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Application of the Merton Model and the Altman Z-score Model in Credit Risk Assessment

- an Empirical Study on Chinese Listed Companies

by

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Abstract

Corporate default poses significant risks to investors and stakeholders, highlighting the importance of predicting and managing financial risk effectively. When the geographical scope is narrowed down to China, the unique characteristics of the Chinese market, such as the lack of comprehensive credit risk databases and the influence of state-owned enterprises and small-medium enterprises, present challenges in accurately assessing creditworthiness. To address these challenges, the study applies two well-established credit risk models: the Merton model and the Altman Z-score model. Both models have undergone extensive empirical testing and provide valuable insights into credit risk assessment but have been poorly tested in China. Thus, by comparing the performance of the Merton model and the Altman Z-score model, this study aims to determine which model is more suitable for predicting the credit risk of companies in the Chinese market. The model performance is then evaluated using various statistical measures, including ROC curve analysis, T-tests, and Mann-Whitney U tests. According to the results, neither of the two models has outstanding performance in assessing default risk in China, but Altman Z-score model is slightly better than the Merton model. This study aims to bridge the research gap in credit risk assessment for Chinese listed companies, and it is expected that the findings will contribute to a better understanding of credit risk modeling in the Chinese market and provide practical implications for financial institutions and investors.

Keywords: Credit risk assessment, the Merton model, the Altman Z-score model, Chinese market.

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1. Introduction

1.1 Background and context

Corporate default is a crucial issue for investors, creditors, and other stakeholders. In the past, several well-known companies have defaulted on their financial obligations, resulting in significant losses for their stakeholders, such as the Lehman Brothers' bankruptcy in 2008. These failures have highlighted the importance of predicting corporate default and managing financial risk effectively.

To mitigate the risk of corporate default, several models have been developed to help stakeholders predict the likelihood of a company defaulting on its financial obligations. Two prominent models for predicting corporate default are the Merton model and the Altman Z-score model. The Merton model is based on the Black-Scholes model for options pricing and is commonly used to estimate the probability of default for a single firm (Merton, 1974). The model considers the market value of a company's assets, liabilities, and equity to determine the probability of default. It assumes that a company's assets follow a lognormal distribution, and that default occurs when the value of the company's assets falls below its liabilities. The Altman Z-score model, on the other hand, was developed by Edward Altman in 1968 and is an accounting-based statistical model that uses financial ratios to predict the likelihood of default (Altman, 1968). Both models are based on a solid theoretical foundation and have undergone extensive empirical testing, making their effectiveness evident. This is a key reason why these two models were chosen.

In China, the application of these models has become increasingly important due to the unique characteristics of the Chinese market. As the world's largest emerging market, China started relatively late and has a shorter development history compared to developed markets such as UK and the United States (Liu, Chang & Lee, 2010). Therefore, the efficiency of the Chinese market still needs to be further improved, and there is a lack of authoritative official default databases in the Chinese market. As a solution, this study employs the "Special Treatment" system, which is a regulatory mechanism used to monitor companies that are at risk of default as an applicable proxy of corporate default (Gou & Gui, 2019). Companies that receive ST status are subject to more stringent regulatory requirements, including increased reporting and disclosure obligations. In addition, China's market is heavily influenced by state-owned enterprises (SOEs) and has a high number of small and medium-sized enterprises (SMEs). These factors make it difficult to assess the creditworthiness of Chinese companies accurately. By examining these models and their applications in the Chinese market, one can gain a better understanding of how to manage default risks and develop effective risk management strategies.

1.2 Research gap

Despite the growing importance of credit risk modeling, research in this area is still limited especially in the Chinese market. The main reason for the research gap is the lack of comprehensive credit risk databases in China. The majority of the existing credit risk models, such as the Merton model and the Altman Z-score model, rely heavily on historical credit data to estimate default probabilities. However, in China, the lack of reliable and comprehensive credit data has hindered the development of credit risk models.

Moreover, most of the credit risk research in China has been focused on a single model, such as the KMV model while emphasizing less on other alternative models (Zhang, Li & Wang, 2010). This narrow approach has limited the ability to accurately estimate credit risk in the Chinese market, where unique economic and regulatory factors play a significant role. It is crucial to use different risk assessment models and compare their accuracy, such as applying models based on accounting information and models based on market information. For example, scholars Castagnaolo and Ferro (2014) uses the Z-score, O score, and Merton model to assess corporate default risk.

Therefore, there is a research gap in the literature regarding the development and application of credit risk models in the Chinese market. It represents a significant challenge for financial institutions and corporations operating in the Chinese market. The development of more effective credit risk models is essential to manage credit risk, ensure financial stability, and support sustainable economic growth. Hence, this research proposes to combine the Merton model with the Altman Z-score that can overcome the challenges associated with the Chinese market and provide more accurate and reliable credit risk assessment.

1.3 Research objectives and questions

The overall objective of this study is to compare the performance of the Merton model and the Altman Z-score model in predicting credit risk for Chinese firms. Specifically, this study aims to achieve the following objectives:

- Review and analyze the literature on credit risk models, with a focus on the Merton model and the Altman Z-score model, in the context of the Chinese market.
- Collect and analyze financial data of Chinese listed companies to construct the Merton model and the Altman Z-score model and compare the predictive accuracy of the two models.
- Provide insights into the applicability and limitations of the two models in the Chinese market, and to identify the dominant model, if any, for predicting credit risk in the Chinese market.
- Contribute to the existing literature on credit risk modeling and provide practical

implications for financial institutions and investors in China.

Based on the research objectives, the main research question of this study is:

Which model, the Merton model or the Altman Z-score model, is more suitable for predicting the credit risk of companies in the Chinese market? Are there any dominant models in the Chinese market?

1.4 Outline of the thesis

This thesis is structured as follows: Section 2 provides a review for the literature of credit risk models' research. Section 3 describes the methodology used in our study, which will mainly focus on discussion of the sample selection and data collection procedures, calculation of the Merton and the Altman Z-score models, and the evaluation of model performance through T-test Mann-Whitney U test and ROC curve analysis. Section 4 presents the empirical results and section 5 resides the discussion of obtained results. Section 6 concludes.

2. Literature review

2.1 Evolution of credit risk models

Credit risk is one of the main financial risks that exist in contemporary economy system. Credit risk, also known in some areas as default risk, is primarily the risk of loss arising from the inability of a counterparty to meet its agreed responsibilities and obligations due to a variety of different reasons during its daily economic activities. Scholars and practitioners have never given up on developing credit risk measurement methods since the past century.

2.1.1 Expert systems (5C)

Developed in the 1970s, the expert systems model is one of the earliest credit risk assessment models. Expert systems model is also called the 5C model, which relies on experts' subjective diagnosis to assesses an obligor's ability to repay its credit by five factors: character, capacity, capital, collateral, and cycle condition (Mohammadi & Fathi, 2016). However, expert systems model could hardly be prevailing in banks because, firstly, it requires a high level of working experience in credit control and secondly, relies exclusively on subjective cognition, which can lead to inaccuracy. Additionally, this model may overlook qualitative factors that are difficult to quantify, such as borrower reputation or relationship with the lender.

2.1.2 Credit score models

The first modern multivariate and quantitative model that predicts bankruptcy was introduced by Edward Altman (1968) in the late 1960s based on discriminant analysis of five accounting numbers (Zamore et al., 2018; Altman et al., 2016). This model intends to relate corporate financial ratios and default event through a regression function, and the outcome is Altman Z-score, which is a financial distress indicator.

Credit scoring models are widely adopted by financial institutions even until now, due to their simplicity and effectiveness in predicting default risk. It has a profound impact on credit risk predicting for bankers, investors, researchers and rating agencies, In 1968, professor Edward Altman of New York University studied the data of several bankrupt companies in the United States and compared them with non-bankrupt companies. His analysis and selection of 22 significant financial measures yielded 5 crucial financial indicators that best reflect the borrower's financial situation, which composes to the renowned 5-variable Z-score model (Altman et al., 2016). Z-score has become a prototype for accounting-based methods, and yet the model is criticized for backward looking on historical accounting data and may not provide useful information in predicting the market (Zamore et al., 2018).

The last century witnessed plentiful research in credit score field such as the logit model and the probit model. Ohlson (1980) develops the logit model and suggested to add in more predictors, Zmijewski (1984) notices the selection bias occurring in financial distress studies and tried to eliminate it by introducing a probit approach, Taffler (1984) measures the Z-score for United Kingdom and proved its applicability.

2.1.3 Structural models

The emergence of structural models can be traced back to the pioneering work of Black and Scholes (1972, 1973) on option pricing theory. Merton (1974) starts with Black-Scholes approach, he proposes to treat corporate equity value as a call option and demonstrates that probability of credit default is intrinsically the likelihood of firm total asset value exceeds debt at maturity date. The method hereby is also called contingent-claims-based approach, and the outcome of Merton model is distance to default, which could be used to determine probability of default. This mechanism has been the foundation of structural models and might be the most influential one for credit risk modeling (Zamore et al., 2018).

Thereafter, further research was proposed to extend and improve the Merton model. Black and Cox (1976) discuss contingent claims under condition of discreteness and attempt to incorporate special provisions, such as safety covenant, into the model. Mason and Bhattacharya (1981) test and confirm the conjecture put forward by Black and Cox in 1976. Additionally, Longstaff and Schwartz (1995) improve the valuation process in the structural models to a continuous-time valuation framework. One vital development of structural approach is the KMV model, established and named by Kealhofer, McQuown and Vasicek in the late 1990s, an incarnation of Merton model, which was acquired by Moody’s. The KMV model differentiates by including empirical default frequency (EDF) to interpret distance to default in the original Meron model, rather than mapping it through a normal distribution. The KMV model is widely used by financial institutions worldwide and Moody’s can train and refine EDF on a daily basis. Nevertheless, critiques point out the assumption that firm will not default until the maturity date is unrealistic, and the corporate asset value in the model is neither traded nor observable in empirical setting (Jarrow, 2009).

2.1.4 Reduced-form models

In contrast to structural models, the reduced-form approach, as proposed by Jarrow and Turnbull (1995) and Duffie and Singleton (1999), does not explicitly establish a relationship between firm asset value, liability status, and default. Instead, it considers default as an unpredictable event governed by a hazard rate process, analogous to the initial jump in the Cox process. Grounded on risk-neutral pricing theory, reduced-form models can value credit derivatives by adjusting the risk-free spot rate, such as U.S. treasury rate (Zhou, 2001). Upon that, Jarrow et al. (1997) attempts to solve credit rate migration by introducing a Markov chain model to match discrete state with credit rating. Furthermore, the issue of default correlation in pricing credit derivatives on baskets or within competitive industries has been examined by researchers (Jarrow, 2009).

The reduced-form approach, although less intuitive compared to structural models due to the absence of firm-specific endogenous variables driving the default event, has gained significant traction as an important paradigm in credit risk modeling (Weigel and Gemmill, 2006). However, since the hazard rate of default is exogenously determined in reduced-form models, providing a satisfactory explanation for the underlying motivation and triggers of default events becomes challenging.

2.1.5 Modern credit measurement tools

Ever since the Bank for International Settlement in Basel promulgated financial stability initiative and put regulation in implementation in 1998, banks are required to use internal tools to evaluate its financial safety and meet minimum capital requirements. Several industry-sponsored tools have been developed for credit risk measurement, including Credit Metrics by JP Morgan, CreditRisk+ proposed by Credit Suisse, and Credit Portfolio View proposed by McKinsey. Modern credit risk measurement models, such as the Credit Metrics model, emerged in the 1990s and primarily employ statistical techniques to estimate credit risk based on market data.

The Credit Metrics model primarily utilizes the estimation of the forward distribution of credit migration to determine the market value and deviation of credit value. It is widely adopted by financial institutions managing portfolios with a value-at-risk (VaR) methodology (Crouhy, Galai & Mark, 2000). The Credit Metrics model is applicable to almost all common credit products or portfolios as long as a historical database of credit rating matrices is provided.

The CreditRisk+ model applies to specifically detect default frequency and loss distribution through an actuarial method that has no assumptions on cause of default event. The model assumes that the probability of default follows a Poisson distribution. For a customer's risk of default, the CreditRisk+ model estimation will describe the risk of default in terms of a continuous random variable and will not result in a specific number to indicate the probability of default.

Last but not least, the Credit Portfolio View model gained its popularity around 2000. It simulates the joint conditional distribution of default and credit migration in different industries and countries (Crouhy, Galai & Mark, 2000). Although the Credit Portfolio View provides a more comprehensive analysis of default risk by incorporating macroeconomic variables to offset the bias of whether the probability of credit migration changes dynamically over time, its limitation is that it only considers systemic risk, while unsystematic risk cannot be taken into account.

