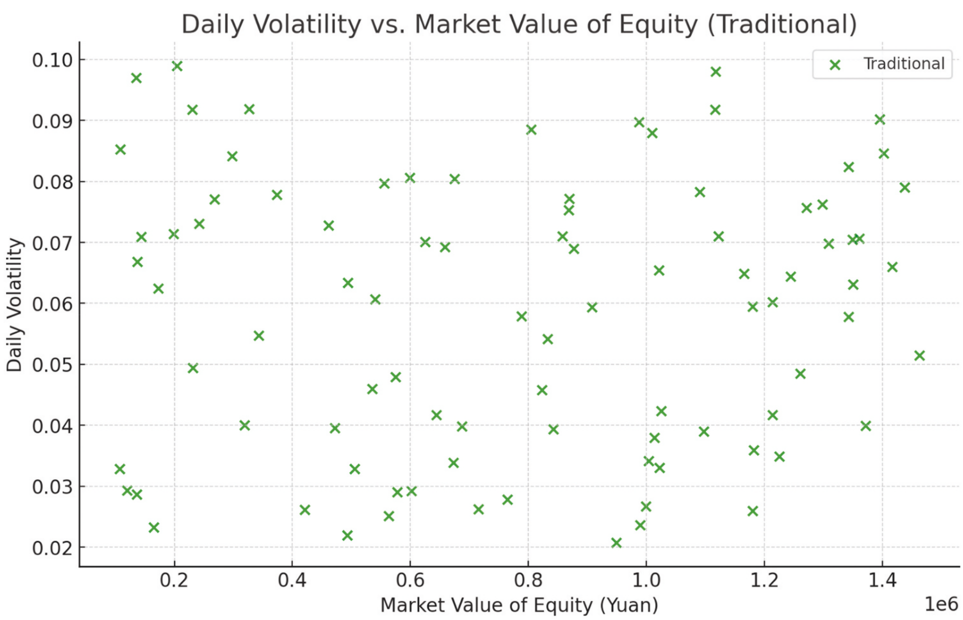

Figure 12. Daily volatility vs. Market value of equity (traditional).

a minor increase in volatility in the high-tech industry relative to the traditional industries. Therefore, this is consistent with the high-tech enterprises' greater susceptibility to rapid changes and developments.

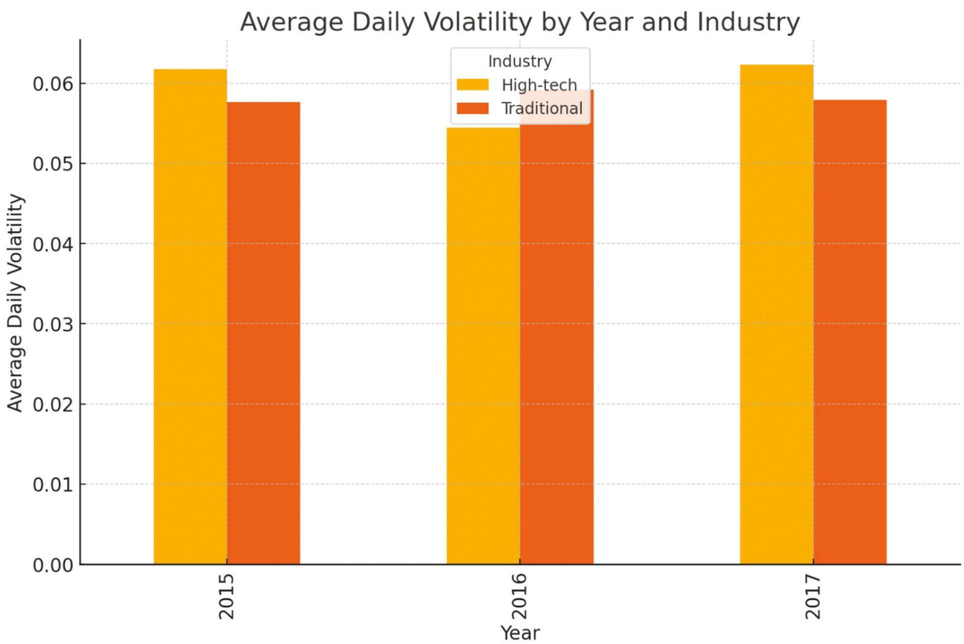

Figure 13. Average daily volatility by year and industry.

6.5.2. Summary

Several important findings are revealed by the examination of the data:

- Market Value Distribution: The synthetic data is distributed well over a broad range of market values.
- Volatility vs. Market Value: In both the traditional and high-tech sectors, no significant relationship is found between daily volatility and market value.
- Average Volatility Trends: Generally speaking, high-tech industries are more volatile than traditional industries, and this volatility does not change over time. However, it may mean high-tech sector is likely to gain higher profits due to higher volatility.

