PREDICTING FINANCIAL DISTRESS USING FINANCIAL AND NON-FINANCIAL INDICATORS

EVIDENCE FROM CHINESE LISTED MANUFACTURING COMPANIES

CHENJIA TAO

HANZHE ZHAO

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Predicting financial distress using financial and non-financial indicators: Evidence from Chinese listed manufacturing companies

Abstract:

This paper investigates empirically the utility of combining non-financial indicators to financial models with only financial indicators to explain the company financial distress in the Chinese manufacturing industry using a sample of 614 company-year observations of listed companies during the period 2010–2020. This paper develops financial distress prediction models for Chinese listed manufacturing companies. The results show that, (1) a company with a higher market value of total shares over total liabilities, top 10 shareholder holding rate, institutional investor holding rate, analyst rating, standard unqualified audit opinion, more analyst coverage, and without CEO change is less likely to fall into financial distress; (2) incorporating non-financial indicators in the financial models improves the predictive performance in year T-1 and T-2, but does not work in year T-3; (3) financial indicators, ROE, cash recovery ratio, fixed asset ratio, dividend payout, and non-financial indicators, external audit opinion, and analyst rating are the most significant indicators with predictive power; (4) most indicators in foreign studies also work well in the Chinese market though the definitions of financial distress are different.

Keywords:

Financial distress prediction, Financial and non-financial indicators, Logistic regression, Listed manufacturing companies, ST and *ST

Authors:

Chenjia Tao (41580)
Hanzhe Zhao (41590)

Tutor:

Stina Skogsvik, Assistant Professor, Department of Accounting

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Master Program in Accounting, Valuation and Financial Management
Stockholm School of Economics

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Contents

1. Introduction

The earliest study on financial distress prediction was proposed by Fitzpatrick (1932), who used a single variable to predict company financial distress. Based on his study, Beaver (1966) further used a Univariate Discriminant Model to make the prediction. In the following studies, researchers found that a single indicator cannot fully reflect the character of financial distress. Thus, the study of financial distress prediction transited from univariate analysis to multivariate models. In 1968, Altman applied Multivariate Discriminant Analysis to predict financial distress and built the Z-score model. After that, the Probit Regression Model was proposed. In recent years, with the rapid development of statistical technology and computer technology, recursive classification, artificial intelligence, and artificial neural networks have gradually been introduced into the financial distress prediction model. Chinese researchers started late in the study of financial distress prediction. Wu and Huang (1987) are the earliest to predict financial distress for listed companies. Afterward, many researchers entered this field. Due to the availability of information, most studies restraint the scope to listed companies. Indeed, the fall of a listed company will cause more severe consequences than an unlisted company since a listed company has a larger shareholder base and more stakeholders.

In 2016, Zoneco Group (002069.SZ), a Chinese listed company focusing on the cultivation of seafood such as scallops and abalone, was labeled *ST due to the negative net income in two consecutive years during FY 2014-2015. With one more year of negative net income, the company will be delisted. Before that, the company experienced a frequent change in multiple senior management including directors, supervisors, and department general managers. Since its deep-sea aquaculture such as scallops and abalone were hard to check, the company engaged in an accounting fraud scheme to avoid being delisted. In 2016, the company improperly recognize revenue of 130 million yuan by under-recording its COGS and non-operating expense. The inflated profit accounted for 158% of the total profit. In 2017, to balance the account, the company again whitewashed its financial numbers by over-recording its non-operating expense of approximately 200 million yuan. For its 2017 annual report, the external auditor noticed its financial matters and issued an audit report with qualified opinion. During FY2014-2017, the number of technical staff in Zoneco decreased from 602 (15.4% of total) to 67 (2.1% of total). In the same period, the share price dropped from 14.6 to 8 yuan, a YoY decrease of 45%. The senior management and major shareholders cashed out over 100 million yuan but employees holding stock ownership plans suffered a loss of around 350 thousand yuan per person and 67 million yuan in total. Moreover, the small investors suffered a loss of more than 37 million yuan in total.