2.2 Comparison of the applicability of credit risk measurement models

The credit risk management models discussed in this study have gained significant popularity in European and American countries. However, given the relatively underdeveloped state of the Chinese capital market, notable disparities exist when compared to the more mature markets of Europe and America. These disparities may result in situations where the assumption conditions and parameters specified in certain models cannot be met. As a consequence, not all models are appropriate for implementation in China, with the divergences primarily manifesting in the following areas.

2.2.1 Credit rating system

Parameters used in the Credit Metrics model and the Credit Portfolio View model need a substantial amount of long-term default historical data and a precise credit rating issued by rating agencies. However, China's credit rating system began rather late. The historical data in national or industry databases might be insufficient to meet the needs of these models. Besides, the independence and accuracy of China's credit rating agencies raise concerns due to the absence of a globally recognized and reliable credit rating system comparable to Standard & Poor's or Moody's. Consequently, the application of models such as the Credit Metrics model and Credit Portfolio View model in China poses challenges.

2.2.2 Availability of Required Data

The Credit Metrics model and the CreditRisk+ model rely on a substantial historical default record, which is currently lacking in China. Additionally, the Credit Portfolio View model necessitates a reliable default database to validate the correlation between macroeconomic variables and default events. It is evident that China lacks a comprehensive database to facilitate the calculations of the Credit Metrics, CreditRisk+, and Credit Portfolio View models.

In contrast, the Merton-based models and the Altman Z-score models rely predominantly on publicly available stock market data and financial statements for their calculations. These models are known for their efficiency and applicability to Chinese listed companies.

2.3 Empirical results in China

Several previous studies have extensively examined and validated the applicability of the Merton and Altman Z-score models in the context of China. These studies have evolved from merely demonstrating the efficiency of the Merton model to adjusting its parameters to ensure greater alignment with the country's specific national conditions.
Gou and Gui (2009) attempts to apply the Merton-based KMV model in China, they analyzed

6 Chinese companies from 2 industries and found out that KMV model can successfully differentiate ST[1] firms from non-ST firms. Besides that, Altman et al. (2016) conducts a global review of efficiency of the Altman Z-score model on different countries, and the results show that the Z-score model performs exceptionally well in China in distinguishing ST firms with non-ST firms. More specifically in certain industries, Zhang, Li and Wang (2010) uses KMV model to test if KMV model can detect financial distress on listed companies from China and U.S. in logistic industry during the period of financial crisis. And it concludes that the KMV model is a valid tool to evaluate default risk in financial crisis. Moreover, Chen and Chu (2014) studies how the KMV model applies to Chinese real estate firms. Their findings highlight the relevance and applicability of both the Merton and the Altman Z-score models in assessing credit risk in Chinese market.

Several studies have conducted in-depth comparative analyses of different credit risk models, exploring the ongoing debate between market-based and accounting-based models in the Chinese context. Peng, Jiang, and Wang (2019) provide a comprehensive categorization of credit risk models, classifying them into accounting-based, market-based, and hybrid approaches. They empirically test the performance of the Merton model, the Altman Z-score model, and a hazard model in predicting bond defaults in the Chinese market. Their findings reveal that the Merton model exhibited the lowest discriminatory power, while the hazard model demonstrates the highest predictive ability. They suggest that the incorporation of collective intelligence, represented by market variables, can enhance the accuracy of accounting-based models by correcting potential misjudgments. Similarly, Liu, Chang, and Lee (2010) argue that the performance of market-based and accounting-based models in predicting defaults depends on the efficiency of the security market. Their research on the Chinese and Taiwanese markets reveals that the Chinese market, characterized by relative inefficiency and high volatility, favors the use of traditional accounting-based models for more accurate credit risk assessment.

Nevertheless, some scholars held a different opinion on comparative discriminating power of credit risk models. Bauer and Agarwal (2014) believe that hybrid model perform better than either accounting-based or market-based model after their research on hazard model. Law and Roache (2015) investigate default risk via a variant of the Merton model, and conclude that equity-based approach is more effective in predicting Chinese firms. And some proposed that there is a very little difference between market-based and accounting-based models (Agarwal & Taffler, 2008).

While the ordinary credit risk models have shown promise, other researchers have explored the limitations and alternatives to these models. Zhang et al. (2020) pioneeringly claims that they

[1] ST is abbreviation of “special treatment”, a warning sign of financial distress in Chinese stock market, the detail about ST will be discussed in 3.1.

have conducted a more in-depth study based on a real default database, instead of a ST-based method, from Credit Research Institution (CRI) in National University of Singapore. The study had verified that default risk in China cannot be fully reflected by structural models, such as the KMV model. Thus, it was concluded that a multinomial logit model including macroeconomic variables and firm-specific factors (leverage, liquidity) has the best performance.

3. Methodology

3.1 Sample selection and data collection

In order to meet the research goal, 200 Chinese listed companies are selected as samples, whose yearly financial data in a magnitude of 10 years from 2012 to 2021 is collected to construct credit risk models in this research. The 200 sample companies in 10 years will contribute to 2000 units of credit risk indexes in the Merton model and the Altman Z-score respectively. It is believed that this amount of data is adequate to generate valid and convincing results to support the argument and conclusion in this study.

"ST" refers to special treatment, which is a regulatory mechanism employed in the Chinese stock market to address concerns regarding financial health and operational stability of listed companies. It represents a classification assigned to companies that fail to meet certain financial criterion, which includes the requirements on net profit and net assets per share. During the auditing process, listed companies that report losses for two consecutive fiscal years, or listed companies whose net assets are lower than their total liabilities, will be classified as ST companies by the China Securities Regulatory Commission (CSRC). As the consequence, ST companies may still trade in the market, but their stock tickers must be marked "ST" as the prefix, facing additional scrutiny. Moreover, a ST company can demark itself in the next fiscal year as long as it turns the red into black. According to the ST criterion above, its focus on profit and net asset, aims to reflect companies' financial viability and stability. Therefore, the ST mechanism intends to serve as an early warning system, alerting investors to potential risks, such as delist event. Under the absence of default database in China, ST mechanism is widely used by many scholars in previous empirical studies (Gou & Gui, 2009; Li, Yang & Zou, 2016). ST will be a significant proxy for default event in this paper.

For the purpose of comparison analysis, samples are divided into two groups: ST group and non-ST group. 100 ST companies and their corresponding 100 non-ST companies were selected and sum to the total of 200 samples. One should notice that there are in total 167 ST companies in Shanghai Stock Exchange and Shenzhen stock Exchange in 2021, 100 companies out of 167 were chosen to ensure they have valid data from fiscal year 2012 to 2021. The 100 ST companies span across various industries, with the exclusion of the financial services sector because the calculation formula of Altman Z-score in this paper is not applicable to financial services industry. In the non-ST group, sample companies were deliberately selected to ensure that each selected ST company has a corresponding non-ST company in the same industry, and with a market capitalization difference within 15%. *Appendix I* shows the detailed list of sample companies in different group and industries.

Data used in this paper are acquired by WIND information terminal, which is a leading information software converging financial information and providing analytical services based in China. It is a substitute for Bloomberg and is more widely used in authoritative Chinese financial services industry, banking, and media. The collected data involve total assets, working capital, short-term liabilities, long-term liabilities, retained earnings, sales, earnings before interest and taxes (EBIT), number of tradable shares, number of non-tradable shares, and daily share price from 2012 to 2021.

It is worthy highlighting that the ST sign is not consistent throughout the entire 10-year period, some companies could experience the ST mark and demark back and forth. To signal this transition between ST and non-ST status, the ST-related events including marking and demarking were collected at a yearly basis. A new column named "default" was added, companies in the ST status at the year were recorded as "1" in the column and that in the non-ST status at the year were recorded "0". As the result, 254 units of data were assigned "1" and the remaining 1746 units data were assigned "0". It implies that in the magnitude of 200 companies in 10 years, 254 is the number of default cases. Then, those data will be imported to Python and Excel to complete the model construction.

3.2 Calculation of the Merton model and the Altman Z-score model

3.2.1 The Merton model

The Merton model, also known as the structural credit risk model, was developed by Robert Merton in 1974. It is a quantitative model that predicts the probability of default of a company or firm by considering the value of its assets and liabilities. There are five key assumptions that Merton model follows:

- Debt is a zero-coupon bond that matures at time T and has a nominal value of K.
- The firm cannot issue any new debt or equity (until time *T*).
- The firm is liquidated at time T.
- This firm either defaults or does not default at time *T*.
- The firm defaults if and only if $V < K$.

The key insight of Merton model is that the 'payoff' to the equity holders is identical to the payoff of a long call option written on assets *A* with strike price *K* (Merton, 1974):

$$E_t = \max[V - K, 0] \tag{3.1}$$

In turn this means, an option pricing model that relates the value of equity and the value of assets will provide probabilistic insights into the likelihood of the default scenario $V < K$. Now The Black-Scholes option pricing model could be applied to this situation (Black & Scholes, 1972). Furthermore, the most fundamental assumption on the underlying in the Black-Scholes model is the value of the underlying asset follows a stochastic process called geometrical Brownian motion.

$$dV = \mu V dt + \sigma_V V dw \tag{3.2}$$

where *A* is the company's value, μ is the expected return of the company's worth, σ_V is the variation of the company's value, and dW is a standard Weiner process.

One important implication of the GBM assumption is that the logarithm of the value of the underlying lnV at time *T* as seen from today follows a normal distribution:

$$lnV_T \sim \Phi\left(lnV_0 + \left(\sigma_V - \frac{\sigma_V^2}{2}\right)T, \sigma_V\sqrt{T}\right) \tag{3.3}$$

Then, we could apply the Black-Scholes-Merton Model to formulate the relationship between company's equity value, total value, and liabilities (Black & Scholes, 1972).

$$E = VN(d1) - Ke^{-rT}N(d2) \tag{3.4}$$

Where:

$$d_1 = \frac{ln\frac{V}{K} + \left(r + \frac{1}{2}\sigma_V\right)^2 T}{\sigma_V\sqrt{T}} \tag{3.5}$$

$$d_2 = d_1 - \sigma_V\sqrt{T} \tag{3.6}$$

Where *E* is the company's equity value, *V* is the company's total value, *K* is the face value of company's total debt, *r* is the risk-free rate, σ_V is the volatility of company's value, *T* is the debt maturity and *N (*)* is the CDF of standard normal distribution. It is obviously that we could obtain other variables directly besides the *V* and σ_V these two key variables.

However, given that the asset value follows a GBM the stochastic process followed by the equity value can be derived using the so-called Ito formula (Merton, 1974).

$$\sigma_E = N(d_1)\frac{V}{E}\sigma_V \tag{3.7}$$

By combining 3.7 with the Black-Scholes formula, we could derive *V* and σ_V easily.
Then, we need to calculate the default point DPT from company's both of short-term debt (STD) and long-term debt (LTD), under specific parameters α and β before the STD and LTD.

$$DPT = \alpha STD + \beta LTD \tag{3.8}$$

Finally, the distance to default can be derived by following key formula,

$$DD = \frac{ln\frac{V}{K} + (\mu_A - \frac{\sigma_V^2}{2})T}{\sigma_V \sqrt{T}} \tag{3.9}$$

We assume $\mu_A = r$ which means the asset value is expected to grow in line with the risk-free rate.

3.2.2 The Merton model's modifications

Given the particularities of the Chinese market, it is necessary to make appropriate modifications to some of the variables in the Merton model to make it more applicable to the Chinese market context.