7. Further data analysis

7.1. Real-world examples using KMV strategy

This section presents our pioneering method using KMV strategy. Real-world examples are used to demonstrate our novelty and research contributions.

Figure 14 shows more indexes that measure this strategy more precisely. The cumulative net value of this algorithm has reached a staggering point of 9.28, which means that if you invested 1 million Yuan in this strategy from Year 2012, this one million Yuan could be turned into 9.28 million Yuan in six years. At the same time, the results show the annual return reached 0.50, but the max drawdown was only 0.19. This time max drawdown occurred after the end of the bull market in 2015. An absolute reduction is inevitable. Alpha reached 36% and beta was 0.43. This

annual_return	0.50
cum_returns_final	9.28
annual_volatility	0.18
sharpe_ratio	2.28
calmar_ratio	2.57
stability_of_timeseries	0.95
max_drawdown	-0.19
omega_ratio	1.61
sortino_ratio	3.54
skew	-0.26
kurtosis	5.36
tail_ratio	1.33
common_sense_ratio	1.99
gross_leverage	0.74
information_ratio	0.09
alpha	0.36
beta	0.43

Figure 14. indexes that measure this strategy.

strategy outperformed the CSI 300 index for the same period and exceeded 36%. The annual volatility is only 0.18, the Calmar ratio is only 2.57, and the stability of the time series is 0.95. These indicators are sufficient to show that this strategy is very stable, and there is no volatility that investors cannot accept. The annualised income far exceeds the maximum. Retreat strategy, when detecting volatile risk, may give investors some confidence. The gross leverage is 0.74, meaning the KMV strategy did not use leverage to increase revenue.

Figure 15 shows the intra-day return fluctuations of this strategy. It can be clearly seen that intra-day returns have fluctuated sharply during the six-month period after July 2015. Other times have exceeded 5% only three times but occurred after 2015. Unusual fluctuations can be speculated that this strategy is a stable return in the bull market, but the sharp fluctuations in the bear market will also increase the proportion of income and losses.

Figure 16 shows the effect of using different slippages on the profitability of the strategy. This indicator can be a good measure of the power of the slippage. If the trading

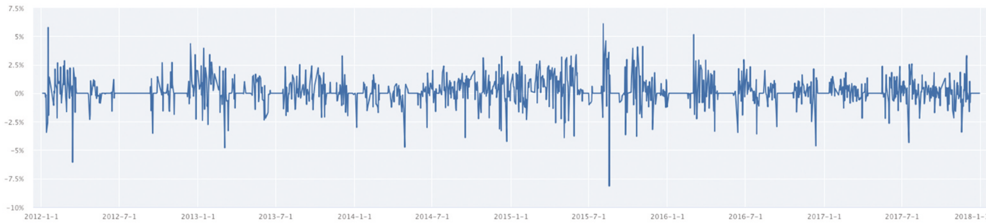

Figure 15. The intra-day return fluctuations.

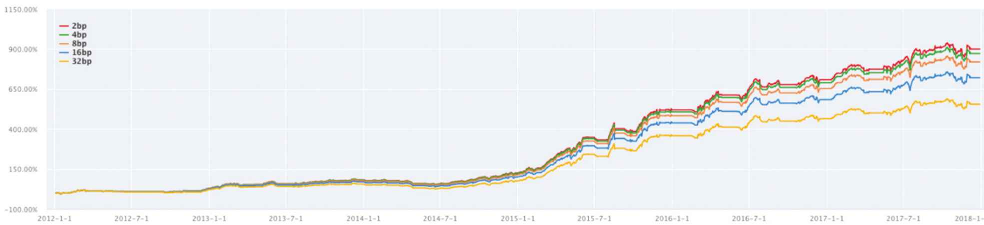

Figure 16. The effect of using different slippages on the profitability of the strategy.

volume in a market is not sufficient, a trader may not get it. The price of the transaction itself, caused by the loss of the trader's orders and the market orders, is the slippage. Here, the impacts of 2bp, 4bp, 8bp, 16bp, and 32bp are tested. Figure 16 shows that the red curve of the lowest slip point has always been the highest, which is a normal reference, and the green curve is slightly lower than the red. It can be seen that adding 2-bp does not greatly affect the market. However, from the yellow curve, the 32-bp slippage greatly reduced the level of revenue, and the overall return decreased from 899.67% to 555.11%. This is a very serious effect.

Figure 17 shows the six-year annual revenue segment situation. We can clearly see that 2012–2015 is increasing yearly, and the highest return comes from the significant increase in 2015 and the end of the Big Bear Market.