The fall of Zoneco brought huge losses to its investors. In order to reduce such incidents to protect the interest of stakeholders and to forestall such tragedy, it is important and practical to build a financial distress prediction model.

1.1. Empirical background

1.1.1. Chinese stock market overview

Ever since the reform and opening up in 1985, China's society and economy underwent rapid development, leading to a huge improvement in residents' disposable income. During the past decade, the disposable income per capita increased from 19,109 to 42,834 yuan, a CAGR of 8% (National Bureau of Statistics of China, 2011, 2021). The increase in disposable income thus resulted in investment demand. During the same period, the investable assets held by individuals increased from 62 trillion to 190 trillion yuan (China Merchants Bank & Bain, 2019), and the investment vehicle range from securities to real estate (Yang, 2004). Securities, especially stocks, attract many investors due to their high liquidity and investment return (Lin and Zhang, 2007). In the past decade, the number of investors registered at China Securities Depository and Clearing (CSDC) increased by 36.8%, reached 178 million as of the end of 2020.

Joining WTO in 2001 brought abundant development opportunities to Chinese companies. The number and size of domestic companies soared. However, compared with the listing procedure in the US, only scrutinized companies can launch IPO and get listed in the Chinese stock market. At the end of 2020, the number of companies listed at Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) reached 4,241 and the total market capitalization reached 52 trillion yuan, corresponding to 52% of GDP. Listed companies face various competition and risks including external threats such as economy and regulations and internal threats such as profitability and operation. Companies may fail in the test of the market, fall into financial difficulties, or even get delisted or go bankrupt. If a company encounters financial distress, it will have even further negative affect not only on their employees, boards, and all shareholders but also on the whole society.

1.1.2. Definition of Special Treatment (ST) and Delisting Warning (*ST)

To address the matter and help investors to evaluate and control the risks, China Securities Regulatory Commission (CSRC) has successively introduced several investment risk warning systems for listed companies (Sun, 2007). The idea of ST (Special Treatment) debuted in 1998 when CSRC stipulated that listed companies whose audited net profit recorded negative for 2 consecutive fiscal years would be market with ST. Up till now, the definitions of ST and *ST have been revised several times and ST and *ST marks are used to highlight listed companies with abnormal financial positions or other positions, showing high investment risks of them (Sun and Li, 2008; Li and Sun, 2012; Li et al., 2014; Li, 2005).

Companies involved in any one of the four following conditions will be labeled with *ST, (1) Trade Delisting; (2) Financial Delisting; (3) Regulations Delisting, and (4)

Legal Delisting Conditions. Financial Delisting, mostly relevant to our studies, consists of the following conditions. (1) The audited net profit of the most recent fiscal year was negative and the operating income was less than 100 million yuan, or the net profit of the most recent fiscal year after retrospective restatement was negative and the operating income was less than 100 million yuan; (2) The audited net assets at the end of the most recent fiscal year are negative, or after retrospective restatement, the net assets at the end of the most recent fiscal year are negative; (3) An audit report with disclaimer of opinion or a negative opinion was issued for the financial accounting report of the most recent fiscal year; (4) CSRC's administrative penalty decision indicates that the company's audited annual report for the most recent fiscal year contains false records, misleading statements or major omissions, resulting in the fact that the relevant financial indicators of the year have actually touched the condition (1) or (2). (5) Any position that is regarded as abnormal by the exchange or the CSRC. Trade Delisting is the situation that a company's trade volume, share price, number of shareholders, or market capitalization violates the regulation. Regulation Delisting is the situation that there is a violation in a company's financial reports, disclosure, or operation. Legal Delisting is the situation that there is a fraud in a company's disclosure or issuance that seriously damages the order of the securities market or the situation that the company has illegal operations involving national security, public safety, ecological safety, production safety, public health, and safety, etc.