3.2.2.1 Equity value

The main particularity of the Chinese market lies in the existence of two types of shares: tradable shares and non-tradable shares. These shares have different acquisition prices, but shareholders have equal cash flow rights and voting rights. This split occurred during China's transition from a traditional planned economy to a market economy, as state-owned enterprises sought to raise capital on the capital market, but the planned economy system prevented these companies from relinquishing control from the government or enterprise groups. Aboud and Diab (2022) examine the relation between corporate governance structure, particularly the ownership structure of state-owned enterprises, and corporate financial performance. The study revealed a significant negative impact of state ownership on firm value. However, reforms in 2005 focused on the stock market, such as equity split reform, were found to enhance the quality of corporate governance (China Securities Regulatory Commission, 2005). To promote this, most companies raised funds by issuing new shares, making the original shares non-tradable and the newly issued shares tradable. With the development of the security market, this division has become increasingly unsuitable. Although the acquisition cost of the two types of shares is different, the returns on the shares are the same, resulting in inequality between shareholders of tradable and non-tradable shares. Xiao (2015) argues that dual class share structure leads to significant conflicts of interest between non-tradable shareholders and tradable shareholders. The limited supply of tradable shares also makes the market susceptible to speculative activities. Moreover, due to the low acquisition cost of non-tradable shares, which is only one-tenth of that of tradable shares, there is concern for the impact of stock price fluctuations on the interests of tradable shareholders. At the same time, because of the existence of different costs, the market price of company stocks cannot reflect their true value and is usually much lower than their face value. Therefore, using the number of outstanding shares multiplied by their price cannot obtain the correct company's market value. In the Merton model, to calculate the total value of the company using the Black-Scholes option pricing formula, an accurate company market value is required. If we still use the traditional way to calculate equity value, since the actual price is much lower than the market price of the stock, the Merton model underestimates the company's credit risk.

The purpose of 2005 reform was to convert non-tradable shares into tradable shares. However, at the same time, tradable shares do not have to circulate on the market and can still be held by the government or enterprise groups.

Although most of the Chinese listed companies have completed the equity 2005 reform, the actual impact of the equity reform is still ongoing, which results in many Chinese listed companies still holding a certain amount of non-tradable shares.

Based on this specific market situation in China, we decide to use the following formula to calculate the company’s equity value:

$$E = N_T P_T + N_{NT} P_{NT} \tag{3.10}$$

Where N_T and N_{NT} are the number of tradable shares and non-tradable shares, P_T and P_{NT} are the price of tradable shares and non-tradable shares. P_T equals to the market share price in the last trading day of a fiscal year, however, different scholars hold different views on this issue. Gou and Gui (2009) simply use the price of tradable stocks as a substitute for the price of non-tradable stocks. Sun, Yue and Luo (2008, cited in Gou & Gui, 2009), on the other hand, apply a regression model to derive a formula for calculating the price of non-tradable stocks, $P_{NT} = 0.0489 + 0.3824 P_T + 0.062 * return\ per\ share + 3.003 * return\ rate\ of\ net\ asset$. Dong, Feng and Wei (2007 cited in Gou & Gui, 2009) use a different formula, which is $P_{NT} = 1.326 + 0.53 * net\ asset\ per\ share$. In this study, we simply employ tradable shares as the price of non-tradable shares.

$$P_T = P_{NT} \tag{3.11}$$

3.2.2.2 The volatility of equity value

The volatility of equity value is generally not directly observable. Thus, following the general methodology used by most scholars, volatility is estimated using equity returns (Bharath & Shumway, 2008; Chen & Chu, 2014; Castagnolo & Ferro, 2014). There are generally two methods for calculating returns.

The first one is percentage price change method:

$$r_t = \frac{P_t - P_{t-1}}{P_t} \tag{3.12}$$

Where r_t is percentage return, P_{t-1} represents the price of the previous day (monthly or weekly), while P_t represents the price of the current day (monthly or weekly).

The second one is logarithmic price change method:

$$r_t = ln \frac{P_t}{P_{t-1}} \tag{3.13}$$

Where r_t is logarithmic return, P_{t-1} represents the price of the previous day (monthly or weekly), while P_t represents the price of the current day (monthly or weekly).

The difference between these two calculation methods lies in their underlying assumptions. The first method assumes that price changes are not continuous, while the logarithmic price change method assumes that price changes are continuous. In an earlier mentioned context, the theoretical foundation of the Merton model was introduced as the BSM model, which assumes that price changes are continuous, and the underlying asset value follows a log-normal distribution (Merton, 1974). Therefore, in this study, the second method of logarithmic price change is applied to calculate stock returns.

In this thesis, authors utilize daily data to calculate equity return, and the daily volatility of equity returns can be estimated using the following formula for standard deviation.

$$\sigma_D = \sqrt{\frac{1}{n-1}\sum_{i-1}^{n}(r_t - \bar{r})^2} \tag{3.14}$$

$$\sigma_Y = \sigma_D * \sqrt{n} \tag{3.15}$$

Where σ_D is the daily volatility of equity, while σ_Y is yearly volatility. And we select $n = 250$ as the number of trading days in one year, r_t represents daily equity return, $\bar{r}$ means the average of r_t.

3.2.2.3 Debt maturity

In this study, the debt maturity *t* is defined as one year.

$$T = 1 \tag{3.16}$$

The Merton model is mainly used to predict the default of listed companies, and the data on corporate debt mainly comes from the financial statements publicly disclosed by listed companies. Although the Chinese securities industry requires the disclosure of quarterly, semi-annual, and annual financial reports, the annual financial report generally requires professional accounting firms to conduct audits and inspections. Therefore, it is believed that the disclosure content of annual reports can better reflect the actual situation and has more reference value.

3.2.2.4 Debt value and default point

One could easily obtain the face value of company's short-term debt (STD) and long-term debt (LTD) from its annual balance sheet because the debt maturity is one year.

The default point, theoretically, should be when the enterprise's asset value equals to its debt, representing a critical trigger state. However, in practice, this is not always the case. KMV Corporation discovered from a large number of cases that some companies do not immediately default when their asset value falls below the total debt amount, because a portion of the total debt shown on the balance sheet is long-term debt, and the maturity of some long-term debt may not have been reached, which can still support operations for a period of time. Part of companies even use this period to continue operating and ultimately repay their debts. Therefore, KMV Corporation believes that the default point is linearly related to both the long-term and short-term debt of the company.

$$DPT = \alpha STD + \beta LTD \tag{3.8}$$

Most of scholars follow $\alpha = 1, \beta = 0.5$ which presented by the original Merton Model (Merton, 1974). In this study, we apply it to our first DPT, in the subsequent sections of this paper, the various default points set to the Merton Model will be revised in the *Appendix II,* followed by an empirical analysis and statistical testing of the revised model.

3.2.2.5 Risk-free rate

In the financial industry, the commonly accepted definition of risk-free rate refers to the rate of return on an investment that guarantees both the principal and returns without taking on any risk. Strictly speaking, there is no strict risk-free rate in China. However, many scholars researching the Chinese market choose to use the one-year deposit rate of the People's Bank of China as the risk-free rate, which is reasonable (Liu, Chang & Lee, 2010; Zhang et al., 2020). The reason for not choosing the Chinese one-year treasury bond rate as the risk-free rate is that bank deposits are more popular and well-known than treasury bonds in China.

Table 1: Interest rates from 2012 to 2021 (%)

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Interest rate	3.00	3.00	2.75	2.13	1.50	1.50	1.50	1.50	1.50	1.50

Source from: the People's Bank of China

3.2.3 The Altman Z-score model

These five financial ratios were used as variables to establish the well-known Altman Z-score model (Altman, 1968). The discrimination model is presented as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (3.17)$$

Where X_1 is working capital/total assets, X_2 is retained earnings/total assets, X_3 is earnings before interest and taxes/total assets, X_4 is market value of equity/book value of total liabilities, X_5 is sales/total assets.

The credit risk of a company is estimated by the Z-score calculated in 3.17. The original evaluation criteria are as follows:

- Z < 1.81 means default very likely - distressed zone ('red zone')
- 1.81 < Z < 2.99 means inconclusive - ('grey zone')
- Z > 2.99 means default very unlikely - safe zone ('green zone')

All the variable information in the model can be obtained from the target company's financial statements, which is why the Altman Z-score model is a typical accounting-based model.

3.3 Model performance evaluation

3.3.1 Statistical Tests

3.3.1.1 T-test

To compare the differences in the Merton distance to default and the Altman Z-score between ST and non-ST companies, a T-test was employed. The T-test is a widely used statistical test that assesses the significance of differences between the means of two independent groups. It enables the determination of whether there are statistically significant differences between ST and non-ST companies.

The T-test assumes that the data are normally distributed and that the variances of the two groups are equal. It calculates a t-value, which represents the standardized difference between the means of the two groups relative to the variation within each group. Additionally, the T-test produces a p-value, which indicates the probability of observing such a difference by chance if the null hypothesis (no difference) were true.

The following null and alternative hypotheses were formulated for the T-test:

H_0: $There\ is\ no\ significant\ difference\ in\ the\ mean\ Merton\ default\ distance\ and\ the\ mean\ Altman\ Z-scores\ between\ ST\ and\ non-ST\ companies.$
H_1: $There\ is\ a\ significant\ difference\ in\ the\ mean\ Merton\ default\ distance\ and\ the\ mean\ Altman\ Z-scores\ between\ ST\ and\ non-ST\ companies.$

A significance level (α) was set to 0.05, the null hypothesis is rejected when tested p-value falls below the threshold, which indicates that the observed differences in the Merton distance to default and the Altman Z-score between ST and non-ST companies are statistically significant.

3.3.1.2 Mann-Whitney U Test

As we know, the T-test assumes that the data are normally distributed and that the variances of the two groups are equal. In most of the situation where these assumptions are not met, an alternative non-parametric test, such as the Mann-Whitney U test, can be employed to provide additional insights.

The Mann-Whitney U test, also known as the Wilcoxon rank-sum test, is a non-parametric test used to compare the distributions of two independent groups. It is applicable when the assumptions of normality and equal variances are not met or when the data are ordinal or skewed (Mann & Whitney, 1947).

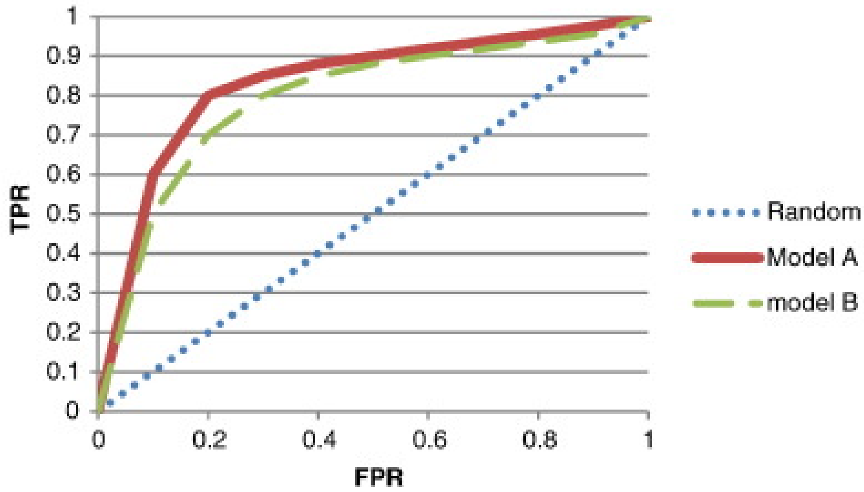
The Mann-Whitney U test serves as a supplementary analysis to the T-test, allowing for a more robust examination of the differences in the Merton distance to default and Altman Z-score between ST and non-ST companies. By considering a non-parametric approach, we can verify the consistency and validity of the findings obtained from the T-test.

The hypotheses and significance level here are completely same with the T-test.

3.3.2 ROC curve

The receiver operating characteristic (ROC) curve is a graphical tool used in finance to evaluate the performance of risk models. It is commonly used by scholars (Zhang et al., 2020, Peng, Jiang & Wang, 2019, Altman, 2016) in credit risk management to assess the ability of a model to discriminate between companies who will default and those who will not. Fawcett (2006) concludes that ROC graphs are an invaluable resource for assessing and evaluating classifiers, unlike simple scalar measures like accuracy, error rate, or error cost, ROC curves offer a more comprehensive measure of classification performance. The ROC curve plots the true positive rate (TPR) against the false positive rate (FPR) for different threshold values of the model's predicted probabilities. The TPR is the proportion of actual defaults that are correctly classified as defaults by the model, while the FPR is the proportion of non-defaults that are incorrectly classified as defaults by the model.

Figure 1: An example of ROC curve



Source from: Afik, Arad & Galil (2016)

The area under the ROC curve (AUC) is used as a measure of the model's ability to correctly identify defaulting companies. An AUC of 1 indicates perfect discrimination, while an AUC of 0.5 indicates that the model is even worse than random model, which is the 45-degree dashed line in the figure 1. In the figure 1, model A is superior to model B when the ROC curve of A is always above the ROC curve of B. (Afik, Arad & Galil, 2016) According to the AUC identification criteria provided by Hosmer, Lemeshow and Sturdivant (2013), if the AUC falls between 0.5 and 0.7, the discriminative ability of the model is relatively weak, if the AUC value is between 0.7 and 0.8, the discriminative ability of the model is acceptable, if the AUC value is between 0.8 and 0.9, the discriminative ability of the model is excellent. In this study, we will use the identification criteria above to test models' power, which refers to the ability of the model to separate default observations from solvency observations.