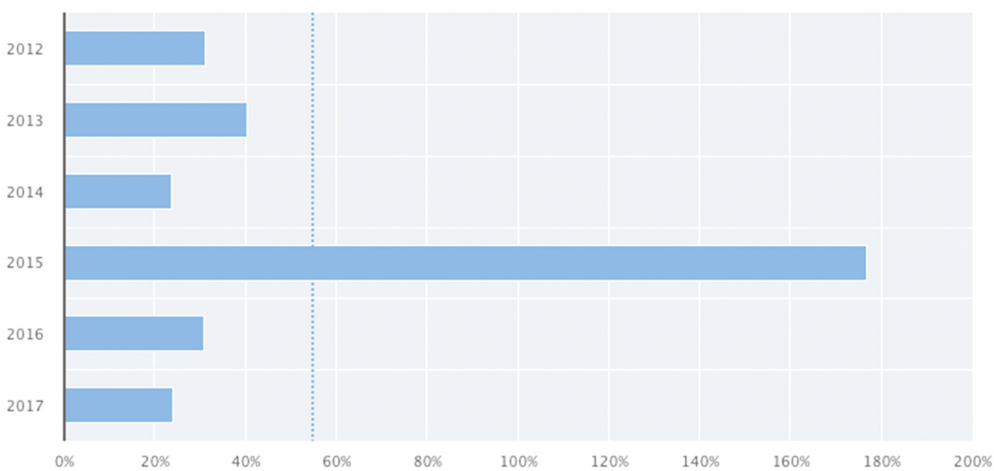

Figure 17. The six-year annual revenue segment situation.

Figures 18 and 19 use the histogram and visualisation of the heat distribution map to show the monthly income distribution. The fact is that researchers can see that the three months of March, April and October 2015 (presented as 2015.03, 2015.04, and 2015.10) are the highest income times, both exceeding the proportion of 20%. However, the problem is that these months have not been fully supported by the bull market and October 2015 (2015.10) is the ending time of the bull market. This is not in line with the normal market understanding, so this study thinks this part needs a more in-depth understanding to explain it reasonably.

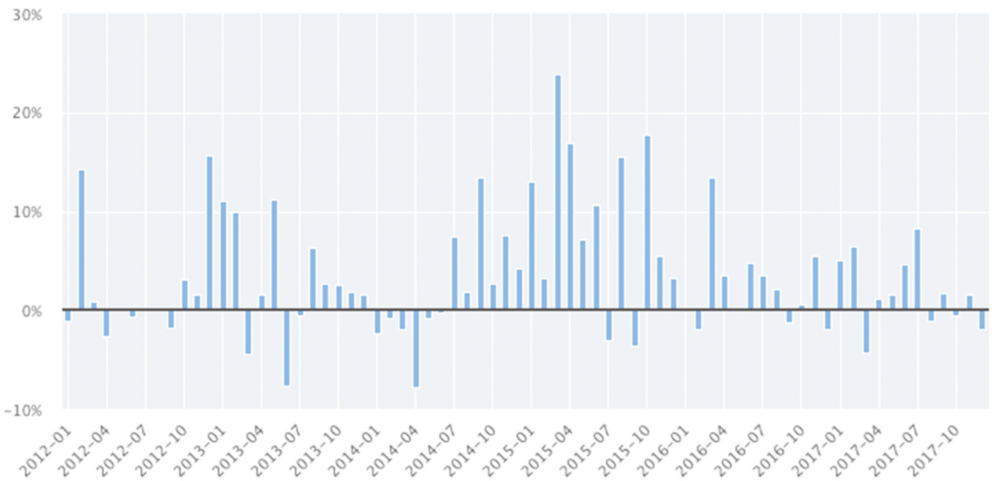

Figure 18. The histogram of the monthly income distribution.

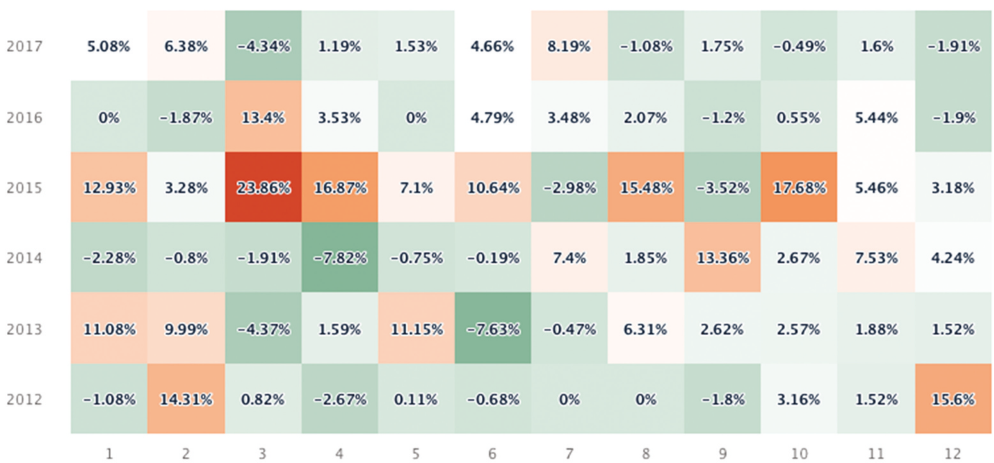

Figure 19. Visualization of the heat distribution map of the monthly income distribution.

