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# Credit Risk Evaluation of Science and Technology Finance Based on Artificial Intelligence and Bayesian Algorithm

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Since the US subprime mortgage crisis (2007–2010), the prevention of financial systemic risks has been a top priority of all regulatory authorities. In the technology finance industry, new technologies based on big data and underpinned by artificial intelligence are infiltrating the technology finance field. Due to the objective and superior ability of AI data processing, credit risk can be predicted to a certain extent. Based on the Bayesian method, this paper discusses the risk spillover effect of the science and technology finance industry. When carrying out Bayesian quantile regression, two main tasks need to be done: first, determine the prior distribution of each parameter; second, obtain the posterior parameter distribution of samples. The experimental results show that the maximum value of parameter Alpha1 reached 0.02762 at 75%. The maximum value of parameter Alpha2 reached 0.3031 at 75%, and the value of parameter Alpha2 was larger than that of parameter Alpha1 on the whole. The posterior simulation method not only does not need to assume that all parameters follow the normal distribution; it can also correct them during simulation. The use of artificial intelligence to analyze any changes of debt yield helps to give a comprehensive indication of the overall risk. In addition to the analysis of volatility, it can also more accurately predict the probability of default.

Keywords: Technology finance credit, risk evaluation, artificial intelligence, Bayesian algorithm

## 1. INTRODUCTION

In recent years, the scale and number of science and technology enterprises have grown rapidly, promoting the rapid development of science and technology finance. At the same time, the relevant theories on science and technology finance and credit risk assessment have also been widely applied. Scientific and technological financial innovation is likely to increase credit risk and accumulate it in systematic financial risk. Due to the short credit cycle, it is difficult to obtain current and comprehensive credit data, and the accuracy of the credit risk correlation model based on big data and algorithms is also very low. The specific control of credit risk is also a difficult point. When strict credit screening is carried out for customers, when there are a certain number of customers, the control of credit risk often imposes certain restrictions on borrowers with low credit levels, thus exerting some pressure on technology finance companies that focus mainly on retail finance.

The science and technology finance system plays an important role in the development of this sector, and is also a major participant in the risk sharing of science and technology finance. Oeltz et al. believed that technological innovation needs financial support. Through in-depth research

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and evaluation of technological innovation enterprises, the researchers chose and supported high-growth technological innovation projects [1]. Heard's research and analysis showed that the transformation of scientific and technological achievements and the adjustment of economic structures were inseparable from the support of financial institutions [2]. Barontini believed that financial development and innovation would exacerbate the current asymmetry in the financial market, thus increasing the amount of credit risk [3]. Gardner believed that the risks associated with science and technology finance and the financial system were inseparable, and that risk allocation can be divided into the horizontal allocation mode dominated by the financial market, and the vertical allocation mode mediated by the banks [4]. Zhao analyzed the characteristics of science and technology finance, and believes that its openness, high technology, and stronger connectivity between industries have revealed the risks and their complexities to a greater extent than previously. The impact of technical risks on financial stability is also growing [5]. Therefore, it is necessary to conduct a comprehensive analysis and evaluation of systematic credit risk in the realm of science and technology finance.

Data is the key to technology finance. With the relevant data, people can control the development of the whole economy. That is why AI can play a huge role in the field of technology and finance. Misra believed that, based on artificial intelligence technology, a science and technology finance risk assessment system should be established to apply its advantages to this sector so as to continuously improve its overall strength [6]. Qu pointed out that financial institutions, especially commercial banks, rely mainly on empirical judgment when evaluating the operation and credit of science and technology enterprises. The adopted appraisal method was mainly based on financial information and mortgaged assets, while ignoring the characteristics of technology enterprises that value technology over assets [7]. St-Hilaire showed that the estimator obtained by using Bayesian algorithm had smaller error, smaller mean square error and more accurate confidence interval than that obtained by traditional methods [8]. Calvetti used Bayesian analysis to obtain the normal distribution of credit risk loss distribution under different sources, and Bayesian correction in the case of multiple sources [9]. It is essential to apply Bayesian theory in credit risk assessment of science and technology finance.

With the rapid development of science and technology, artificial intelligence has pervaded most, if not all, sectors of the economy, including the financial industry. The application of AI technology in the financial industry (known as FinTech) has improved the operational efficiency of this industry. However, credit risk involves various financial activities. With the rapid development of scientific and technological financial markets, credit risk is becoming increasingly complex and difficult to assess. Based on Bayesian theory, this paper studies the quality, industry characteristics, business cycle and other factors pertinent to each debtor by using potential factors, and establishes a multi-level model by using hierarchical priority distribution to solve the problems related to arrears and debtor heterogeneity. The calculated results are accurate and the statistical reasoning is clear.

# 2. CREDIT RISK EVALUATION OF SCIENCE AND TECHNOLOGY FINANCE

## 2.1 Related Algorithms Based on Artificial Intelligence

AI is closely related to the development of the Internet, Internet of Things, big data, cloud computing and other technologies. AI is not isolated, but interdependent with them [10]. Cloud computing is a security protection, and access channel for massive data resources, which reduces the cost of data storage and analysis, and improves computing efficiency. The application of big data technology also promotes the development of technologies such as the Internet of Animals and cloud computing. The core of AI is deep learning, which is based on big data and powerful computing ability. In recent years, AI technology has developed rapidly, largely due to the successful application of deep learning algorithms and the availability of a large amount of data. Essentially, deep learning is a multi-level feature learning, which can transform the original data from a simple, nonlinear model to a higher level of abstraction [11]. Deep learning algorithms can automatically extract knowledge and rules that can be applied by computers to similar big data so as to achieve specific prediction.