The use of ROC curve analysis in risk management allows practitioners to compare the performance of different risk models and select the one that best fits their needs. It also provides a way to evaluate the trade-off between the TPR and FPR, as increasing the TPR often comes at the cost of increasing the FPR. By using the ROC curve, practitioners can make informed decisions about the level of risk they are willing to tolerate.

4. Empirical results

4.1 Descriptive statistics

4.1.1 The Merton distance to default

To obtain the Merton distance to default, authors first calculate the equity value and its volatility using Equation (3.10) (3.13) (3.14) and (3.15). Then, we derive the DPT using Equation (3.8). Finally, by simultaneously solving Equations (3.4) (3.7) and (3.9), one can derive the two key variables of interest, $V$and σ_V, and eventually compute distance to default. Following is the descriptive statistics of the results:

Table 2: Overall descriptive statistics of distance to default[2]

	ST DD	Non-ST DD
Obs	1000	1000
Mean	53.9	66.7
Std	57.5	38.2
Min	4.1	6.3
Max	1061.2	289.6

Table 3: Yearly descriptive statistics for distance to default

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
ST obs	100	100	100	100	100	100	100	100	100	100
ST mean	54.5	50.9	64.1	51.2	64.6	94.6	44.8	41.5	38.5	43.1
ST std	33.3	29.7	39.1	32.7	35.6	108.3	31.3	29.7	99.8	31.7
ST min	6.3	4.1	6.0	6.0	6.2	7.5	6.2	5.4	5.9	4.6
ST max	197.0	132.5	221.1	233.9	181.6	1061.2	141.1	170.6	181.1	147.4
Non-ST obs	100	100	100	100	100	100	100	100	100	100
Non-ST mean	67.4	69.2	80.9	53.7	73.6	92.3	56.6	61.4	52.0	59.5
Non-ST std	38.9	38.6	42.5	28.9	33.6	50.0	32.2	34.6	25.8	32.9
Non-ST min	9.8	10.7	13.0	7.8	11.3	16.1	8.1	8.8	6.3	10.7
Non-ST max	171.6	203.5	186.5	180.9	148.2	289.6	209.3	171.8	122.1	184.1

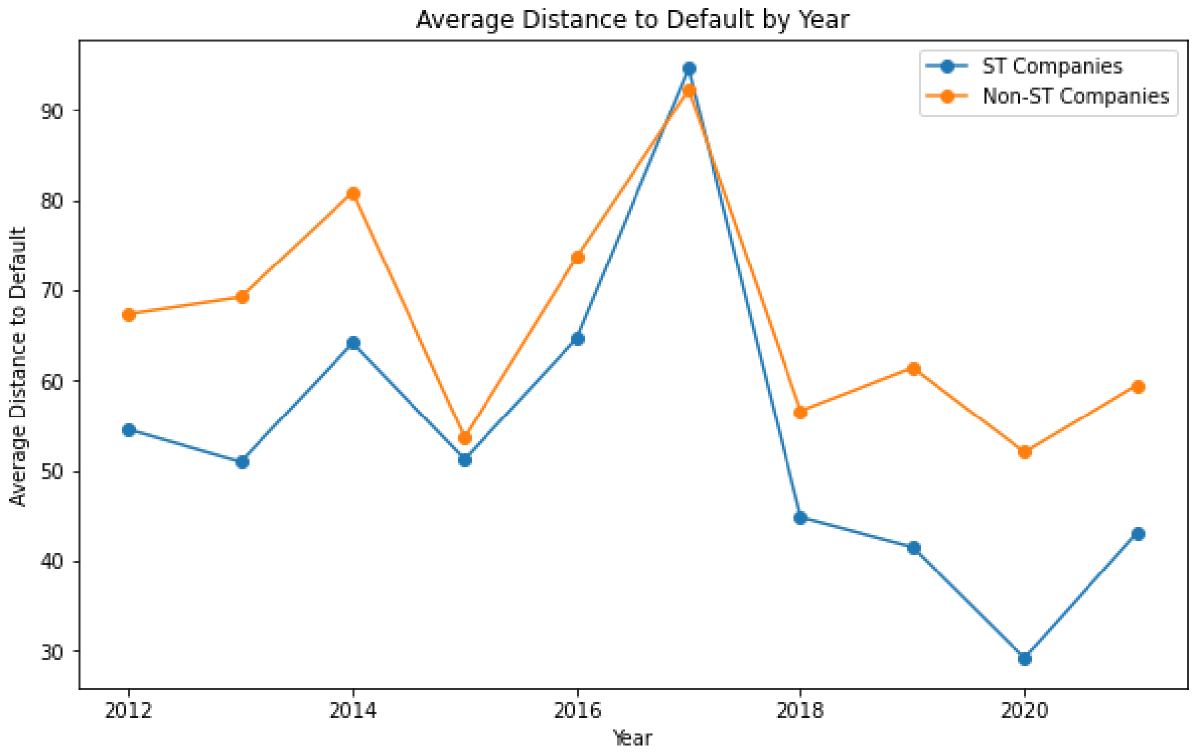
The descriptive dataset comprises 100 companies in each category, and the Merton distance to default were recorded annually over a period of ten years.

For the ST companies, the descriptive statistics reveal that the mean Merton distance to default ranged from 29.17 in 2020 to 94.59 in 2017. The standard deviation varied between 29.67 and 108.33, indicating the dispersion of data around the mean. Comparing the average distance to default between ST and non-ST companies over the entire ten-year period, it is observed that the Merton distance to default values for ST companies are significantly lower than those for

[2] DD is the abbreviation of distance to default in this paper.

non-ST companies. However, it is important to note that not all years exhibit higher the Merton distance to default for ST companies compared to non-ST companies. In some certain years, the Merton distance to default between the two groups are very close, and in some cases, such as in 2017, the distance to default for ST companies slightly surpasses that of non-ST companies. This observation can be attributed to the fact that not all selected ST companies remained in the ST category throughout the entire ten-year period. Continuously maintaining ST status over a prolonged period is rare, as extended periods of ST classification often lead to delisting.

Figure 2: Average distance to default by year



Through data visualization, it is evident from the line graph (figure 2) that both ST and non-ST companies exhibit similar patterns in the Merton distance to default. The maximum values for both groups occurred in 2017, while the minimum values were observed in 2020. Furthermore, the upward and downward trends in the Merton distance to default show a convergence between the two groups. The year 2020 witnessed the largest disparity between ST and non-ST companies. It is important to consider that the selection of ST companies is based on their status in 2021, and most of the chosen ST companies were classified as such between 2020 and 2021.

4.1.2 The Altman Z-score

Compared to the Merton distance to default, the Z-score is easier to obtain. After collecting and organizing financial information from 200 companies, authors calculated the Z-score for each company annually in Excel. Following is the descriptive statistics:

Table 4: Overall descriptive statistics of Z-score

	ST Z	Non-ST Z
Obs	1000	1000
Mean	3.5	6.6
Std	6.9	10.5
Min	-10.0	-49.9
Max	106.5	194.7

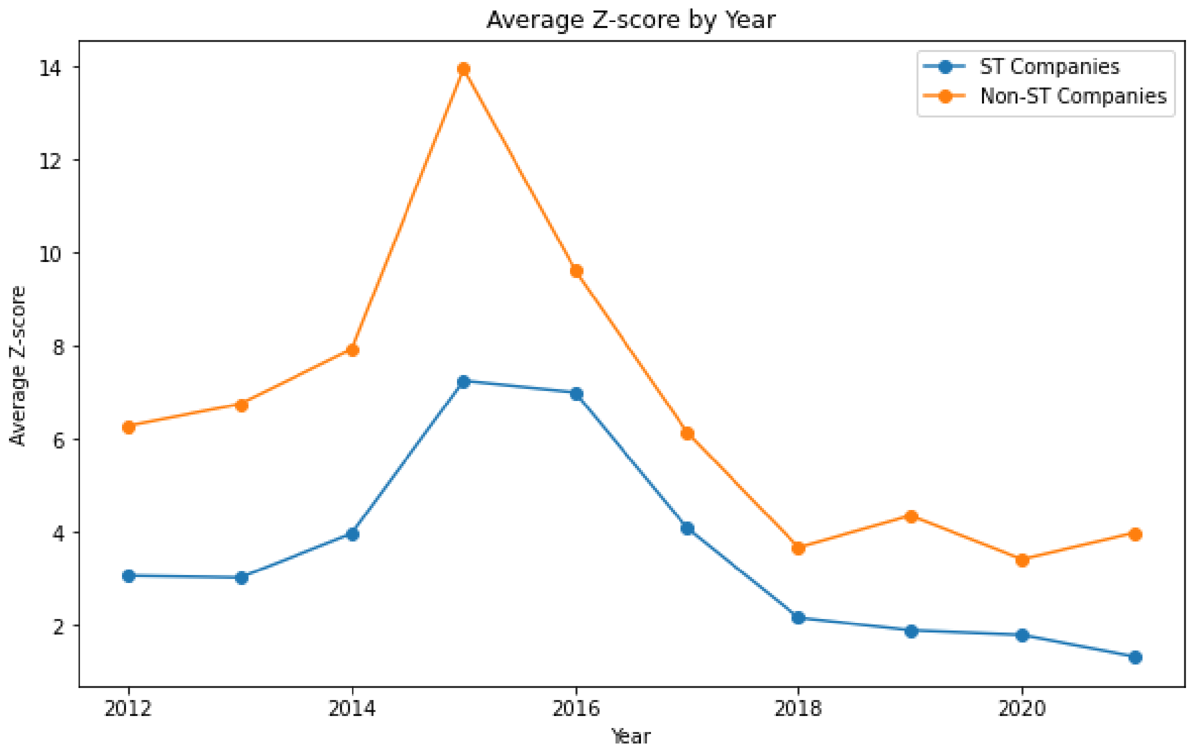
Table 5: Yearly descriptive statistics of Z-score

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
ST obs	100	100	100	100	100	100	100	100	100	100
ST mean	3.1	3.0	4.0	7.2	7.0	4.1	2.2	1.9	1.8	1.3
ST std	4.4	3.0	5.5	9.8	13.4	5.8	2.6	4.0	4.7	4.6
ST min	-1.1	-1.3	-0.6	0.3	0.1	-0.7	-4.5	-6.7	-3.6	-10.0
ST max	38.6	18.4	41.2	54.9	106.5	51.5	15.1	23.1	34.1	26.0
NONST obs	100	100	100	100	100	100	100	100	100	100
NONST mean	6.3	6.7	7.9	13.9	9.6	6.1	3.7	4.3	3.4	4.0
NONST std	6.7	8.8	9.9	22.8	11.0	7.2	4.2	5.0	6.7	4.0
NONST min	-5.4	-3.8	0.1	-0.5	0.3	0.6	-25.0	-19.9	-49.9	-4.9
NONST max	35.4	62.6	66.0	194.7	59.8	65.0	17.4	22.1	22.5	16.5

For the ST group, the mean Z-score ranged from 1.3 in 2021 to 7.2 in 2015 (table 5). The standard deviation varied from 3.0 in 2013 to 13.4 in 2016. The minimum and maximum Z-score for ST companies were -10.0 and 106.5, respectively.

It is worth noting that the ST group generally exhibited lower mean Z-score in all ten years compared to the non-ST group, indicating a relatively higher default risk in the ST group. On the other hand, both groups displayed variability in their Z-score, as reflected by the standard deviations, the range of Z-score varied across different years for both ST and non-ST companies.

Figure 3: Average Z-score by year



Based on the visualization of Z-score data in figure 3, it is evident that both ST and non-ST companies exhibit similar patterns. The line chart (figure 3) reveals that both groups reached their highest Z-score in 2015, and their upward and downward trends are comparable. However, unlike the distance to default metric, there is a consistent difference between the two groups throughout the ten-year period, with non-ST companies consistently surpassing ST companies.

4.2 Statistical tests results

4.2.1 T-test

Before conducting the T-test to the data, the normality assumption of the data should be verified. Authors applied D'Agostino-Pearson normality tests on the Merton distance to default and the Z-score of both ST and non-ST companies.

Table 6: Normality test

	p-value
ST DD	0.000
Non-ST DD	0.000
ST Z-score	0.000
Non-ST Z-score	0.000

The results of the normality tests indicate significant departures from normality for all variables examined. For the Merton distance to default of ST companies, the obtained p-value was extremely small ($p < 0.001$), suggesting a statistically significant deviation from normal distribution. Similarly, the Merton distance to default of non-ST companies exhibited a significantly non-normal distribution ($p < 0.001$). Additionally, the Z score of both ST and non-ST companies displayed significant departures from normality ($p < 0.001$).