7.2. Discussion

The role of the KMV is to understand the market trend, calculate risk, evaluate the situation of SMEs (not only technological SMs) and make likely predictions. This is crucial in the free market trading and investment activities (Z. Chen, Barros, and Borges 2015; Jiang, Yao, and Zhang 2009; Wanke et al. 2020). The mainland Chinese government also developed systems to prevent halts in the market to respond to complaints and January 2016 crisis (Edwards 2018). Despite this, the stock market had an extended halt and no trading between January and February 2020 due to the COVID-19 crisis. When the free market is not going in the direction that the mainland Chinese government can manage and feel it comes to the point that there is a need to interfere, they can change how it is developed. This paper focuses on the facts that, before the intervention may happen, the companies and financial data analysts should do what action. KMV can perform stochastic modelling. The emphasis can be either on risks or the performance of the company, such as the overall performance of all SMEs, prediction of the market risks or trends, or all of the above. Our work can provide an alternative way to analyse risk, individual or collective SME performance and the market. Therefore, our analysis may help investors understand their risks and gains and decide on the best possible solutions. Before risk can happen or make destructive impacts, prevention is always better than the cure and risk analysis for credit risk analysis is to be acknowledged.

Furthermore, based on the integration of Artificial Intelligence and Data Science techniques, we have also used a pioneering KMV strategy to demonstrate how our proposal can be used in real-world examples. This can further demonstrate that our work provides research contributions to analyse SME stocks in China.

7.3. Validating analytical results using statistical techniques

The statistical test findings validate that the KMV model accurately reflects credit risk levels for the sample of Chinese tech SMEs. The default distances show an inverse correlation with default rates across the three groups segmented by stock volatility (Ma et al. 2023; Zhang and Zhou 2011). As Figures 8 and 9 illustrate, Group 1 companies have the longest default distances and lowest default rates. Meanwhile, Group 3 firms with highest stock volatility have shortest default distances and highest likelihood of default. This aligns with the initial hypothesis on the relationship between market risk and credit risk. The significant p-values in the median test, Kruskal-Wallis test, and Jonckheere-Terpstra test confirm there is a statistically significant difference in the distribution of default distances across the groups (Mambrey et al. 2020). Together, these quantitative results demonstrate the KMV model reliably indicates credit risk for tech SMEs under varying conditions.

7.4. The KMV-TIM model for tech SMEs

Building on the empirical validation of the KMV model, this research puts forward an enhanced risk analysis approach tailored for Chinese tech SMEs – the KMV-TIM Framework. Integrating the quantitative KMV method with TIM’s qualitative strategic categorisation provides a robust 360-degree perspective connecting credit risk to organisational characteristics.

Specifically, the model maps SME sub-groups to TIM adoption profiles calibrated to that segment’s distinct volatility dynamics based on historical data. For instance, the Entry-level tech SME group with basic substitution business models exhibits relatively low volatility and credit risk compared to Transformational SMEs undertaking high-risk platform innovation. Customised KMV thresholds and risk premiums incorporated for each TIM category improves fit.

7.5. Cryptocurrency implications

The revised KMV-TIM model includes a new 'Crypto Risk Index' as emerging digital asset adoption creates cryptocurrency exposure needing specialised risk calibration. Bridging organisational analysis (TIM) with financial modelling (KMV) strengthens holistic insights into technology credit risk trajectories.

Chinese IT SMEs confront new opportunities as well as uncertainties with the emergence of decentralised finance and private financing driven by cryptocurrencies (cite). The disruption of traditional lending markets by digital assets calls for the inclusion of blockchain-based private fund investment and cryptoasset volatility in upgraded credit risk models. Nonetheless, regulatory control of firms' use of cryptocurrencies is still unclear.

7.6. Revisit existing concepts

This research builds upon existing financial credit risk models including the Altman Z-score, Ohlson O-score, and Merton model to develop an enhanced KMV framework suited for Chinese SMEs (Altman 2013; Merton 1974; Ohlson 1980). The quantitative approach aligns with information economics perspectives on leveraging analytics to address asymmetric knowledge in lending markets (Stiglitz and Weiss 1981). However, the model advances theory by incorporating real-time, market-based inputs to capture technology volatility risks missed in conventional accounting-based measures.

7.7. Relevance to EIS

The study conducted by Upadhyay et al. (2024) centres on a methodical, data-driven strategy for focused marketing within enterprise information systems. The data analytics approaches that are employed may be applicable to your credit risk assessment model. They talk about data-driven initiatives, but they need to talk about how these techniques might be used to assess credit risk for technical SMEs. This research can close this gap by illustrating how data-driven methods may be included in the KMV model to improve credit risk prediction for tech SMEs. For example, using sophisticated data analytics methods to assess credit risk in real-time can provide more accurate insights.