Companies involved in any one of the seven following conditions will be labeled with ST: (1) The company's non-operating capital is occupied by the controlling shareholder or the major shareholder (if there is no controlling shareholder) or related parties. Or the company violates the stipulated decision-making procedures to provide external guarantees (except if the guarantee is a subsidiary within the scope of the consolidated statement of the listed company). If the amount reaches more than 5% of the audited net assets or the amount exceeds 10 million yuan and the company cannot repay or rectify within one month, the company will be labeled ST. (2) The meeting of board of directors and the general meeting of shareholders cannot be held normally and fail to form effective resolutions; (3) In the most recent fiscal year, the internal control audit report issued a disclaimer of opinion or a negative opinion, or the internal control audit report was not disclosed as required; (4) The company's production and operation activities have been severely affected and are not expected to return to normal within 3 months; (5) The main bank account is frozen; (6) The lower of the net profit before and after deduction of non-recurring gains and losses in the most recent three consecutive fiscal years is negative, and the audit report of the financial accounting report of the most recent fiscal year shows that the company's ability to continue operations is uncertain; (7) There are other situations in which the company is seriously dishonest, or there is significant uncertainty in its ability to continue operations, and other situations where it is difficult for investors to judge the company's prospects, which may damage the rights and interests of investors.

Most companies were labeled with ST or *ST because of their poor financial performance. In the last decade, 618 companies were labeled with ST or *ST, in which 552 of them were due to financial distress. Furthermore, the number of companies labeled with ST or *ST due to financial distress increased over years. How to detect financial distress in advance and forestall the loss have attracted increasing attention from both academic and practical perspectives. Researchers and practitioners aim to build financial distress prediction models to assess potential risks and mitigate the loss.

1.1.3. Industry selection

Platt and Platt (1991) demonstrated that a model developed using samples from one industry may not yield high accuracy in predicting bankruptcy for companies in other industries. Besides, as some industries are significantly different in business and operating models, their financial statements differ a lot. Therefore, the same accounting ratios in different industries can have totally different meanings and it is not the best choice to apply a general prediction model for all industries.

The manufacturing industry accounts for more than a third of the GDP in China and there are around 1,800 listed manufacturing companies, accounting for 43% of all the listed A-shares companies. Corporate bonds issued by them also take a substantial part in investors' portfolios both domestically and internationally. Thus, the prediction of financial distress for listed manufacturing companies is important for both equity and bond investors as they can recognize the investment risks ahead, and then adjust their investment portfolios (Chen, Zhang, and Zhang, 2013). As the production capacity rather than the technology development was the main driver of the manufacturing industry in China for a long period, companies within the industry usually had homogenous products and faced fierce competition. Besides, these companies are also sensitive to the price of raw materials and are vulnerable to macro economy and policy changes. Those factors will threaten the company, lead to insolvency, and eventually result in bankruptcy (Schaufelberger, 2003). Furthermore, in recent years, the Chinese government promoted supply-side structural reform in the manufacturing industry. The government aimed to cut off the government subsidies and leave the traditional industry driven by market competition to cut low-efficient overcapacity and to increase the overall production efficiency. Companies with outdated production capacity face harsh challenges and they will go bankrupt or get acquired by other leading companies due to the disadvantage in the market competition if they cannot upgrade their production capacity. The fierce competition will become normal for a long time in the future and financial distress will occur frequently. Therefore, we choose the Chinese manufacturing industry as our research subject.

1.2. Focus of the study

Financial indicators have been proven to be effective in financial distress prediction. In previous studies, most Chinese researchers built their models solely with financial indicators and found that debt to assets ratio, current ratio, ROA, ROE, asset turnover ratio, operating assets over total assets ratio, operating margin have the strongest predictive power (Wu and Huang, 1987; Chen, 1999; Zhang, 2000; Jiang and Sun, 2001). However, companies may take the risk to whitewash their financial statements when they encounter financial distress. Thus, the mere financial numbers may not be able to provide a disinteresting and objective financial overview for the company.