Based on these findings, the assumption of normality for the Merton distance to default and the Z score of both ST and non-ST companies is rejected. These results indicate that the data may not conform to a normal distribution, implying the need for alternative statistical approaches that do not rely on the normality assumption. However, according to the central limit theorem in statistics, as the sample size increases, the distribution tends to approach a normal distribution. In this case, having a total of 4000 data points provides a relatively large sample size, which enhances the validity of assuming normality.

Table 7: T-test of distance to default and Z-score

	t-value	p-value	Mean Diff	Std. Error Diff	95% Confidence Interval of the Diff	
DD	-5.8610	**0.000**	-12.7903	1.9978	-16.7107	-8.8699
Z-score	-7.6959	**0.000**	-3.0538	0.3736	-3.7868	-2.3207

Based on the results of the T-test, one can draw the following conclusions regarding the significant difference in the Merton distance to default and the Z score between ST and non-ST companies:

For the Merton distance to default, the t-value of -5.8610 indicates a significant difference between ST and non-ST companies. The corresponding p-value of 0.000 suggests strong evidence against the null hypothesis, supporting the presence of a significant difference. The mean difference of -12.7903 indicates that, on average, ST companies have a lower distance to default compared to non-ST companies. The standard error of the difference, 1.9978, reflects the precision of the estimate.

For the Z-score, the t-value of -7.6959 also reveals a significant distinction between ST and non-ST companies. The associated p-value of 0.000 provides compelling evidence against the null hypothesis H_0, indicating a substantial difference. The mean difference of -3.0538 suggests that, on average, ST companies have a lower Z score compared to non-ST companies. The standard error of the difference, 0.3736, reflects the precision of the estimate.

In conclusion, the results of the T-test demonstrate that there is a significant difference in both distance to default and Z score between ST and non-ST companies. ST companies exhibit lower distance to default and Z score values compared to non-ST companies, indicating a distinct financial profile.

4.2.2 Mann-Whitney U test

The results of the independent samples T-test indicate a significant difference between the two groups in terms of the mean values. However, since the assumption of normality made in the T-test does not hold in reality, in order to enhance the persuasiveness of the statistical analysis, further non-parametric tests will be conducted on the distance to default of the two groups. Non-parametric tests allow for inference and hypothesis testing without making any assumptions about the population distribution, focusing solely on the available data (Mann-Whitney, 1947). The non-parametric tests suitable for independent samples include the Mann-Whitney U test, Kolmogorov-Smirnov test, Wald-Wolfowitz runs test, and Moses Extreme Reactions test, among others. In this section, the Mann-Whitney U test will be employed to assess the significance between the two groups based on the obtained data.

According to the analysis results shown in table 8, the two-tailed test's p-value (asymptotic significance) is 0.000, which is lower than the confidence level of 0.05. Therefore, it is concluded that there is a significant difference between the two sample groups, indicating that the model has strong discriminative power over the samples.

Table 8: Mann-Whitney U test of distance to default and Z-score

	Mann-Whitney U	Wilcoxon W	Z value	Asymp. Sig.(2-tailed)
DD	389611.00	168693.00	-8.55	**0.000**
Z-score	315530.00	118498.00	-14.29	**0.000**

4.3 ROC curve analysis

In general, the ROC curve requires model predictions and true labels to compute true positive rate and false positive rate. In the following part, the Merton distance to default values and the Z-scores, which have been calculated in the previous steps, represent model prediction, and the default column mentioned in chapter 3.1 represents true labels. Since there are 254 cases of default, the ROC curve provides an overall assessment whether credit risk models can detect those 254 default events and its false prediction rate.

Before drawing the ROC curve in Python, it has to be adjusted to fit in distance to default and Z-score's setup, because according to the formula, the larger distance to default value and the Z-score, the less likely default event would happen. Figure 4 and 5 show the ROC curve of model prediction by the Merton distance to default values and Z-scores respectively.

Figure 4: ROC curve based on DD values

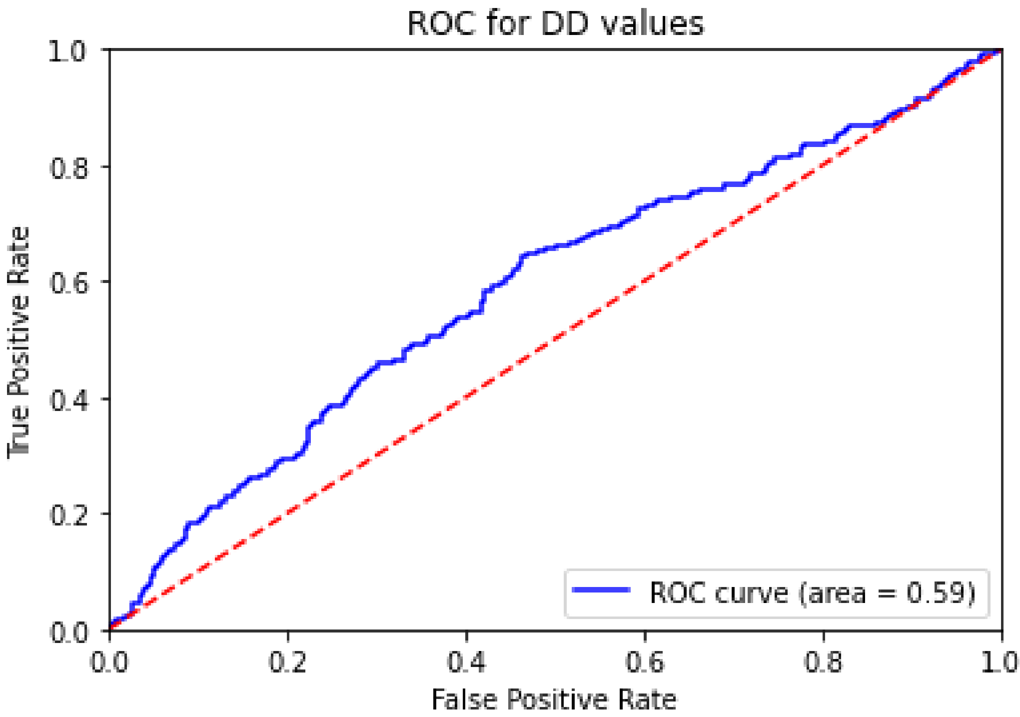
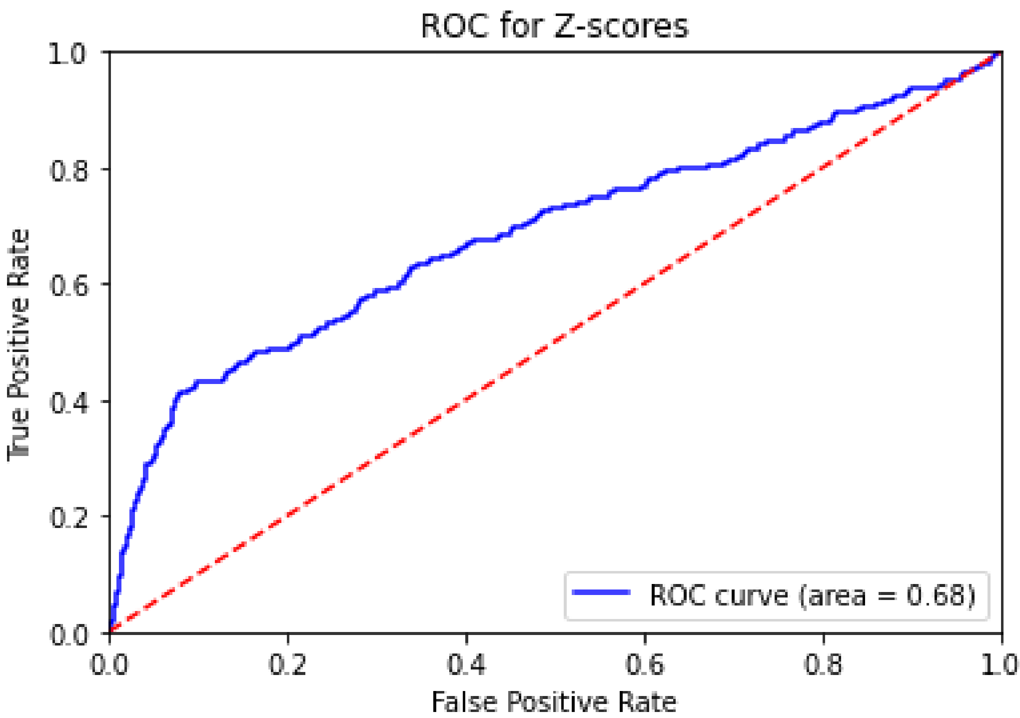


Figure 5: ROC curve based on Z-score



The area under curve (AUC) of the Merton model and the Z-score model are 0,59 and 0,68 respectively. In accordance with Hosmer, Lemeshow and Sturdivant (2013), these numbers indicate that the two models only have a relatively weak performance (AUC < 0,7). On the other hand, it can also be observed that the Z-score model has a better discriminating power compared to the Merton model.

4.4 Prediction power

The results of descriptive statistics and hypothesis tests listed above can already be summarized to indicate the relative accuracy of the Merton and the Z-score model. On the other hand, prediction power of credit risk model is an intriguing topic as well. Theoretically, both two models are dynamic and time-sensitive because the distance to default and the Z-score derive its strength from reliance on dynamic financial information, such as equity value, liabilities, and profitability, which reflect the current situation of the company as well as investors' expectation, thus demonstrate a strong real-time predictive capability. When it falls to practical applications, the progression from operational issues in a company to deteriorating financial conditions and eventual default is a gradual process, where certain current data often serve as precursors to future default events. Therefore, it is necessary to evaluate how the Merton model and Z-score model can monitor the potential default risk beforehand.

For this purpose, the data was reorganized to ensure that prediction values (DD values and Z-scores) at time T are corresponded to default status at time T+1, T+2, and T+3 respectively. In this manner, data is transformed into a format suitable for further analysis, the ROC curves will be used to assess the accuracy of the Merton distance to default and Z-score in forecasting default event on a scope from one to three years. Figure 6 and figure 7 showcase the results.