Over the past few decades, the scientific and technological finance industry has generally been evaluated by analysts using mathematical and statistical methods or more traditional machine learning technologies have been used. The latter induces and models the rules of data through machines to measure credit risk [12]. Previously, the traditional mathematical model did not need to consider too many factors, and could well predict the actual risk. However, in the age of big data, due to the wide range of data sources, the strong mobility of data, and the various forms of data (structured and unstructured), it is difficult to use traditional models directly. The risk assessment model based on deep learning can effectively extract weak features, that are different from traditional strong features, from a large number of complex and unstructured data, accurately depict them, and iterate them repeatedly, so as to continuously improve their accuracy and stability. In practice, this method is carried out with computers and software, and uses different calculation methods.

Value at Risk (VaR) refers to the maximum loss of a single financial asset or a group of assets caused by the overall market fluctuation within a period of time. Under a certain level of credibility $\beta$, the calculation formula is as follows:

$$Q(Lost \leq VaR(\beta)) = 1 - \beta \tag{1}$$

The calculation of VaR is based on the risk position, which is low cost and simple to calculate. It combines different market factors and various risks faced by financial assets. Not only can it deal with the complex dynamics of financial markets; it also aligns with the trend of global financial market integration. It is the most commonly-used measurement method [13–14]. The calculation methods of VaR include the delta normal division method and the historical simulation method. With these methods, the delta normal classification assumes that the income is normally distributed, and the result is obtained by multiplying the standard deviation of the income by the quantile of the corresponding confidence interval. It is equal to the asset VaR value corresponding to the corresponding quantile with confidence level.

$$VaR = X_{\beta} \cdot \sigma \cdot \sqrt{\Delta s} \tag{2}$$

At the confidence level $\beta$, the quantile $X_{\beta}$ of the standard normal distribution, $\sigma$ is the standard deviation of the return, and $\Delta s$ is the holding time.

Recurrent neural networks (RNN) and long short-term memory (LSTM) were used to predict the volatility time series [15]. The input layer, hidden layer and output layer of RNN network are represented by c, d and p respectively. The number of input layer, hidden layer and output layer is M and D respectively. The output weight of hidden layer is $q_{dc}$, the input weight of hidden layer is $q_{d'd}$, and the input weight of output layer is $q_{pd}$.

The hidden layer input is calculated as:

$$x_d^s = \sum_{j=1}^{M} \omega_{dc} a_j^s + \sum_{d'=1}^{D} q_{d'd} y_{d'}^{s-1} \tag{3}$$

The hidden layer output is:

$$y_d^s = \theta_d(x_d^s) \tag{4}$$

The input of the output layer is:

$$x_p^s = \sum_{d=1}^{D} q_{pd} y_d^s \tag{5}$$

The output of neurons in the output layer is:

$$y_p^s = \theta_d(x_p^s) \tag{6}$$

$x$ is the calculated value of the active function, $x_d^s$ is the output value of the hidden layer after the activation function, and $y$ is the aggregated calculated value, reflecting the weighted input of the hidden layer at $s$ time. $a_j^s$ represents the input values of $j$ neurons in the input layer at time $s$.

In practical applications, time series are usually mixed with high volatility components, which may make it difficult for a single RNN model to fully explain them. After receiving the financial transaction data, preliminarily calculate the fluctuation time series $\{b_s\}$.

The volatility time series $\{b_s\}$ is divided into low volatility series $\{k_s\}$ and high volatility series $\{g_s\}$:

$$b_s = k_s + g_s \tag{7}$$

LSTM model is used to predict high volatility series, because it can only fully explain nonlinear series, and then use $g_{s-1}, g_{s-2}, \ldots, g_{s-m}$ to make positive prediction:

$$g_s = f(g_{s-1}, g_{s-2}, \ldots, g_{s-m}) + \varepsilon_s \tag{8}$$

The LSTM neural network is represented by $f(\cdot)$, which is used to determine the final predictive value $\hat{b}_s$ of the time series:

$$\hat{b}_s = \hat{k}_s + \hat{g}_s \tag{9}$$

## 2.2 Credit Risk of Science and Technology Finance

**(1) Theoretical Basis of Science and Technology Finance**

The financial innovation theory organically combines technology and economy, and discusses the impact of technological innovation on economic development from a new perspective [16]. This theory holds that innovation should be carried out at the level of the system and the organization, then the production factors should be redistributed, and the production conditions should be combined. Financial innovation is a new thing created or introduced by financial institutions through the reintegration and creative change of financial elements [17]. The emergence of science and technology finance requires a re-formation of the system and organization.

According to the financial development theory, it is necessary for the overall financial system to have an impact on economic development. However, relatively mature banks can screen and evaluate enterprises and invest in products and technologies that have advantages or larger markets. The financial development theory concerns the results of financial development research, and discusses the financial structure, financial repression, financial functions and other issues in depth according to different perspectives. The specific research contents are shown in Figure 1.