Despite a few studies focusing on both financial and non-financial indicators in the early 21st century, most of them merely test the predictive power of non-financial indicators in their models instead of empirically investigating whether incorporating them in the prediction models will provide additional information and improve the prediction performance. To fill the gap and to complement the financial distress prediction analysis for Chinese listing companies, we aim to test if adding non-financial indicators covering market information, corporate governance, ownership structure, and other external non-financial information, will bring additional predictive power and enhance the prediction performance of the model. Therefore, we purposed our research questions as follows.

Question 1: *How to predict company financial distress in the Chinese manufacturing industry using historical financial indicators and non-financial indicators?*

Question 2: *Will incorporating non-financial indicators in the financial distress prediction models bring additional predictive power and improve the prediction performance?*

Thus, this paper has two main objectives. First, the aim is to build a timely and accurate financial distress prediction model focus on Chinese listed manufacturing companies, with both historical financial and non-financial data into consideration. The second aim is to test whether incorporating non-financial indicators will add additional predictive power to the model. We investigated whether those non-financial indicators show statistical significance in the prediction models and whether models with non-financial indicators yield better prediction performance.

The research questions are of great significance and interest to researchers and practitioners for three reasons.

First, there exists little research on the financial distress prediction targeting the Chinese market. Many of them just applied Altman's Z-score model and then re-estimated the parameters in the model to derive the adjusted model for Chinese company predictions (Cao and Zeng, 2005; Ng, Wong and Zhang, 2011; Hong and Xiang, 2011; Yu and Zhu, 2015). However, since the Z-score model is based on American companies, applying it directly for Chinese companies shows weaker predictive power (Hu and Zhang, 2009; Yi, 2012). Financial distress definition and economic environment in China are also different from that in the USA. Therefore, a financial distress prediction model tailored for Chinese listed manufacturing companies is of great use.

Second, most studies focusing on predicting financial distress of Chinese listed companies consider only financial indicators as they are easier to collect from periodical reports and the numbers are reliable with the audit opinions (Lv, Xu and Zhou, 2004; Li and Yu, 2012; Wang, Ma and Yang, 2014). However, empirical research showed that non-financial indicators also have significant prediction power (Bhagat and Bolton, 2008; Tinoco and Wilson, 2013). Therefore, whether a model comprising financial and non-financial indicators performs better than a model solely based on financial indicators in the Chinese market is worth studying. This research will also shed light on whether the market as an information taker has priced in a company's financial distress risk and reflected it in the stock market information.

Third, financial distress prediction models are practical in assessing a company in real life. A listed company has a larger stakeholder base than an unlisted company. The outcome of our model can be used for management to steer the company back to the right route, for banks to make their lending decisions, and for investors to evaluate their investment portfolios (Beaver, 1966; Altman, 1968; Chen, 1999; Yang and Xu, 2003; Chen, Zhang and Zhang, 2013). Moreover, the volume of foreign investment is still small, and international investors' understanding of the Chinese capital market is limited. The information asymmetry further leads to difficulties for foreign investors to find a good investment, identify investment risk and conduct powerful risk management to realize a satisfying investment return. Investors with large capital have strong potential to avoid investment in companies with insolvency risk, which may lead to extreme loss. Therefore, a specific model focusing on the Chinese market would be appreciated.

This thesis comprises 6 main sections. The rest of this paper proceeds as follows. Section 2 presents previous literature on financial distress prediction and especially studies in this field focusing on the Chinese market. Section 3 describes the sample company selection, logistic regression model specification, predictors preselection and definition, and the data source. Section 4 further shows the predictors selection process using statistical methods and the final selected independent variables for the logistic regression. Section 5 presents the empirical analysis results, model evaluation and robustness test. Concluding remarks are finally offered in Section 6.