Figure 6: ROC curves for DD for three different prediction horizons

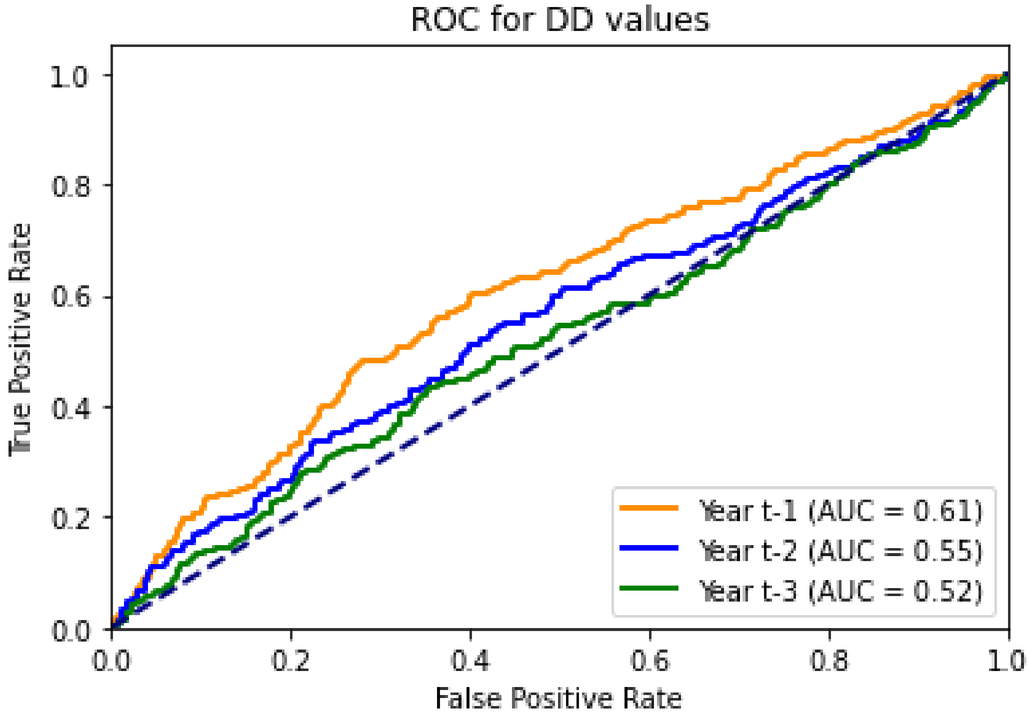
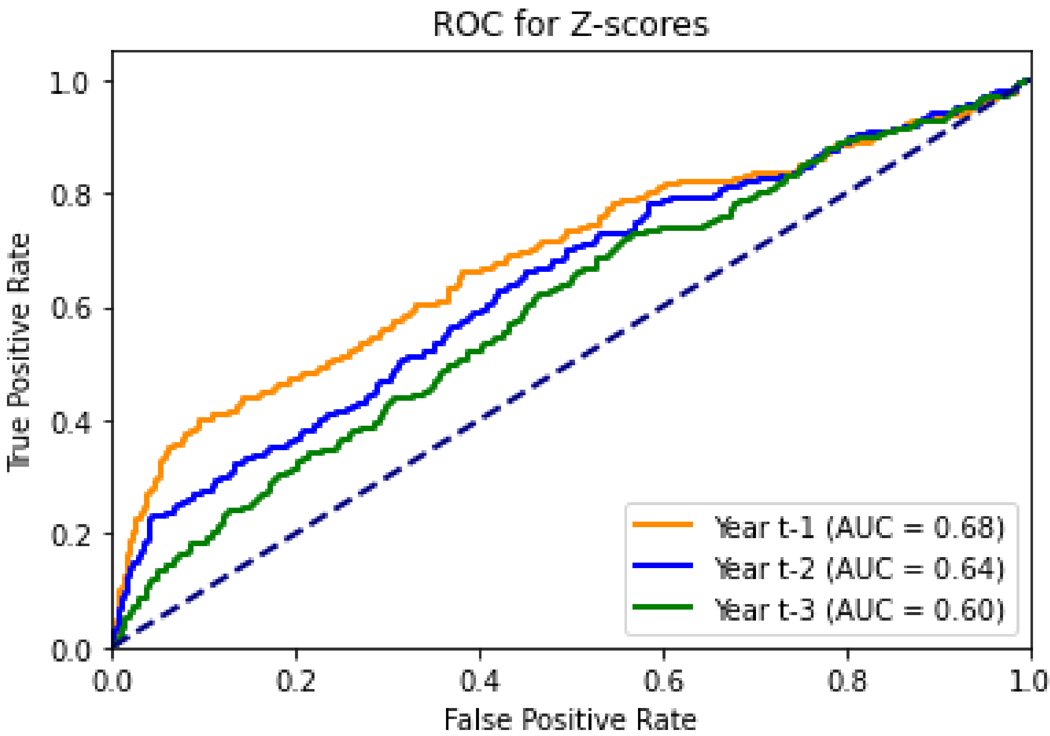


Figure 7: ROC curves for Z-score for three different prediction horizons



As seen in the two figures above, two models have very similar pattern, both have a decaying prediction power as the time span extends. For the Merton model, distance to default (DD) has a relatively weak performance when predicting default in 1 year (AUC of 0,61), but when it comes to prediction in 3 years, DD almost has no predicting power (AUC of 0,52). As for the Z-score, prediction power from 1 year to 3 years performs rather good (AUC of 0,68, 0,64, 0,60 respectively). In general, the Z-score model performs better than the Merton model in predicting default event in one to three years.

5. Discussion

5.1 Empirical findings

The empirical findings from both the distance to default and Z-score models for the period from 2012 to 2022 consistently indicate that ST companies are associated with higher risk. Statistical tests, including T-tests and Mann-Whitney U tests, demonstrate the significant ability of these models to distinguish between ST and non-ST companies. Notably, the average distance to default, as computed by the Merton model, does not exhibit the expected large disparity between ST and non-ST companies. In fact, in 2017, the distance to default for ST companies even slightly surpasses that of non-ST companies. This can be attributed to the fact that not all ST companies in the sample remained classified as ST throughout the entire ten-year period. Furthermore, based on our selection criteria, each corresponding non-ST company chosen for the ST companies belonged to the same industry with a market value difference within 15%. Hence, in certain years, when the current ST companies were still non-ST companies, there may have been some similarity in their financial conditions with the corresponding non-ST companies. Furthermore, in 2020 and 2021, the disparity between ST and non-ST companies reaches its maximum (figure 2), likely due to the majority of ST companies in the sample being recently classified as ST.

In contrast to the Merton distance to default, the average Z-score for ST companies is consistently lower than that for non-ST companies, indicating a higher default risk. This disparity is visually evident from the graphical representation (figure 3), which does not exhibit the clustering phenomenon observed in the Merton distance to default plot (figure 2). From this perspective, the Z-score model demonstrates stronger discriminatory power. It is inferred that this can be attributed to the fact that the classification of Chinese listed companies as ST primarily relies on accounting indicators, which aligns with the calculation methodology of the Z-score model based on accounting information.

It is worth noting that both models exhibit a similar trend in the changes of the distance to default and Z-score for ST and non-ST companies (figure 2 and 3). They both reach their lowest points during the period of 2019-2021, indicating a peak in default risk. Since the selected companies span a wide range of industries and cover a substantial portion of the market, it is believed that due to the unique characteristics of the Chinese market, listed companies are significantly influenced by real-time policies and other systematic macroeconomic factors, with relatively smaller contributions from idiosyncratic factors. Moreover, the years 2019-2021 coincide with the severe impact of the COVID-19 pandemic on the economy. Both models signal high default risk during this period. In conclusion, the Merton model and Altman Z-score models can effectively capture the credit risk signals.

Further analysis on the ROC curves reveals that neither the Merton model nor the Z-score model falls within the acceptable range of model performance defined by Hosmer, Lemeshow, and Sturdivant (2013) of $0.7 < AUC < 0.8$. Both models exhibit relatively weak discriminatory power, with the Merton model performing particularly poorly, with an AUC of only 0.59, marginally better than a random model (AUC=0.5). On the other hand, the Z-score model achieves an AUC of 0.68. Furthermore, both models demonstrate average predictive capabilities that decline over time, indicating a high sensitivity to the prediction period.

To investigate why both models perform weakly, authors examined the specific reasons behind the 254 cases of ST classification, finding that only 202 listed companies were designated as ST due to "negative net profit for the past two or three consecutive accounting years after deducting non-recurring losses". The remaining 52 cases were attributed to other reasons, including instances where companies received an internal control audit report or attestation report with a qualified opinion or adverse opinion, non-operational funds misappropriation or violation of decision-making procedures by major shareholders and their related parties, freezing of major bank accounts, and more vague reasons such as "other abnormal conditions". Apart from the inherent limitations of using ST companies as default proxies, the 52 cases classified as ST for other reasons are difficult to predict accurately by the models, leading to a decrease in their discriminatory power.

However, compared to the Merton model, the Z-score model demonstrates superior performance in the Chinese market. Corporate defaults typically do not occur suddenly, and it is rare for companies with strong and sustainable profitability to file for bankruptcy due to sudden changes in the economic environment or other unforeseen adverse events. Similar to the criteria for evaluating ST companies, corporate defaults are often due to the culmination of several years of poor operational performance, which will be significantly reflected on the corporate's accounting statements. According to Agarwal and Taffler (2008), loan covenants typically rely on accounting figures, making accounting-ratio-based models more likely to incorporate this information. Liu, Chang, and Lee (2010) conclude in their study on default prediction models in the Taiwanese and Chinese markets that the relative default predictive performance between market-based and accounting-based models should be related to the maturity of the securities market. In financial markets with insufficient maturity, low efficiency, and relatively high volatility, such as Chinese stock market, traditional accounting-based credit risk assessment models should be employed to estimate credit risk. While the market-based Merton model is theoretically appealing, its practical performance varies. Gou and Gui (2009) as well as Zhang, Li, and Wang (2010) have conducted research on the application of the Merton model in the Chinese market, finding it to be effective. However, their sample sizes were relatively small, including only six listed companies with different operational conditions and ten Chinese logistics listed companies, respectively.

In summary, in response to the research question posed in our study, the Z-score model appears to be more suitable for predicting credit risk in the Chinese market. However, neither the Merton model nor the Z-score model demonstrates dominant effectiveness in the Chinese market.

5.2 Limitations

This study has various limitations, including not only inherent theoretical deficiencies but also subjective flaws in data collection process.

As been mentioned in literature review, structural models and the Altman Z-score have limitations from a theoretical perspective. Firstly, the assumptions of the Merton model are inconsistent with reality sometimes. The model assumes that the value of a firm's assets follows a normal distribution and a fixed and unchanging corporate debt structure. However, under real-world conditions, changes in stock market valuations are not purely random, and corporate structure is vulnerable especially in financial distress. Secondly, for the Altman Z-score, it assumes a linear relationship between financial ratios and default risk and may not capture certain industry-specific and macroeconomic nuances.

In addition, parameters in the models should be modified to fit in Chinese market, and the modification implemented in this study might not be adequate and precise. For example, the calculation of equity value in the Merton model was modified to adjust to the existence of non-tradable share in China, but the assumption that the price of non-tradable share equals to that of tradable shares is questionable.

Moreover, the setting of default point referring to Equation 3.8 should be dynamic to variations in financial environments and policies across different countries, as well as the disparities among industries. Although authors have tried to test a best-performing default point that suits to Chinese market in *Appendix II*, there is no significant difference between the different default point settings (figure 8). This finding may imply that debt structure does not apply a significant influence on company valuation for Chinese listed companies, because debt occupies a negligible proportion. This study did not address the impact of different variables on the overall calculation of distance to default within the Merton model, and this aspect warrants further discussion. In the Altman Z-score model, this study adopts an original formula that Edward Altman proposed in 1968, whose validation ability may not be as sensitive in today's context, especially in Chinese market. In addition, this formula has a specific focus on manufacturing business, but the sample firms in this paper comprises of a variety of industry such as electricity, environment facilities, real estate, computer services, retailing.

Furthermore, the Chinese stock market at present may lacks strict regularization and supervision, which makes it a low-efficient market compared to the west, where credit model function more smoothly (Liu, Chang & Lee, 2010). There is possibility that the accounting and market information is subject to varying degrees of manipulation, thereby potentially impeding the model's capacity.

Most importantly, the methodology in this study that substitutes default event with ST event should be the main issue of controversy. Strictly speaking, ST mechanism is different from the definition of default in the credit risk model, companies that encounter difficulties in profitability or liquidity do not necessarily end up defaulting but could be part of corporate strategy. Additionally, since ST firms can demark itself, the transition between ST state and non-ST state also violates how default is defined, a firm cannot delist or go bankrupt several times in a row. Nevertheless, due to the lack of default database in China, ST mechanism is already the most suitable proxy for default that is available to public. The debate on this issue has never stopped in previous studies. Gou and Gui in 2009 affirm the ST approach and applied ST data in their research on KMV model and Chinese listed companies. Li, Yang and Zou (2016) conduct the comparison analysis on ZPP model and KMV model using ST-related data. On the contrary, Peng, Jiang and Wang (2019) criticize the widely used ST approach in Chinese credit risk research, they pointed out that ST is unreliable and could not be related to default. Instead, they used default database of Chinese market from CRI in National University of Singapore, but unfortunately that databased is not available to public or researchers unrelated to CRI and is not an official default database endorsed by CSRC either.

5.3 Reformation in Chinese stock market

As have been discussed above, the lack of default database and immature market system are the main obstacles while researching credit risk in China. This is a difficulty that cannot be solved in this study. However, it is noticeable that a registration-based reformation in stock market is being implemented by CSRC, and it would be a revitalizing catalyst for credit risk studies in China.

China's capital market historically operated under a system where regulatory authorities exercised strict control especially over initial public offerings (IPOs). Nevertheless, this system faced challenges such as redundant approval processes, low efficiency, information asymmetry, and potential manipulation. The comprehensive registration-based reform was initiated by authorities to address these issues and create a more transparent, efficient, and market-driven IPO system (China Securities Regulatory Commission, 2023).

The reform firstly establishes a registration-based system, where companies seeking to list on the stock exchanges only need to register the willingness. The focus shifts from administrative approvals to verifying the completeness and accuracy of information provided by issuers. In addition, the reform shed light on transparency and simplification, listed companies will need to be more responsible to investors but not the authorities. In a nutshell, market-driven stock exchange will play a dominant role in the capital market, and the issuance and delisting in the market could be very frequent in the future.