As shown in Figure 1, financial development essentially refers to the evolution of the financial system, that is, its organizational form, nature and relative scale. Essentially, financial theory can be applied to measure and evaluate a country's level of economic development by examining the characteristics of its financial structure. According to the financial deepening theory, interest rates have the greatest impact on financial development, in addition to the distortion of interest rates, exchange rates and other prices. The typical feature of the overall economic development strategy of developing countries is financial repression, which makes it difficult for many SMEs to enter the financial market to engage in financial activities. According to the theory of financial functions, through the reform of the financial system and the rational allocation of various resources, potential investment opportunities can be explored, companies can be effectively supervised, risks can be effectively prevented and controlled, market liquidity can be improved, and the use efficiency of deposits can be increased. Financial institutions realize their functions through capital markets and credit markets [18]. According to the current financial structure classification standard, based on the different functions of the financial system (mainly banks and financial markets), they are divided into two categories: banks and markets.

**(2)] Functions and Forms of Science and Technology Finance**

In 1993, the China Association for the Promotion of Science, Technology and Finance was established with the aim of adapting to economic and social development [19–20]. Science and technology finance involves many types of subjects and a wide range of fields, and its related subjects and service objects are specific. The relevant subjects and

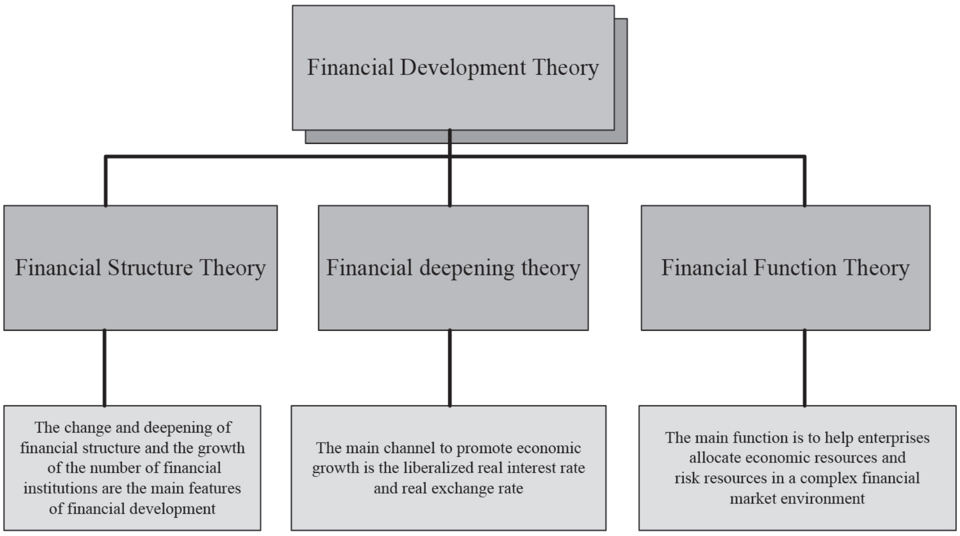



**Figure 1** Specific research contents of financial development theory.

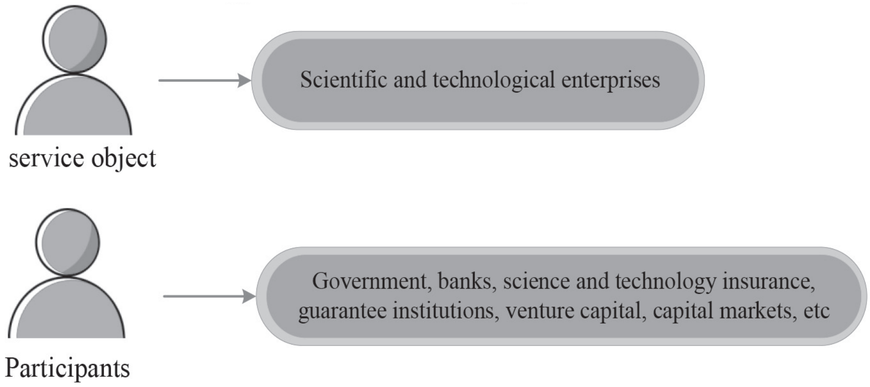



**Figure 2** Related subjects and service objects of science and technology finance.

service objects of science and technology finance are shown in Figure 2.

As shown in Figure 2, the service objects of science and technology finance are mainly science and technology enterprises, and the participants include the government, banks, science and technology insurance, guarantee institutions, venture capital and capital markets [21]. Science and technology finance takes science and technology enterprises, particularly the small and medium-sized ones, as the main body, so its functions and forms are specialized. These aspects of science and technology finance are shown in Figure 3.

As shown in Figure 3, as a kind of financial service, science and technology finance is targeted and policy-oriented to support science and technology enterprises. Science and technology finance also plays a role in risk sharing. The risks to science and technology enterprises are significant. Science and technology finance can share the risk through the overall financial system, so as to achieve risk dispersion and resolution. There are two forms of science and technology finance: direct and indirect. The direct form involves the venture capital institution as the financial participant. The indirect form involves an institution that provides indirect financing for science and technology companies with commercial banks, science and technology insurance institutions, etc. These two entities work together to provide strong support for technology companies [22].