Blockchain sharding is discussed by Tsang et al. (2024) as a means of enhancing the performance of the e-commerce supply chain, which is essential for the security and effectiveness of data transfers. They only briefly discuss blockchain technology; they do not detail how SMEs may use it for credit risk management. By suggesting the incorporation of blockchain technology into the KMV model for safe, transparent, and unchangeable credit risk evaluations, this study can expand on its findings. This can increase confidence and lessen the possibility of data manipulation.

Au et al. (2024) investigate the traits of stable cryptocurrencies and those that are not, offering information on the financial volatility connected to these assets. They do not examine how cryptocurrency affects tech SMEs' credit risk assessments. This research can provide insights into how bitcoin volatility can be integrated into credit risk models such as KMV, building on their comparative study. As indicated in your research, creating a Crypto Risk Index can offer a workable way to determine how bitcoin holdings affect SME credit risk.

In order to examine ERP system utilisation in China, Sun and Bhattacherjee (2011) used a multi-level analysis technique, emphasising the significance of organisational context in information systems research. Both the special difficulties faced by tech SMEs and credit risk assessment are relatively covered by them. This study can build on their multi-level analysis by adding organisational, technological, and market-level elements to the KMV-TIM model for a thorough risk assessment framework. This method can assist in customising credit risk models to match the distinctive qualities of Chinese IT SMEs more closely.

A novel approach to decision-making with important limitations is presented by Xu et al. (2008) and can be used in enterprise information systems to optimise operations. They need to concentrate on SMEs' financial issues or credit risk assessment. Our research can optimise risk assessment procedures by integrating the KMV model with their decision-making framework. Their approach to constraint-based decision-making can help improve the precision and dependability of credit risk assessments for small and medium-sized enterprises.

8. Conclusion

This paper first explains the origin of risk analysis and its areas to focus on, such as credit risk analysis. The reason was this could provide stability to economic and SME development since SMEs could contribute to peacebuilding and risk analysis through economic development, social stability and government policies. The paper introduced the definition and characteristics of technological SMEs in China from the theoretical point of view and expounded on their credit and financing status. Then four typical credit risk evaluation models were introduced. The comparison showed the KMV model had dynamic and forward-looking characteristics, which the other models did not have. Based on previous studies, the paper finally put forward reasonable policy recommendations for preventing credit risks of technological SMEs. The recommendations were mainly engaged in three aspects: prevention in advance, control in the event, and governance afterwards.

8.1. Summary of the empirical analysis with the KMV model as a risk model

The empirical part was based on the theoretical study of the KMV model in Section 4. This paper selected 30 technological SMEs from the GEM of China as the research samples. The 30 technological SMEs were divided into three groups and their related data in 2016 were collected. Using the operation formulas of the KMV model, their equity value, default point, asset value, and volatility were calculated through the statistical software to get their default distance and default probability finally. The test part mainly used a statistical method to test the empirical results of each group. The results showed that the empirical hypothesis is correct and the independent samples have a significant difference. Moreover, the KMV model could reflect the credit risk of listed SMEs in China effectively.

The author's main contribution is to develop this improved KMV model to calculate fair and accurate risk analysis of all types. Additionally, it is one of few papers offering detailed studies of technological SMEs in China.

8.1.1. Through empirical research, the following conclusions for risk analysis were drawn

(1) The asset market value of a company included equity value and net liabilities, and net liabilities were generally positive. Hence, the asset market value of a company was usually greater than its equity value.
(2) The standard deviation could reflect the degree of discretisation of the data. The market risk of enterprises with a large daily stock price difference was large, and the default risk was relatively high.
(3) The credit rating of Chinese GEM-listed technology-based SMEs was not high, which meant that their credit risk was relatively high, and their credit situation was poor.
(4) We consolidated a risk analysis model for risk analysis and used China as a specific example and case study, including the use of the KMV Strategy, presented in Section 7.

Based on previous studies, the paper finally put forward reasonable policy recommendations on how to prevent credit risks of technological SMEs. The recommendations were mainly engaged in three aspects of prevention in advance, control in the event and governance afterwards. Suggestions on how to use the KMV model more effectively were also included.

8.2. Practical implications

The KMV framework provides an advanced risk analysis solution allowing both SMEs and lending institutions to make informed decisions through accurate credit ratings and real-time monitoring (Liu et al. 2022). Technological capabilities can encode the quantitative model to automate early warnings and financial advisory for struggling startups based on predictive risk scores. Developing risk-based partnership ecosystems between investors, banks and SMEs could better match capital supply have based on risk appetite.