Conclusively, the reform implies that default event will be driven by the market mechanism and be common in China’s capital market, which can greatly enhance the completeness and quality of default database in the near future. Since the reform was just put into implementation on February 17th, 2023, it will be unable for this study to capture the effect of this reform (China Securities Regulatory Commission, 2023). However, it can be expected that China's securities market will become highly competitive, yielding a substantial amount of credit risk-related data for research purposes.

6. Conclusion

Previous literature has offered numerous empirical findings and different perspectives on credit risk models' discriminating power and prediction. However, those studies put the focus on very broad analyses that give limited insight for investors in a specific geographical market. Most of the studies, even with special focus on Chinese market, do not provide a comprehensive analysis on both models simultaneously. The authors were inspired and motivated by the aim to contribute valuable understanding of credit risk assessment in China for risk-conscious investors, highlight the strengths and limitations of the two models and emphasize the importance of future research in this area.

The Merton model and the Altman Z-score model were selected in this research among numerous credit risk measurement models primarily because these two models rely on parameters and data derived from market data and financial statements. The data from these sources are publicly available, easily accessible, and relatively objective. In this study, 100 ST companies, which are considered default samples, were selected from the listed non-financial service companies in China. Additionally, 100 normal trading companies from the same industry with comparable market capitalization were chosen as the normal sample group. Authors modified the two models based on Chinese market specialties and calculate the Merton default distance and Z-score for a period of ten years, parametric and non-parametric statistical tests were then conducted on these variables. The empirical results indicate that the Altman Z-score model showed a relatively better performance compared to the Merton model. Despite that, neither the Merton default distance nor the Z-score demonstrate strong discriminatory power for default events. Furthermore, the two models do not have an outstanding discriminating power in predicting default events over a one- to three-year timeframe.

To wrap it up, we suggest that the Merton model and the Z-score model, which are based on ST companies as proxies for default in this study, do not exhibit significant predictive power, despite demonstrating some predictive ability. Moreover, it is important to note that the definition of ST status does not directly imply default risk and is not a reliable indicator of default.

Within the limitations of this study, ranging from the existence of a considerable number of non-tradable shares in Chinese listed companies following the equity split reform in 2005 to the lack of an official default database, it is evident that stronger financial liberalization reforms are urgently needed, as the ongoing registration system reform in the Chinese market. Additionally, the Chinese stock market currently requires an authoritative official default database to assist listed companies and various financial institutions in better assessing and mitigating credit risk. We believe that with the support of multidimensional financial reforms and the establishment of an official default database, models such as the Merton model and the

Z-score model will find broader applications in the Chinese market.

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Appendix I

Table AI: Sample list; Left are ST companies and right are non-ST companies

CUSIP	NAME	INDUSTRY	CUSIP	NAME
000005.SZ	Shenzhen Fountain Corporation	Environment and Facilities Services	300262.SZ	SafBon Water Service (Holding) Inc.,Shanghai
600601.SH	Founder Technology Group Co.,Ltd.	Comprehensive	600648.SH	Shanghai Waigaoqiao Free Trade Zone Group Co.,Ltd.
600654.SH	China Security Co., Ltd	Computer Service	600355.SH	Routon Electronic Co.,Ltd.
000004.SZ	Shenzhen GuoHua Network Security Technology Co., Ltd.	Internet Software & Services	002316.SZ	Jilin Asia Link Technology Development Co.,Ltd.
600608.SH	Shanghai Broadband Technology Co.,Ltd.	Steel	000638.SZ	Vanfund Urban Investment&Development Co.,Ltd.
600666.SH	Aurora Optoelectronics Co.,Ltd.	Professional setting	002278.SZ	Shanghai SK Petroleum and Chemical Equipment Corporation Ltd
600671.SH	Hangzhou TianMuShan Pharmaceutical Enterprise Co.,Ltd.	Chinese medicine production	000790.SZ	Chengdu huasun technology group Inc., LTD.
000525.SZ	Nanjing Red Sun Co.,Ltd.	Fertilisers and agrochemicals	002391.SZ	Jiangsu Changqing Agrochemical Co.,Ltd
600804.SH	DR. PENG TELECOM&MEDIA GROUP CO., LTD.	Telecommunication services	002467.SZ	Net263 Ltd.
000564.SZ	Ccoop Group Co.,Ltd.	Retail	600859.SH	Wangfujing Group Co.,Ltd.
000571.SZ	SUNDIRO HOLDING CO., LTD.	Comprehensive	600408.SH	Shanxi Antai Group Co., Ltd.
000038.SZ	Shenzhen Capstone Industrial Co.,Ltd.	Advertisement	300269.SZ	Shenzhen Liantronics Co., Ltd.
600726.SH	Huadian Energy Company Limited	Electricity	600310.SH	Guangxi Guidong Electric Power Co.,Ltd.

000410.SZ	Shenyang Machine Tool Co.,Ltd	General Equipment	600765.SH	AVIC HEAVY MACHINERY CO., LTD.
600734.SH	Fujian Start Group Co.,Ltd.	Communication equipment	600776.SH	Eastern Communications Co.,Ltd.
000606.SZ	Shunliban Information Service Co.,Ltd	Internet Software & Services	002591.SZ	Jiangxi Hengda Hi-Tech Co., Ltd.
600759.SH	Geo-Jade Petroleum Corporation	Cruid oid & Gas	000968.SZ	Shanxi Blue Flame Holding Company Limited
000616.SZ	HNA INVESTMENT GROUP CO.,LTD.	Real estate	002188.SZ	ZHONGTIAN SERVICE CO., LTD.
600767.SH	WINSAN(CHENGDU) MEDICAL SCIENCE AND TECHNOLOGY COMPANY LIMITED	Medical service	600571.SH	SUNYARD TECHNOLOGY CO.,LTD
000669.SZ	Jinhong Holding Group Co., Ltd.	Gas	000593.SZ	DELONG COMPOSITE ENERGY GROUP CO., LTD
600781.SH	FUREN Group Pharmaceutical Co., Ltd.	Chinese medicine production	000590.SZ	TUS-PHARMACEUTICAL GROUP CO., LTD.
000692.SZ	Shenyang Huitian Thermal Power Co.,Ltd.	Public utility	600719.SH	DALIAN THERMAL POWER CO.,LTD.
000697.SZ	Ligeance Aerospace Technology Co.,Ltd.	Aerospace, Aviation and Defense	002383.SZ	Beijing UniStrong Science & Technology CO.,LTD
000752.SZ	TIBET DEVELOPMENT CO.,LTD.	Beverage	000929.SZ	Lanzhou Huanghe Enterprise Co.,Ltd.
600078.SH	Jiangsu ChengXing Phosph-Chemical Co.,Ltd	Chemicals	000819.SZ	Yueyang Xingchang Petro-Chemical Co.,Ltd.
000796.SZ	CAISSA TOSUN DEVELOPMENT CO.,LTD.	Consumer Service	000610.SZ	XI'AN TOURISM CO., LTD.
000732.SZ	TAHOE GROUP CO., LTD.	Real Estate	000014.SZ	Shahe Industrial Co.,Ltd.
000839.SZ	CITIC Guoan Information Industry Co., Ltd.	Cable and satellite television	000917.SZ	Hunan Tv & Broadcast Intermediary Co., Ltd
600112.SH	GUIZHOU CHANGZHENG	Power transmission and	002112.SZ	San Bian Science & Technology Co.,Ltd.

	TIANCHENG HOLDING CO.,LTD	transformation equipment		
000889.SZ	ZJBC Information Technology Co.,Ltd	Communication equipment	300050.SZ	Dingli Corp., Ltd
600136.SH	WUHAN DDMC CULTURE & SPORTS CO.,LTD.	Film and Entertainment	600892.SH	Dasheng Times Cultural Investment Co.,Ltd.
000806.SZ	Galaxy Biomedical Investment Co.,Ltd.	Power transmission and transformation equipment	000533.SZ	Guangdong Shunna Electric Co., Ltd.
600122.SH	Jiangsu Hongtu High Technology Co.,Ltd.	Retail	600293.SH	Hubei Sanxia New Building Materials Co.,Ltd.
000809.SZ	Tieling Newcity Investment Holding (Group) Limited	Public utility	600168.SH	Wuhan Sanzhen Industry Holding Co.,Ltd.
600182.SH	Giti Tire Corporation	Automotive parts	600469.SH	Aeolus Tyre Co.,Ltd.
600226.SH	Zhejiang Huge Leaf Co., Ltd.	Fertilisers and agrochemicals	002215.SZ	SHENZHEN NOPOSION AGROCHEMICALS CO.,LTD.
600239.SH	YunNan Metropolitan Real Estate Development Co.,Ltd.	Real estate	600533.SH	NANJING CHIXIA DEVELOPMENT CO., LTD.
000971.SZ	GOSUN HOLDINGS CO., LTD.	Internet service	300017.SZ	Wangsu Science & Technology Co.,Ltd.
600289.SH	Bright Oceans Inter-Telecom Corporation	Communication device	002231.SZ	ALLWIN TELECOMMUNICATION CO.LTD
000150.SZ	YIHUA HEALTHCARE CO.,LTD	Health care service	002044.SZ	Meinian Onehealth Healthcare Holdings Co., Ltd.
000995.SZ	Gansu Huangtai Wine-Marketing Industry Co.,Ltd.	Beverage	600573.SH	Fujian Yanjing Huiquan Brewery Co.,Ltd.
600265.SH	Yunnan Jinggu Forestry Co.,Ltd.	Forestry	600076.SH	KANGXIN NEW MATERIALS CO.,LTD
600290.SH	HUAYI ELECTRIC COMPANY LIMITED	Power transmission and transformation equipment	600192.SH	Lanzhou GreatWall Electrical Co.,Ltd.

600241.SH	Liaoning Shidai Wanheng Co.,Ltd.	Eletrical equipment	600379.SH	SHAANXI BAOGUANG VACUUM ELECTRIC DEVICE CO., LTD.
600242.SH	Zhongchang Big Data Corporation Limited.	Internet Software & Services	002103.SZ	Guangbo Group Stock Co.,Ltd.
600303.SH	Liaoning SG Automotive Group Co.,Ltd.	Automobile manufacturing	600213.SH	Yangzhou YaxingMotor Coach Co.,Ltd.
600306.SH	Shenyang Commercial City Co.,Ltd.	Retail	600697.SH	Chang Chun Eurasia Group Co.,Ltd.
600388.SH	Fujian Longking Co.,Ltd.	Industrial Machinery	601608.SH	CITIC HEAVY INDUSTRIES CO.,LTD.
600365.SH	Tonghua Grape Wine Co.,ltd.	Beverage	600616.SH	ShangHai JinFeng Wine Company Limited
600382.SH	Guangdong Mingzhu Group Co., Ltd.	Trading and Industrial Companies	000626.SZ	Grand Industrial Holding Co.,Ltd.
600518.SH	Kangmei Pharmaceutical Co.,Ltd	Chinese medicine production	600252.SH	Guangxi Wuzhou Zhongheng Group Co.,Ltd.
600396.SH	Shenyang Jinshan Energy Co.,Ltd.	Public utility	200037.SZ	Shenzhen Nanshan Power Co.,Ltd.
600568.SH	ZhongZhu Healthcare Holding Co.,Ltd	Medical Devices	600327.SH	Wuxi Commercial Mansion Grand Orient Co.,Ltd.
600589.SH	Guangdong Rongtai Industry Co.,Ltd.	Speciality Chemicals	300243.SZ	Shandong Ruifeng Chemical Co., Ltd.
600532.SH	Shanghai Topcare Medical Services Co.,Ltd.	Materials	002295.SZ	Guangdong JingYi Metal CO.,Ltd.
600462.SH	Hubei Geoway Investment Co.,Ltd.	Electronic device	600353.SH	Chengdu Xuguang Electronics Co.,Ltd.
002005.SZ	Elec-Tech International Co.,Ltd.	Optoelectronics	002189.SZ	Costar Group Co., Ltd.
002021.SZ	Zoje Resources Investment Co.,Ltd.	Professional setting	300022.SZ	Gifore Agricultural Science & Technology Service Co., Ltd.
002024.SZ	Suning.Com Co.,LTD.	Retail	000851.SZ	Gohigh Networks Co.,Ltd