**(3) Channel analysis of scientific and technological financial risks**

According to the theory of product life cycle, like human life, products also undergo the process of formation/creation, growth, maturity and decline. From this perspective, science and technology finance has developed from the growth stage to the maturity stage, exposing it to financial risks. From the perspective of growth stage, although mature technology finance has received certain regulation, there is still a lag in regulation. With the continuous adjustment and evolution of the technology finance system, its development mechanism is becoming increasingly perfect, but there are still shortcomings in terms of regulation. Its lag effect has become increasingly prominent, and has become a prominent feature of financial supervision in this period. Its manifestation is the spontaneous lag caused by the structural characteristics of financial supervision itself, and the self-consciousness lag caused by the development space of innovation. The two cycles in the development of science and technology finance and financial supervision are shown in Figure 4.

As shown in Figure 4, Phase S1 is the early stage of financial innovation from entrepreneurship to maturity, while Phase S2

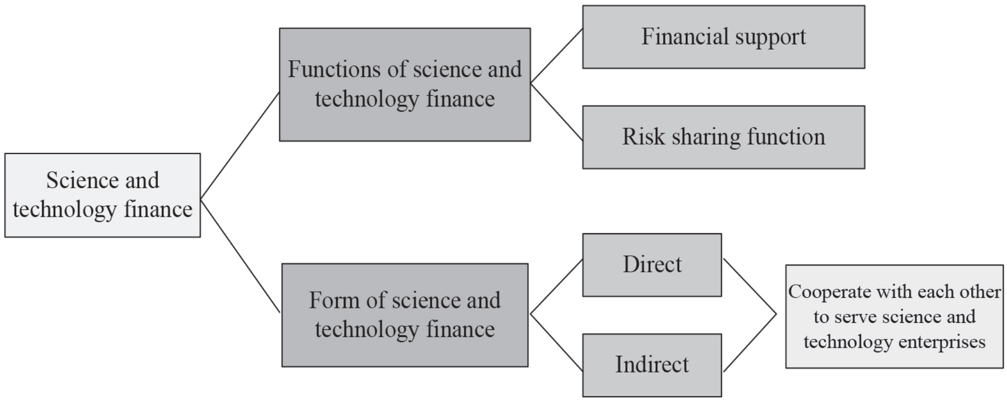



**Figure 3** Functions and Forms of Science and Technology Finance.

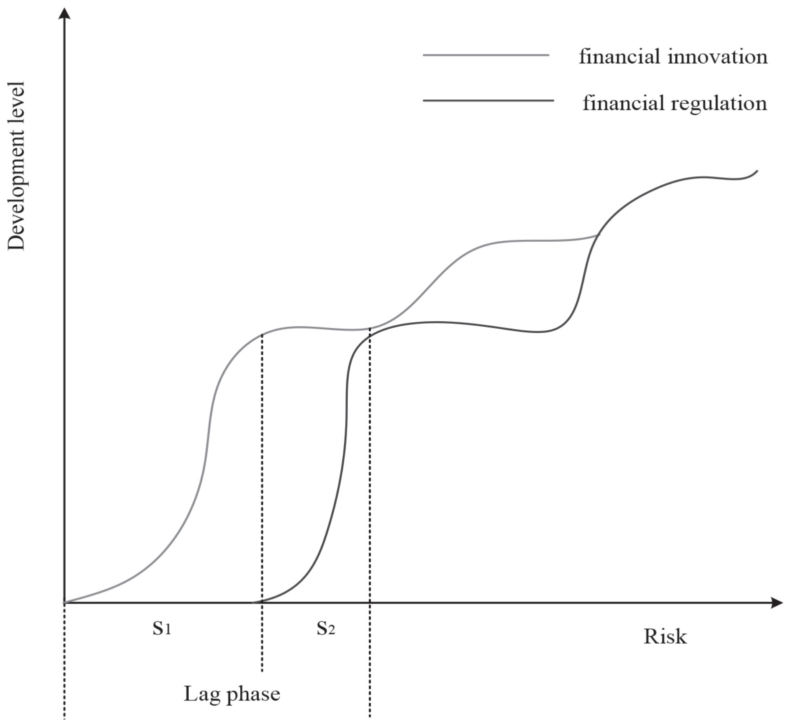



**Figure 4** Two cycles in the development of science and technology finance and financial supervision.

is the mature stage of financial innovation, as well as the process of financial supervision from the star to maturity. However, the current regulatory environment of technological finance does not meet this requirement, that is, technological financial innovation lacks certain regulatory foresight, which exacerbates credit risk and market risk. Because technical finance also plays a certain role in producing the "herd effect" when the market is unstable, resonance would occur, thus increasing the pro cycle of risk, causing fluctuations, and increasing the risk posed to the entire financial system. This transmission path is a result of the improvement of service efficiency by science and technology finance. On the one hand, the behavior of the participants in the transaction is becoming increasingly similar. On the other hand, the rate of risk diffusion could also accelerate with the improvement of service efficiency, thus increasing the volatility of the financial market.