8.3. Limitations

The limitations are as follows. First, in the choice of the risk-free interest rate, weighted China's one-year Treasury bond yield in 2016 was calculated as the risk-free interest rate in the model based on the literature. However, none of the previous articles could explain well why this choice was reasonable. Second, the default point calculation: for the default point (liability face value), this paper directly used the formula of the KMV model. That was, the default point was equal to the sum of the short-term liabilities and half of the long-term liabilities, but whether the coefficient of 0.5 of the long-term liabilities was applicable to technological SMEs in China remains to be verified. Third, only technological SMEs listed on the China GEM were selected as research samples in this paper. It was insufficient that unlisted technological SMEs were not studied due to the difficulty of data collection. Last, the model parameters also involve assumptions around debt structure and risk-free rates grounded in past literature that should be re-examined for Chinese technological SMEs. Furthermore, the 2016 snapshot data should be expanded to cover longer time horizons. Additional validation on out-of-sample SMEs would bolster reliability. Complementary qualitative approaches are recommended to enrich the empirical findings.

Acknowledgments

The author would like to thank Mr. Qiqing Wang, who worked as an assistant for a few months on this project. He left academia completely nearly three years ago. Even so, the author is extremely grateful for his help.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work is partly supported by VC Research [VCR 0000099].

References

Altman, E. 1968. "Financial Ratios, Discriminate Analysis and the Prediction of Corporate Bankruptcy." *The Journal of Finance* 23 (4): 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x.

Altman, E. I. 2013. "Predicting financial distress of companies: revisiting the Z-score and ZETA® models." In *Handbook of research methods and applications in empirical finance*, 428–456. Edward Elgar Publishing.

Altman, E. I., R. G. Haldeman, and P. Narayanan. 1977. "A New Model to Identify Bankruptcy Risk of corporations." *Journal of Banking and Finance* 1 (1): 29–54. https://doi.org/10.1016/0378-4266(77)90017-6.

Altman, E. I., and G. Sabato. 2007. "Modelling Credit Risk for SMEs: Evidence from the US Market." *Abacus-A Journal of Accounting Finance and Business Studies* 43 (3): 332–357. https://doi.org/10.1111/j.1467-6281.2007.00234.x.

Au, C. H., G. Li, W. S. Hsu, P. H. Shieh, and K. M. Law. 2024. "Characteristics of Proliferating Cryptocurrencies: A Comparative Study Between Stable and Non-Stable Cryptocurrencies." *Enterprise Information Systems* 18 (7): 2356771. https://doi.org/10.1080/17517575.2024.2356771.

Azeem, M., M. Ahmed, S. Haider, and M. Sajjad. 2021. "Expanding Competitive Advantage Through Organizational Culture, Knowledge Sharing and Organizational Innovation." *Technology in Society* 66:101635. https://doi.org/10.1016/j.techsoc.2021.101635.

Banerjee, A. V., T. W. Besley, and T. W. Guinnane. 1994. "The Neighbor is Keeper: The Design of a Credit Cooperative with Theory and a Test." *Quarterly Journal of Economics,* 109 (2): 491–515. https://doi.org/10.2307/2118471.

Bates, T. 1997. "Financing Small Business Creation: The Case of Chinese and Korean Immigrant Entrepreneurs." *Journal of Business Venturing* 12 (2): 109–124. https://doi.org/10.1016/S0883-9026(96)00054-7.

Beaver. 1952. "An Empirical Estimation of Default Risk of the UK Real Estate Companies." *The Journal of Real Estate Finance & Economics* 321:22–26. https://doi.org/10.1007/s11146-005-5176-x.

Berger, A. N., and G. F. Udell. 1995. “Relationship Lending and Lines of Credit in Small Firm Finance.” *The Journal of Business* 68 (3): 351–381. https://doi.org/10.1086/296668.

Black, F., and M. Scholes. 1973. “The Pricing of Options and Corporate Liabilities.” *Journal of Political Economy* 81 (3): 637–654.

Boot, A. 2000. “Relationship Banking: What Do We Know.” *Journal of Financial Intermediation* 2000 (10): 7–25. https://doi.org/10.1006/jfin.2000.0282.

Câmara, A., I. Popova, and B. Simkins. 2012. “A Comparative Study of the Probability of Default for Global Financial Firms.” *Journal of Banking and Finance* 36 (3): 717–732.

Chen, M., W. Feng, and Z. Peng. 2012. “Research on Credit Risk of Real Estate Business Based on the KMV Model.” *Journal of Hunan Finance and Economics University* 28 (140): 1–10.

Chen, Z., C. P. Barros, and M. R. Borges. 2015. “A Bayesian Stochastic Frontier Analysis of Chinese Fossil-Fuel Electricity Generation companies.” *Energy Economics* 48:136–144. https://doi.org/10.1016/j.eneco.2014.12.020.

Crosbie, P., and J. Bohn. 2003. “Modeling Default Risk-Modeling Methodology. Moody’s KMV Company LLC. 6–31. accessed on June 1. https://www.moodysanalytics.com/-/media/whitepaper/before-2011/12-18-03-modeling-default-risk.pdf .