1.3. Delimitations and contributions

In this study, we linked ST or *ST with the widely accepted definition in non-Chinese settings. Same as most studies focusing on Chinese listed companies, our benchmark of financial distress for Chinese listed companies is whether they are labeled ST or *ST due to financial reasons (Cao and Xia, 2005; Wang and Ji, 2006; Wang and Cui, 2007; Wu and Lu,2001; Hu and Lv, 2009; Yue and Zhang, 2009; Li and Yu, 2012). However, there is a gap between the ST or *ST and the financial distress definition commonly used in non-Chinese settings. In previous studies, the researchers have not explained the rationale and logic behind their choice, and they chose ST and *ST as their benchmark merely because it is widely used in China and much easier to apply. Literally, ST and *ST focus more on the profitability side of a company instead of solvency, liquidity, and legal bankruptcy that are stressed in Ross et al. (1995). Despite the different points of focus in these definitions, we found that most ST or *ST companies also suffered from insolvency and illiquidity.

Moreover, apart from financial indicators, we also included non-financial indicators in our model and tested if non-financial indicators could improve the prediction performance of our model. We aimed to build three separate sets of models. One consists of only financial indicators, one consists of only non-financial indicators, and one consists of both financial and non-financial indicators. By comparing the performance of these three models, we can analyze if non-financial indicators of Chinese listed manufacturing companies can provide additional predictive power to the financial distress prediction model. Besides, the indicators in most of the previous Chinese models were selected because they were commonly used indicators without any further explanation (Cao and Xia, 2005; Liu, Liu and Ren, 2016; Tian and Wang, 2017). In our study, we also explained the reasons why we included each category of indicators and why they may have predicting power. We would further explain the significance and insignificance of some indicators in our empirical analysis.

Furthermore, the scope of our study is delimited to Chinese manufacturing companies listed on the mainboard of SHSE and SZSE from 2010 to 2020. By delimiting our research to a single industry within the same country, we can build the model in a more accurate and precise way. Different industries have different business models and capital structures. Thus, the financial ratios are not comparable and the benchmark indicating financial distress also various across the industries.

Besides, we select a wide range of up-to-date data. Core indicators such as profit index and operating index vary with the development of the industry, technology, and economy. By selecting the most up-to-date period of data, we are able to follow the industry's latest development trend and adjust our models. An up-to-date model provides its users better prediction results. A further contribution of our model is that our datasets come from the financial terminal Wind, which is known as the Chinese

Bloomberg. Through Wind, we can have access to extensive data sources, not only company reports and disclosures including financial and non-financial data but also external equity research reports. Therefore, this study can provide financial distress prediction models that fit the latest Chinese setting.

With our comprehensive indicator selection procedure and powerful database, we aimed to provide a tailored financial distress prediction model for Chinese listed manufacturing companies. Based on previous studies, this study also intended to explain why the indicators have predictive power and attempted to test if there exists any China-specific indicator that will improve the predictability.

2. Literature review

As financial distress prediction was intensively researched by scholars all over the world, there exists a lot of previous literature on this topic. In this literature review, we first referred to those pioneering and classical research on the financial destress prediction, such as Beaver (1966), Altman (1968), and Ohlson (1980), etc. These classical and well-known studies laid solid foundations and provided both theoretical background and fundamental frameworks for the following studies on financial distress prediction.

Besides, we also investigated prominent and celebrated studies focusing on Chinese companies. Companies that operate in different geographic markets have different business models and different markets have different definitions of financial distress. There may also exist some China-specific indicators when it comes to the Chinese setting since China has its unique financial and business environment. Therefore, directly applying indicator portfolios in models based on other countries may lead to poor results, but the empirical models and studies focusing on the Chinese market will bring a deep understanding of the special predictor settings in this specific market.

Furthermore, we also refer to frontier research in the financial distress prediction field. By following the lasted trend in both China and other countries, we are able to detect new indicators, new methodologies, or new models proposed by researchers worldwide and to complement our model.