In the market, the variety and number of securities held by individuals are limited by transaction costs. Therefore, intermediaries can replace individual traders, thereby saving individual transaction costs, and bringing cost advantages to market participants. When the information dissemination mechanism is highly developed and direct financing becomes the most effective means of capital distribution, the whole financial industry is characterized by "financial disintermediation". In the competition between financial intermediary organizations, those who can better perform their financial functions are those who can win the market. Science and technology finance is a dynamic financial innovation comprising financial intermediaries and financial markets. Science and technology finance has produced more advanced and effective intermediary organizations, and organizations that complement traditional financial intermediary functions such as bank deposits and capital financing. The competition in the financial market and the diversification of financial demand promote the development of science and technology finance. The emergence of financial disintermediation would allow more science and technology companies to enter the financial field.

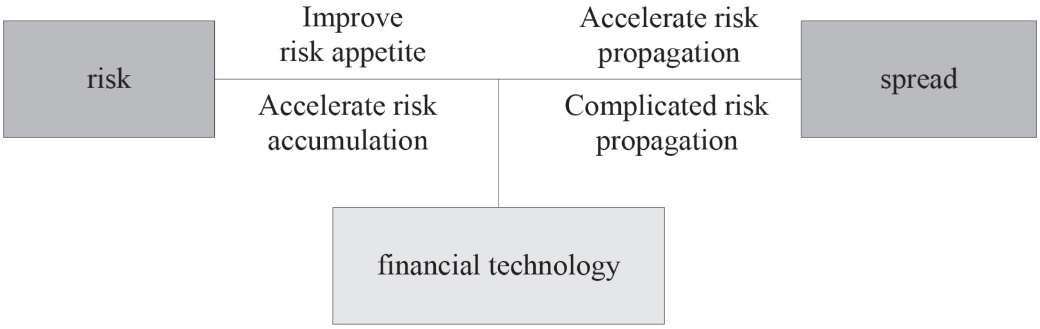



**Figure 5** Impact of science and technology finance on systemic financial risk.

Technology finance closes the gap between financial institutions, technology enterprises and enterprises. Technology companies and other non-financial organizations entering the financial industry have certain shortcomings in terms of information technology risk management, and these shortcomings are the main factors that cause the three types of companies to have negative effects on each other, and may lead to the increase of system risk. At the same time, compared with traditional financial institutions, their daily operations, system maintenance, risk monitoring, etc. have greatly increased their dependence on technology. Some technology and finance businesses use the same blockchain, digital password and other network information technologies. If they are cracked or hacked, the entire technology and financial system would be paralyzed, resulting in a large number of user information leaks.

Science and technology finance would increase the risks posed to the financial system, thus increasing the speed and scope of risk transmission. The impact of science and technology finance on systemic financial risks is shown in Figure 5.

As shown in Figure 5, the systemic risk of the financial system has been increased in terms of innovation, relevance and regulation of technical finance. Among them, relevance refers to the increased relevance of different types of financial institutions, financial institutions and technology companies after the application of technology finance, which leads to the mutual influence of risks on various industries, thus leading to the systematic risk of the financial system. Regulation avoidance means that science and technology finance is able to evade the regulation of traditional financial activities. The lower the control of science and technology finance activities, the more active the science and technology finance activities will be. It increases the information technology and legal risks of science and technology finance, and thus has a direct impact on the risk to the overall financial system.

## 2.3 Credit Risk Measurement Model Based on Bayesian Algorithm

Credit risk measurement focuses on quantitative risk, as it measures the default probability of influencing factors. Credit risk measurement refers to the qualitative and quantitative analyses of the overall credit risk of an enterprise. Measurement is done by selecting information related to the credit status of the credit risk evaluation target through a variety of subjective or objective means, and estimating the potential credit losses of each credit business through the estimated risk factors, including both expected and unexpected losses. Credit risk management is a concept related to the degree of credit risk. Credit risk management is a branch of financial risk management that is part of overall risk management. Credit rating is used to analyze, evaluate and predict the potential risks arising from changes in solvency. Credit rating is an important indicator used to measure the solvency and default risk of enterprises, and the key to classifying it is its default probability.

The probability space is the location of the random variable, and also the location where the uncertainty of the future state is transferred. Suppose a risky loan portfolio is taken as an asset. Let it become an observable random variable, the time $t$ asset value is $C(t)$, and the asset value loss of $t, t+\Delta$ in 1 day or 10 days is:

$$K_{[t,t+\Delta]} = -(C(t+\Delta) - C(t)) \tag{10}$$

The probability distribution of random variable $K_{[t,t+\Delta]}$ is called loss distribution in the formula. It can be seen that it spans time $t+\Delta$. Starting from time $t$, it has a conditional loss distribution. After considering all available information, it is divided into unconditional loss distribution.