Crouhy, M. Crouhy, D. Galai, and R. Mark. 2000. “A Comparative Analysis of Current Credit Risk models.” *Journal of Banking & Finance, 2000* 24 (1–2): 59–117. https://doi.org/10.1016/S0378-4266(99)00053-9.

Distinguin, I., C. Rugemintwari, and R. Tacneng. 2016. “Can Informal Firms Hurt Registered SMEs’ Access to Credit?” *World Development* 84:18–40. https://doi.org/10.1016/j.worlddev.2016.04.006.

Dwyer, D. W. 2007. “The Distribution of Defaults and Bayesian Model Validation.” *The Journal of Risk Model Validation* 1 (1): 23–53.

Edwards, C. 2018. “China’s Stock Markets are Increasingly Desperate to Lure Foreign Investors and This Latest Move Just Might Do the trick’[A].” *Article, Business Insider*. Accessed October 25, 2020. https://www.businessinsider.com/chinas-stock-markets-plan-to-to-limit-trading-halts-to-curb-abuse-2018-11?r=US&IR=T.

Eggers, F. 2020. “Masters of Disasters? Challenges and Opportunities for SMEs in Times of Crisis.” *Journal of Business Research* 116:199–208.

Elbannan, M. A., and O. Farooq. 2020. “Do More Financing Obstacles Trigger Tax Avoidance Behavior? Evidence from Indian SMEs.” *Journal of Economics & Finance* 44 (1): 161–178. https://doi.org/10.1007/s12197-019-09481-9.

Faruqee, H. 2003. “Debt, Deficits, and Age-Specific mortality.” *Review of Economic Dynamics* 6 (2): 300–312. https://doi.org/10.1016/S1094-2025(02)00020-0.

Gangopadhyay, T. 2012. “IFS Fractals Generated by Affine Transformation with Trigonometric Coefficients and Their transformations.” *International Journal of Computer Applications* 53 (15): 29–32. https://doi.org/10.5120/8499-2447.

Ge, X., Y. Jin, Q. Li, X. Yao, S. Liu, and D. Shen. 2021. “Research on a Dynamic Evaluation of Financial Risks of Intellectual Property Pledge Financing of High-Tech Enterprises.” *Discrete Dynamics in Nature and Society, 2021* 2021:1–11. https://doi.org/10.1155/2021/2048811.

Goodhart, C. 2011. *The Basel Committee on Banking Supervision: A History of the Early Years 1974–1997’ [B]*. Cambridge, UK: Cambridge University Press.

Harmes, J. C., J. L. Welsh, and R. J. Winkelman. 2016. “A framework for defining and evaluating technology integration in the instruction of real-world skills.” In *Handbook of research on technology tools for real-world skill development*, 137–162. IGI Global.

Hsu, G. 2010. *‘Capital Structure Decision and Financing Service System of Small and Medium Sized Technological Enterprises’ [M]*. Beijing: Science Press, 2010.

Jiang, C., S. Yao, and Z. Zhang. 2009. “The Effects of Governance Changes on Bank Efficiency in China: A Stochastic Distance Function approach.” *China Economic Review* 20 (4): 717–731. https://doi.org/10.1016/j.chieco.2009.05.005.

Kurbat, M., and I. Korbalev. 2002. “Methodology for Testing the Level of the EDF Credit Measure.” *Journal of KMV Corporation* 20729. Accessed June 1, 2024.

Liu, J., J. Li, J. Wang, M. M. Uddin, and B. Zhang. 2022. "Research on the Application of Blockchain Technology in Coal Supply Chain Finance." *Sustainability* 14 (16): 10099. https://doi.org/10.3390/su141610099.

Lyu, J. 2015. "On Financing Constraints of Small and Medium Enterprises." *Journal of Finance Research* 11:115–123. http://www.jryj.org.cn/EN/abstract/abstract419.shtml .

Ma, Y., P. Zhang, S. Duan, and T. Zhang. 2023. "Credit Default Prediction of Chinese Real Estate Listed Companies Based on Explainable Machine Learning." *Finance Research Letters* 58:104305. https://doi.org/10.1016/j.frl.2023.104305.

Mambrey, V., S. Rakete, M. Tobollik, D. Shoko, D. Moyo, P. Schutzmeier, and S. Bose-O'Reilly. 2020. "Artisanal and Small-Scale Gold Mining: A Cross-Sectional Assessment of Occupational Mercury Exposure and Exposure Risk Factors in Kadoma and Shurugwi, Zimbabwe." *Environmental Research* 184:109379. https://doi.org/10.1016/j.envres.2020.109379.

McQuown, J. A. 1993. *A Comment on Market Vs. Accounting Based Measures of Default Risk. Mimeo*. KMV Corporation.