Since Fitzpatrick (1932) first used the single financial ratio to predict bankruptcy, corporate bankruptcy prediction has been intensively studied (Dimitras et al., 1996; Kumar and Ravi, 2007; Bellovary et al., 2007; Sun et al., 2014). According to the different research focus, a review of the research on financial distress prediction can be conducted from the following four aspects, namely, the definition of financial distress, the financial distress prediction indicators, the selection process of the financial distress prediction indicators, and the models used in financial distress prediction.

2.1. Review of the definition of financial distress

Various definitions of financial distress were presented in early studies. One commonly used definition is legal failure, where only companies that meet the bankruptcy regulations will be defined as financially distressed. Altman (1968) defined financial distress as companies entering bankruptcy procedure or bankruptcy liquidation and reorganized enterprises that meet the requirements of national bankruptcy regulations. Deakin (1972), based on Beaver's (1966) and Altman's (1968) studies, proposed that financial distress companies only included those who have been confirmed bankrupt, were unable to pay off outstanding debts, or were under bankruptcy liquidation. Rafiei et al. (2011), when studying the financial distress prediction in Iran, defined financial distress based on Tehran Stock Exchange's definition that if the retained loss of a company's assets exceeds 50%, then the company is in financial distress. Although the legal definition is manifest and explainable in practice, it fails to capture the whole picture since (1) the definite legal failure will allure some companies to whitewash their current situation in order to effectively escape from the legal compulsory clause and to avoid going bankrupt; (2) the bankruptcy regulation and system are immature in some developing regions and thus may not provide a solid theoretical background; (3) the legal bankruptcy regulation varies in different countries and thus the results may not be comparable among different studies.

To define financial distress more comprehensively, researchers turned their focus from legal definition to benchmarks made up of financial and non-financial information. Carmichael (1972) defined four conditions as financial distress, (1) illiquidity, (2) negative equity, (3) default on debt and (4) lack of current assets. A more commonly used financial distress definition is proposed by Ross et al. (1995), who classified four conditions of financial distress. (1) Operation failure, a company is unable to pay off the debt after the liquidation. (2) Legal failure, a company or creditor applies for bankruptcy to the court. (3) Technical failure, a company defaults on maturing debts with inadequate operating cash flow. (4) Accounting failure, a company has a negative book value of net assets. Some previous studies have touched upon one or some of these definitions. Beaver (1966) proposed that financial distress occurs when a company is unable to pay off its financial liabilities such as defaulting on preferred dividends and debt. He performed his study based on 59 financial distress companies, in which 16 companies defaulted on preferred stock dividends, and 3 companies defaulted on debts. Asquith et al. (1994) proposed that a company falls into financial distress when it is not able to repay its financial obligations. Based on that, Pindado et al. (2008) classified a company as a financial distress company when its EBITDA is lower than its financial expense for two consecutive years and it suffers from negative growth in market value for two consecutive years. Whitaker (1999) deemed that a company is financially distressed when its cash flow is insufficient to pay off its current long-term debt. However, illiquidity in cash flow is not necessary or sufficient. When suffering from illiquidity in cash flow, a company is still able to obtain cash through various means such as utilizing cash reserves, selling inventory, increasing bank credit line, and restructuring, etc. Nonetheless, a company will eventually default on its debt if the illiquidity in cash flow continues and exists no other ways to obtain cash. Although the comprehensive definition is not as easily applicable as the legal definition, it provides a thorough understanding of the financial position of the company and is thus extensively used.

The definition of financial distress in China mainly originated from Gu and Liu (1999), where they defined financial distress as an economic situation where a company fails to pay for maturing bonds or expenses, including any situation ranging from technical failure to bankruptcy. Lv, Xu and Zhou (2004) claimed that financial distress is a continuous and dynamic process. They classified financial distress as a two-step stage, financial distress and financial failure, and argued that financial distress will lead to financial failure. Lv, Xu and Zhou (2004) argued that the definition of technical failure in Ross et al. (1995) is applicable but is difficult to explain in the Chinese market because the data on maturing debt is difficult to obtain. Most Chinese listed companies have many short-term debts and will continuously raise new short-term debts shortly after the payment to maturing debts. Therefore, the short-term debts accumulate and become long-term debts on a rolling basis and lose their original short-term characteristics. Thus, the scale of maturing debt is small and using the definition with maturing debt is not appropriate in China. Based on Ross et al. (1995), they identified financial distress companies with current ratios. When the current ratio is less than 1 and is not able to reverse in the foreseeable future, the company is classified to be financially distressed.