Under the general risk analysis framework, loss allocation usually considers the following situations:

$$K_{s+1} = K_{[s\Delta,(s+1)\Delta]} = -(C_{s+1} - C_s) \tag{11}$$

The asset value $C_s$ depends on the dimension $d$ of the random vector $X_s = (X_{s,1}, \ldots, X_{s,d})'$ and the passage of time $s$.

$$C_s = g(s, X_s) \tag{12}$$

In other words, risk factor $X_s$ is generally considered as an observable variable, or a variable with a known value over time $s$. The logarithm of asset price or yield is a common risk factor. Risk mapping is the process of using the above formula to describe the portfolio value. $(Y_s)_{s\in M}$ shows the change of risk factor $Y_{s+1} = X_{s+1} - X_s$ over time. Considering the asset loss, the expression is:

$$K_{s+1} = -(g(s+1, X_s + Y_{s+1}) - g(s, X_s)) \tag{13}$$

Credit risk is related to its related credit assets, so when studying credit risk, the factors that are likely to affect the

**Table 1** Measurement of Financial Stress Index and Volatility Index.

| Variable name | Pressure index | Volatility index |
|---|---|---|
| Sample size | 120 | 120 |
| Mean value | $-8.63\hat{}10^{-6}$ | $-3.63\hat{}10^{-2}$ |
| Standard deviation | 0.5542 | 0.3336 |
| Minimum value | −2.1042 | −1.9583 |
| Maximum value | 1.5012 | 1.2368 |

**Table 2** Statistics for Innovation Index.

| Variable name | Financial product innovation | Innovation in financing methods |
|---|---|---|
| Sample size | 120 | 120 |
| Standard deviation | 0.0734 | 98.71 |
| Minimum value | 0.1021 | 11 |
| Maximum | 0.4861 | 463 |

corresponding credit loss are considered. The Bayesian method can be used as a tool to parameterize risk models in risk analysis. The Bayesian algorithm can be extended to random variables and their distributions, and a posterior distribution can be constructed, which can be reduced to an external variable.

Suppose that the observed value $\theta$ follows a normal distribution with a mean of 5, and $y = 10$ and $y$ follow a normal distribution with a mean of $\theta$ and a variance of 1.5.

$$o(\theta) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(\theta-5)^2}{2}\right) \tag{14}$$

Ignoring the scale constant, it can get:

$$o(y|\theta) = \frac{1}{\sqrt{3\pi}} \exp\left(-\frac{(y-\theta)^2}{3}\right) \tag{15}$$

That is, when there is new sample size data, the posterior distribution is used as a prior distribution, and the above methods are repeated. Bayesian updating helps to accumulate knowledge. During the data collection process, it can be updated continuously. Data collection can be terminated at any time without setting the sample size in advance. This shows that the Bayesian algorithm has good adaptability and flexibility, and it can obtain more accurate results in unexpected situations and events that often occur in risk analysis.

In principle, the Bayesian algorithm can help analysts and policy makers to establish a unified risk assessment and effective management strategy. The traditional spectrum theory can draw a conclusion only regarding whether to deny that the original assumption is based on a data set. In this conclusion, two types of errors are generally not considered: only the negation of the first error is controlled, and the conclusion without evidence is ambiguous. When making actual decisions, analysts and policy makers must consider these two costs and weigh their impacts. The Bayesian algorithm is used to express uncertainty as probability, thus ensuring the consistency of decision-making. The Bayesian algorithm is the theoretical basis of comprehensive decision analysis, which can thoroughly describe the analysis method applied to risk management.

# 3. CREDIT RISK EVALUATION IMPROVEMENT ALGORITHM EXPERIMENT

## 3.1 Descriptive Statistics of Risk Measurement Indicators

Due to the large number of internal parameters of the model method, it is difficult to collect sufficient sample indicators, so a stress index method combined with the financial stress index is used to measure systemic financial risk. The financial stress index is a comprehensive index that reflects the influence of various factors and the overall pressure caused by such factors. The experiment conducted in this study measured the financial pressure index of a province from 2009 to 2021. This is shown in Table 1.

As seen in Table 1, through the analysis of financial pressure indicators from 2009 to 2021, it can be seen that during the sampling period, the average financial pressure index among cities in the province is low, with the lowest being −2.1042 and the highest being 1.5012. The difference between the two is 3.6054. The lowest volatility index is −1.9583, the highest is 1.2368, and the difference between the two is 3.1951. This shows that the financial pressure index of different cities shows great difference in different years, indicating that risk level changes according to time and place (region).

Some of the research today is focusing on the impact of financial technology innovation on the innovation level of the financial system. At present, the development of science and technology finance in China is still in the initial stage; that is, the innovation stage of product application and financing mode. It has little impact on the financial institutions themselves and the financial system, and it is also very difficult. Therefore, in this current study, financial product innovation is combined with with financing mode innovation for the purpose of conducting a quantitative analysis of scientific and technological financial innovation. The statistical description of the innovation index is given in Table 2.

As shown in Table 2, the standard deviation of the financial product innovation index is very small, only 0.0734, which indicates that the average level of the index changes a little in

**Table 3** Relevant individual and overall indexes.

| Variable name | Overall relevance | Micro correlation degree |
|---|---|---|
| Sample size | 120 | 120 |
| Mean value | 0.2697 | 0.0657 |
| Standard deviation | 0.1721 | 0.0273 |
| Minimum value | 0.0151 | 0.114 |
| Maximum value | 0.8976 | 0.173 |

**Table 4** Standard deviation and median of default probability and macro impact coefficient.

| Grade and coefficient | Standard Deviation | Median |
|---|---|---|
| Grade A | 0.00015 | 0.00035 |
| Grade B | 0.0008 | 0.00145 |
| Grade C | 0.00146 | 0.1661 |
| Coefficient q | 0.0306 | 0.0812 |

different periods, but it is not significant. At the same time, the minimum financial innovation index is 11, and the maximum is 463. The difference between the two is 452, indicating that the financial innovation index fluctuates greatly with the change of time and region.