002052.SZ	Shenzhen Coship Electronics Co.,Ltd.	Consumer Electronics	600083.SH	Jiangsu Boxin Investing & Holdings Co., Ltd.
002069.SZ	ZONECO GROUP CO.,LTD.	Food	600191.SH	Baotou Huazi Industry Co.,Ltd.
002086.SZ	Shandong Oriental Ocean Sci-Tech Co., Ltd.	Fishery	600257.SH	Dahu Aquaculture Co.,Ltd.
002089.SZ	NEW SEA UNION TECHNOLOGY GROUP CO.,LTD.	Communicatio n device	000586.SZ	Sichuan Huiyuan Optical Communications Co.,Ltd.
002102.SZ	Guanfu Holdings CO.,Ltd.	Trading	600278.SH	Orient International Enterprise, Ltd.
002113.SZ	Hunan Tianrun Digital Entertainment & Cultural Media Co.,Ltd.	Software and Service	002168.SZ	Shenzhen Hifuture Information Technology Co., Ltd.
002177.SZ	Guangzhou Kingteller Technology Co.,Ltd.	Computer Hardware	300076.SZ	Ningbo GQY Video & Telecom Joint-Stock Co., Ltd.
002200.SZ	YCIC Eco-Technology Co.,Ltd.	Building Construction	000628.SZ	ChengDu Hi-Tech Development Co.,Ltd.
002211.SZ	Shanghai Hongda New Material Co.,Ltd.	Chemicals	000691.SZ	GANSU YATAI INDUSTRIAL DEVELOPENT CO., LTD.
002259.SZ	Sichuan Shengda Forestry Industry Co.,Ltd.	Gas	600333.SH	Changchun Gas Co.,Ltd.
002289.SZ	Shenzhen Success Electronics Co., Ltd.	Electronic device	300032.SZ	Jinlong Machinery & Electronic Co.,Ltd
300010.SZ	DOUSHEN(BEIJING) EDUCATION&TECH NOLOGY INC.	Educational Service	000526.SZ	XUEDA (XIAMEN) EDUCATION TECHNOLOGY GROUP CO.,LTD
002309.SZ	Jiangsu Zhongli Group Co.,Ltd	Electrical Equipment	002196.SZ	Zhejiang Founder Motor Co.,Ltd.
002313.SZ	Sunsea AIoT Technology Co., Ltd.	Communicatio n Equipment	600130.SH	Ningbo Bird Co.,Ltd.
002321.SZ	Henan Huaying Agricultural Development Co. Ltd.	Food	600965.SH	Fortune Ng Fung Food (Hebei) Co.,Ltd.

300029.SZ	Jiangsu Huasheng Tianlong Photoeletric Co.,Ltd.	Semiconductors	002077.SZ	Jiangsu Dagang Co.,Ltd.
002366.SZ	Taihai Manoir Nuclear Equipment Co.,Ltd.	Electrical Equipment	300129.SZ	Shanghai Taisheng Wind Power Equipment Co., Ltd.
002411.SZ	YanAn Bicon Pharmaceutical Listed Company	Chinese medicine production	002082.SZ	WANBANGDE PHARMACEUTICAL HOLDING GROUP CO.,LTD.
002417.SZ	Suna Co.,Ltd	Software and Service	600476.SH	Hunan Copote Science Technology Co., Ltd
002427.SZ	ZHEJIANG UNIFULL INDUSTRIAL FIBRE CO.,LTD	Chemicals	600810.SH	Shenma Industry Co.Ltd
002433.SZ	Guangdong Taiantang Pharmaceutical Co., Ltd.	Chinese medicine production	600538.SH	Beihai Gofar Chuanshan Biological Co.,Ltd.
300089.SZ	The Great Wall Of Culture Group Holding Co., Ltd. Guangdong	Educational Service	002659.SZ	Beijing Kaiwen Education Technology Co., Ltd
300108.SZ	Ji Yao Holding Group Co., Ltd.	Chinese medicine production	002107.SZ	Shandong Wohua Pharmaceutical Co., Ltd.
002470.SZ	Kingenta Ecological Engineering Group Co., Ltd	Fertilisers and agrochemicals	000731.SZ	Sichuan Meifeng Chemical Industry Co.,Ltd.
002482.SZ	Shenzhen Grandland Group Co.,Ltd.	Construction and Enginering	002628.SZ	Chengdu Road & Bridge Engineering Co., Ltd.
002485.SZ	Cedar Development Co.,Ltd.	Transportation	300240.SZ	Jiangsu Feiliks International Logistics Inc.
002503.SZ	SOUYUTE GROUP CO.,LTD.	Clothing and luxury accessories	600107.SH	Hubei Mailyard Share Co.,Ltd.
002504.SZ	Beijing Honggao Creative Architectural Design Co., Ltd	Construction and Enginering	600193.SH	Shanghai Prosolar Resources Development Co.,Ltd.
300159.SZ	Xinjiang Machinery Research Institute Co., Ltd	Aerospace, Aviation and Defense	002297.SZ	Hunan Boyun New Materials Co.,Ltd.
002535.SZ	Linzhou Heavy Machinery Group Co., Ltd.	Industrial Machinery	000530.SZ	Bingshan Refrigeration & Heat Transfer Technologies Co.,Ltd.
300167.SZ	Shenzhen Dvision Co.,Ltd.	Information Technology Consulting	300074.SZ	AVCON Information Technology Co.,Ltd.

002569.SZ	ZHEJIANG BUSEN GARMENTS CO., LTD.	Clothing and luxury accessories	600137.SH	Sichuan Langsha Holding Ltd.
300209.SZ	Youkeshu Technology Co.,Ltd	Information Technology Consulting	300150.SZ	Beijing Century Real Technology Co.,Ltd.
002586.SZ	ZHEJIANG RECLAIM CONSTRUCTION GROUP CO., LTD.	Construction and Enginering	600769.SH	Wuhan Xianglong Power Industry Co.,Ltd.
300256.SZ	Jiangxi Firstar Panel Technology Co.,Ltd.	Electronic components	002106.SZ	Shenzhen Laibao High-tech Co., Ltd.
300268.SZ	JOYVIO FOOD CO., LTD	Food	000798.SZ	CNFC OVERSEAS FISHERIES CO.,LTD
300273.SZ	Zhuhai Hokai Medical Instruments Co., Ltd.	Medical Devices	300246.SZ	Guangdong Biolight Meditech Co., Ltd.
002592.SZ	Nanning Baling Technology Co.,Ltd	Automotive parts	600148.SH	Changchun Yidong Clutch Co.,Ltd.
300282.SZ	Sansheng Intellectual Education Technology CO.,LTD.	Educational Service	600661.SH	SHANGHAI XINNANYANG ONLY EDUCATION & TECHNOLOGY CO., LTD
002656.SZ	Modern Avenue Group Co.,Ltd.	Clothing and luxury accessories	002494.SZ	Huasi Holding Company Limited
300297.SZ	BLUEDON INFORMATION SECURITY TECHNOLOGIES Co., Ltd.	Software and Service	002296.SZ	HeNan Splendor Science & Technology Co., Ltd.

Source from: WIND

Appendix II

In Chapter 4, the default point formula (3-8) of the Merton model was the basis for calculations. In this section, different values of "α" and "β" will be assigned to the default point calculation formula DPT (3-8), resulting in different default point calculation formulas. By computing the corresponding distance to default, the optimal and most suitable default point for Chinese listed companies should be determined.

i. Setting of different default points

$$DPT1 = STD + 0.5LTD \qquad (AII.1)$$

$$DPT2 = STD + 0.1LTD \qquad (AII.2)$$

$$DPT3 = 1.25STD + LTD \qquad (AII.3)$$

$$DPT4 = 1..25STD + 0.5LTD \qquad (AII.4)$$

Following is the descriptive statistics:

Table 9: Overall descriptive statistics of distance to default (various DPT)

	ST DD	ST DD2	ST DD3	ST DD4
Obs	1000	987	998	999
Mean	53.9	57.3	48.7	50.7
Std	57.5	41.9	36.0	36.2
Min	4.1	-132.3	-4.1	-25.8
Max	1061.2	270.0	224.8	231.9
	NONST DD	NONST DD2	NONST DD3	NONST DD4
Obs	1000	999	1000	1000
Mean	66.7	70.7	61.2	62.9
Std	38.2	39.5	36.7	36.8
Min	6.3	-60.7	-7.6	-3.4
Max	289.6	290.2	270.7	271.0

From the table, it can be observed that among the four distance to default categories, the average value of DPT2 is higher than the other default samples, while the DPT1 for the sample group ranks second. The remaining mean values of default points, which have a larger proportion on short-term debt (DPT3, DPT4), are inferior to the first two groups.

ii. T-test of different default points

Table 10: T-test (different DPT)

	t-value	p-value	Mean Diff	Std. Error Diff	95% Confidence Interval of the Diff	
DD1	-5.8610	**0.0000**	-12.7903	1.9978	-16.7107	-8.8699
DD2	-7.6415	**0.0000**	-13.9299	1.5813	-17.0329	-10.8269
DD3	-7.7044	**0.0000**	-12.5115	1.4132	-15.2846	-9.7384
DD4	-7.5357	**0.0000**	-12.3134	1.4115	-15.0833	-9.5434

Assuming that the distribution of the sample population approximates a normal distribution, separate mean T-tests were conducted for the additional three distance to default groups. The p-values for all distance to default groups were found to be less than 0.05, indicating that there were significant differences between the two sample groups (ST and non-ST). Therefore, all distance to default groups were able to effectively discern the credit risk of the default group.

iii. Mann-Whitney U test

Table 11: Mann-Whitney U test (different DPT)

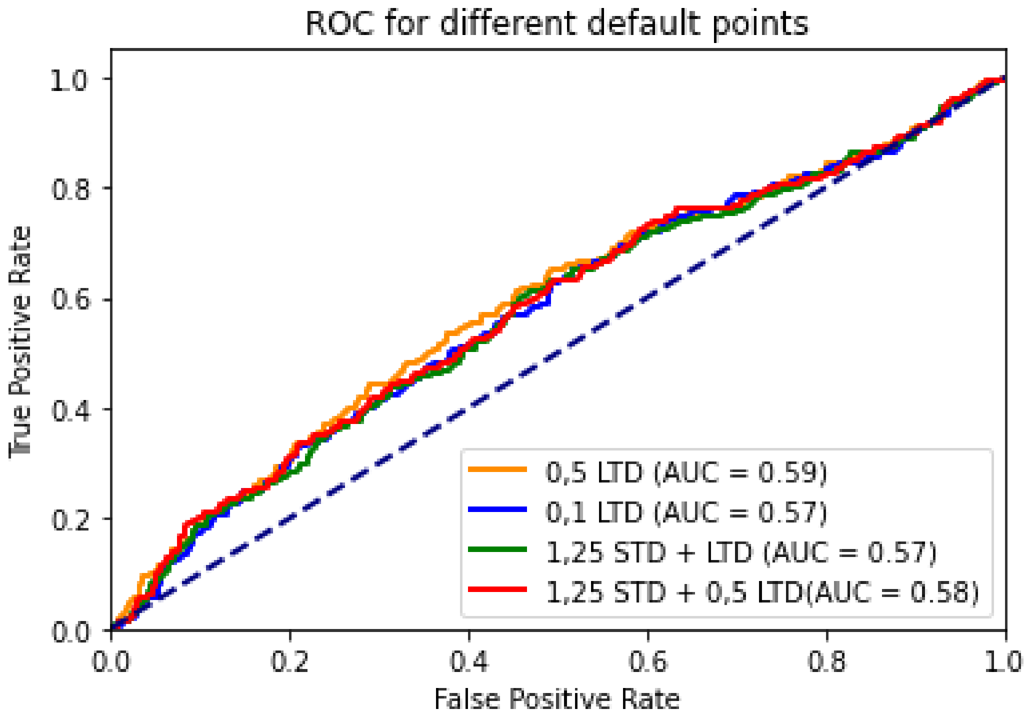
	Mann-Whitney U	Wilcoxon W	Z value	Asymp. Sig.(2-tailed)
DD1	389611.00	168693.00	-8.55	**0.000**
DD2	391633.00	168948.00	-8.39	**0.000**
DD3	388816.00	167224.00	-8.61	**0.000**
DD4	391026.00	167847.00	-8.44	**0.000**

The additional three sets of data were also calculated using Python, and the results of the Mann-Whitney U test are shown above. From the asymptotic significance (2-tailed), it is evident that the p-values for all four distance to default groups are less than 0.05, leading to the rejection of the null hypothesis (H_0). This indicates that all four distance to default groups can significantly differentiate our two sample groups (ST and non-ST).

iv. ROC curve

The following ROC diagram represents the ROC curves of Merton model under different settings of default point (*AII*.1 to *AII*.4).

Figure 8: Roc curve for different default points setting



In figure 4, it is observed that no significant difference exists between different settings of default point, because the AUCs are very similar to each other (0,59, 0,57, 0,57, 0,58 respectively).