Merton, R. C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *The Journal of Finance* 29 (2): 449–470. https://doi.org/10.1111/j.1540-6261.1974.tb03058.x.

Nowak, P., and M. Romaniuk. 2013. "Pricing and Simulations of Catastrophe Bonds." *Insurance, Mathematics & Economics* 52 (1): 18–28. https://doi.org/10.1016/j.insmatheco.2012.10.006.

Ohlson, J. A. 1980. "Financial Ratios and the Probabilistic Prediction of Bankruptcy." *Journal of Account Research* 18 (1): 109–131. https://doi.org/10.2307/2490395.

Piqiang, Z., and Z. Hancheng. 2011. "The Credit Risk Measurement of China's Listed Companies Based on the KMV Model." In *Quantitative Financial Risk Management*, 137–160. Berlin Heidelberg: Springer.

Sonmez Cakir, F., and Z. Adiguzel. 2020. "Analysis of Leader Effectiveness in Organization and Knowledge Sharing Behavior on Employees and Organization." *Sage Open* 10 (1): 2158244020914634.

Stiglitz, J. E., and A. Weiss. 1981. "Credit Rationing in Markets with Imperfect Information." *The American Economic Review* 71 (3): 393–410.

St-Pierre, J., and M. Bahri. 2011. "The Determinants of Risk Premium: The Case of Bank Lines of Credit Granted to SMEs." *Journal of Developmental Entrepreneurship* 16 (4): 459–476. https://doi.org/10.1142/S108494671100194X.

Sun, Y., and A. Bhattacherjee. 2011. "Multi-Level Analysis in Information Systems Research: The Case of Enterprise Resource Planning System Usage in China." *Enterprise Information Systems [J]* 5 (4): 469–494. https://doi.org/10.1080/17517575.2011.610904.

Sutton, P. 2020. "The Geometry and Trigonometry of the Corporate Insolvency and Governance Bill - What's the Pensions Angle?' [A] Technical Article." *Square Patton Boggs, Financial Investment Firm*, 1–4. Accessed October 25, 2020. https://www.pensionsandbenefits.blog/2020/06/the-geometry-and-trigonometry-of-the-corporate-insolvency-and-governance-bill-whats-the-pensions-angle/ .

Tinoco, M. H., and N. Wilson. 2013. "Financial Distress and Bankruptcy Prediction Among Listed Companies Using Accounting, Market and Macroeconomic Variables." *International Review of Financial Analysis [J]* 30:394–419. https://doi.org/10.1016/j.irfa.2013.02.013.

Tsang, Y. P., Y. Fan, C. K. Lee, and H. C. Lau. 2024. "Blockchain Sharding for E-Commerce Supply Chain Performance Analytics Towards Industry 5.0." *Enterprise Information Systems[j]* 2311807. 18 (4). https://doi.org/10.1080/17517575.2024.2311807.

Upadhyay, U., A. Kumar, G. Sharma, S. Sharma, V. Arya, P. K. Panigrahi, and B. B. Gupta. 2024. "A Systematic Data-Driven Approach for Targeted Marketing in Enterprise Information System." *Enterprise Information Systems [J]* 2356770.https://doi.org/10.1080/17517575.2024.2356770.

Wang, H., P. Yang, and Y. Shen. 2008. *'Research on the Success Factors of Small and Medium Sized Enterprises in Science and technology' [M]*. Shanghai: Shanghai University of Finance and Economics Press. 14 February.

Wanke, P., Y. Tan, J. Antunes, and A. Hadi-Vencheh. 2020. *Business Environment Drivers and Technical Efficiency in the Chinese Energy Industry: A Robust Bayesian Stochastic Frontier analysis*, 106487. Computers & Industrial Engineering.

Xu, W. X., L. Xu, X. M. Liu, and J. D. Jones. 2008. "A New Approach to Decision-Making with Key Constraint and Its Application in Enterprise Information Systems." *Enterprise Information Systems [J]* 2 (3): 287–308. https://doi.org/10.1080/17517570802302341.

Yeh, C., F. Lin, and C. Hus. 2012. "A Hybrid KMV Model, Random Forests and Rough Set Theory Approach for Credit rating." *Journal of Knowledge-Based Systems* 33:103–107. Accessed 9 November 2017. https://doi.org/10.1016/j.knosys.2012.04.004.

You, C. 2011. "Financial Service Research on the Development of Small and Medium Sized Enterprises by Small Banks." *Journal of Hainan Finance* 3:76–79.

Zeng, D. Z. 2006. "How Technology and Innovation Drive Two Emerging Giants: China and India?." *Asian International Studies Review* 7 (1): 1–27.

Zhang, S., Li, Q., and Wang, D. 2010, October. Global Financial Crisis's Impact on the Credit Risk of Logistics Companies: Comparative Analysis Between China and Us with KMV Model. In 2010 International Conference on Management of e-Commerce and e-Government, 116–121. IEEE.