Relevance refers to the correlation between the financial industry and related high-tech industries caused by the development of science and technology finance, as well as the correlation at the individual level, such as the increase in the proportion of advanced technologies used by financial companies in daily life, and the overall income growth of high-tech companies. When high-tech enterprises are engaged in scientific and technological development and risk activities, they need to be subsidized by various financial institutions. These financing demands can be long term, so the income of high-tech enterprises can reflect the investment of the financial industry in technology research and development to a certain extent. Given the effectiveness and feasibility of the comprehensive evaluation index, the ratio of high-tech enterprises' income to GDP is selected as the overall correlation evaluation index. Using the above measurement methods, the overall and individual relevant indexes are calculated for the province from 2009 to 2021, as shown in Table 3.

As shown in Table 3, during the sampling period, the ratio of high-tech companies' income to GDP is very small, with a maximum value of 0.8976 and a minimum of 0.0151. That is to say, the ratio of income to GDP of high-tech companies is close to zero, and the overall correlation between various regions is very different. At the same time, the personal correlation index also fluctuates according to region and time, but within a very small range. Compared with the overall correlation, the time and regional differences are not significant.

## 3.2 Experimental Analysis of Actual Data

The above models and methods can be verified by using the time series consisting of default data. However, the current credit rating data records are not exhaustive, and the time span is short, so it is difficult to test them accurately. This paper uses the default report of Standard & Poor's Company to organize and analyze the relevant data. The report provides information on credit ratings for 12 years from 2009 to 2021, as well as different levels of default risk, including data on A, B and C.

The model was iterated 200 times using the iterative method, and the simulation results of 0.2817 were obtained, which showed the feasibility of the method. Therefore, the parameters can be obtained by sampling the iterative values. Subsequently, the median and standard deviation of each relevant parameter are obtained. The results are given in Table 4.

As shown in Table 4, the macroeconomic covariates of each credit level have a positive impact on the factor q of each level, and they are very significant. The posterior mean of macroeconomic covariates is shown in Figure 6.

As shown in Figure 6, if the parameter value is positive, indicating that the probability of default would decrease with the increase of macroeconomic covariates, that is, the improvement of economic conditions. According to general economic principles, when the credit level is decreased from A to C, the lower the credit level, the greater the probability of default. Although the above parameters can also be estimated using traditional methods, the difference between the two is not large, but the biggest difference is that the covariant of macroeconomic can be estimated using Bayesian method, without using complex backward fitting method and secondary estimation. The mean and observed values of default probability predicted by traditional methods and Bayesian models are shown in Figure 7.

As shown in Figure 7(a), due to the lack of data, it is difficult to achieve model calibration of assets with low probability of default using conventional spectral analysis methods. As shown in Figure 7(b), the multi-level Bayesian analysis method has been used to effectively study the model calibration problem, and various models have been tested. The main goal is to determine their advantages and disadvantages compared with traditional models. This method can infer all interested parameters, including the confidence interval of the transfer probability, thus solving the non-sample testing problem that managers are concerned about.

According to the default probability calculated above, when the loss at default rate is a constant and the default exposure

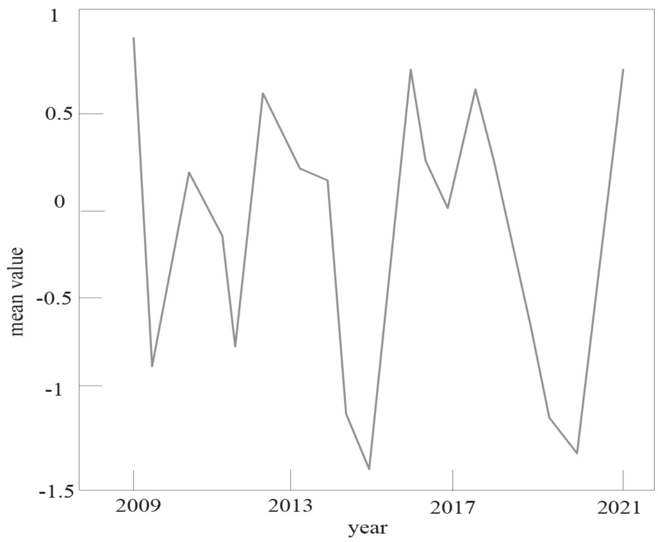
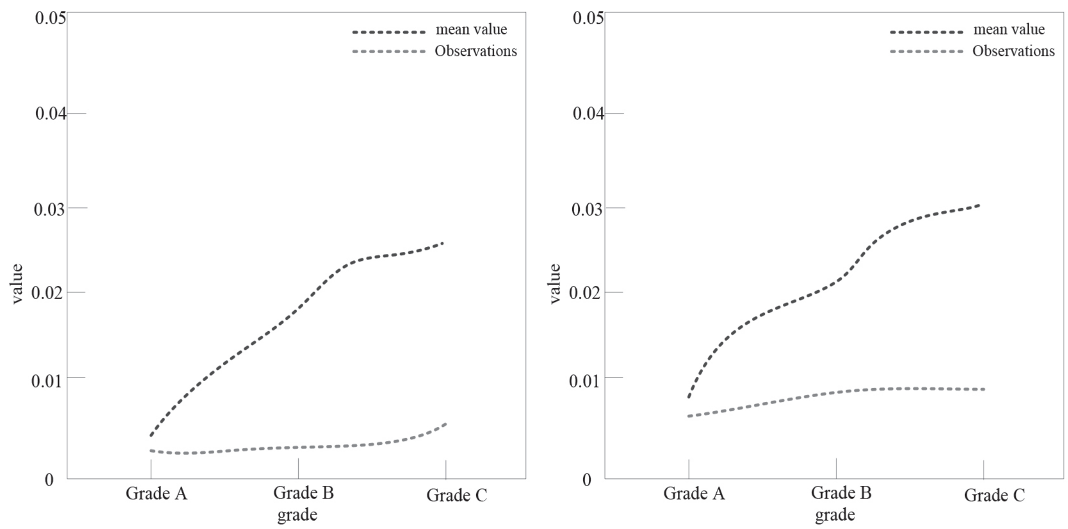



**Figure 6** A posteriori means of macroeconomic covariates.




(a) Mean value and observation value of default probability predicted by traditional methods (b). Mean value and observation value of default probability predicted by Bayesian model

**Figure 7** Mean value and observation of default probability predicted by traditional methods and Bayesian model.

is known, the expected loss can be expressed by the product of default risk and default risk. The relationship between VaR and loss distribution is shown in Figure 8.

As shown in Figure 8, credit risk refers to a risk that occurs in bank loans or investment bonds in risk measurement, which is the risk of borrowers' default. However, because only 12 years of annual data were used, the sample size is too small to well explain the fluctuation of losses. Therefore, based on the monthly expected loss data calculated above, 120 numerical simulations were conducted with 2 parallel Markov chains. Theautocorrelation diagnosis results of the parameters are given in Table 5.

As shown in Table 5, since the simulated distribution of the two parameters does not conform to the normal distribution of the conventional assumptions, the risk would be underestimated using the conventional assumptions. The minimum value of parameter Alpha1 is 0.005108 at 5% and the maximum value is 0.02762 at 75%. At 75%, the maximum value of parameter Alpha2 is 0.3031, and its parameter Alpha2 is generally larger than the parameter Alpha1. Therefore, by using a posteriori simulation method, the parameters do not have to be assumed to follow the normal distribution, and they can also be corrected during simulation. The expected loss test, which combines Bayesian algorithm with artificial intelligence, is not only simple, intuitive and easy to implement; it can also give a better understanding of the volatility of expected loss.

## 4. CONCLUSIONS

In today's rapidly-changing finance sector, the use of artificial intelligence to evaluate the credit risk of technology-enabled activities finance can promote the healthy and orderly development of science and technology enterprises, provide scientific basis for the credit status of these enterprises and financial institutions, and promote finance to better serve the industrial transformation and development. Risk

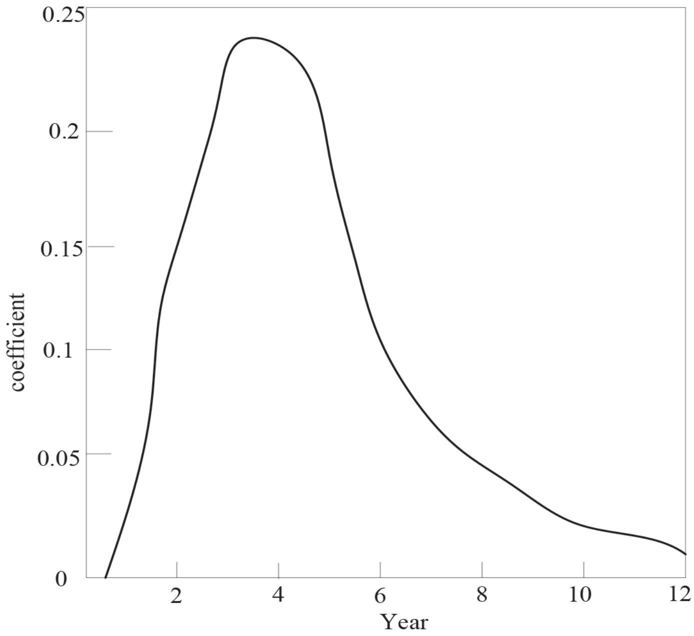



**Figure 8** Relationship between VaR and loss distribution.

**Table 5** Parameter Autocorrelation Diagnosis Results.

| Parameters | Alpha1 | Alpha2 |
|---|---|---|
| 5% | 0.005108 | 0.073996 |
| 25% | 0.01292 | 0.15529 |
| 50% | 0.01758 | 0.2227 |
| 75% | 0.02762 | 0.3031 |

assessment plays an important role in science and technology finance services. In addition to high risk and low credit assets, science and technology enterprises lack an appropriate index system for risk assessment. In this paper, from the perspective of credit risk measurement, the application of credit risk measurement in loan portfolio risk measurement is described in detail, and it is combined with Bayesian algorithm to comprehensively consider the change of default rate. The experimental results show that the evaluation effect is good. Therefore, it is of great theoretical and practical significance to vigorously develop AI technology and promote the application of Bayesian theory in credit risk assessment of science and technology finance.

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