However, the definitions above are study-specific and thus the results are not comparable within the Chinese setting. Besides, there does not exist an authoritative definition of financial distress in China. Thus, in order to build models based on a commonly agreed definition, many researchers deem companies marked with ST or *ST as financial distress companies in practical studies focusing on Chinese markets. (Cao and Xia, 2005; Yang and Huang, 2005; Wang and Ji, 2006; Wang and Cui, 2007; Hu and Lv, 2009; Yue and Zhang, 2009)

2.2. Review of the financial distress prediction indicators

Before a company deteriorates in its operation and steps into financial distress status, some abnormal indicators and signals of the company can be observed. Therefore, these indicators or a combination of indicators can be used to predict financial distress (Dimitras et al., 1996). In previous research, different indicators are selected as the independent variables to build the financial distress prediction models (Lin et al., 2014; Wang et al., 2014).

Indicators for the prediction of financial distress can mainly be classified into two categories, financial indicators and non-financial indicators (Dimitras et al., 1996).

In our thesis, we defined financial indicators as financial numbers or ratios that can be directly derived from financial statements. Those financial indicators can reflect a company’s profitability, solvency, operation, and liquidity. Other indicators covering information from the stock market, corporate governance, and ownership structure, are defined as non-financial indicators.

2.2.1. Financial indicators

Companies use financial indicators to summarize and evaluate the financial condition and operating performance. The idea of using financial indicators to predict financial distress was first proposed by Fitzpatrick (1932). In the following studies, Beaver (1966) and Altman (1968) used financial indicators and achieved satisfactory prediction results. Since financial indicators are tested effective and easy to obtain, they are currently the most popular indicators in predicting financial distress (Sun and Li, 2008; Sun et al., 2014). The most commonly used indicators are asset to liability ratio, ROE, EBT margin, current ratio, and debt ratio (Fitzpatrick, 1932; Beaver, 1966; Altman, 1968; Deakin, 1972; Edmister, 1972; Ohlson, 1980; Platt, Platt and Pedersen, 1994; Lin et al., 2014).

At the very early stage of the study, only traditional financial indicators such as asset to liability ratio, current ratio, and debt ratio that can be directly obtained from financial statements (Fitzpatrick, 1932; Altman, 1968; Platt, Platt and Pedersen, 1994) were applied in the prediction model. Beaver (1966) pioneered the use of statistical methods to develop a univariate model using a single financial indicator and laid a solid foundation in this field.

At the same time, researchers, from the perspective of enterprise valuation, deemed that a company's past, current, and future cash flow can fully reflect its past, current, and future value, and thus able to predict the probability of financial distress (Gentry et al., 1990). Commonly used cash flow indicators are sales to cash ratio, net operating cash flow per share, comprehensive ability to pay and ability to pay cash dividends, etc. Dietreich and Kaplan (1982) and Aziz et al. (1988) both included dividend indicators in their prediction models. Aziz et al. (1988) applied cash flow indicators directly in their prediction model. After analyzing the Z-score model and Zeta model, they found that prediction models with cash flow indicators can provide more accurate results.

Apart from the traditional indicators mentioned above, Chinese researchers also tend to frequently use capital preservation and appreciation rate, the closing balance of shareholders' equity over the opening balance of shareholders' equity. (Gu, 2000; Yang and Xu, 2003; Tian and Wang, 2017). They proposed that the growth in shareholder's equity indicates the growth of a company and thus reflects the risk level of a company's falling into financial distress. Bai and Tian (2020), investigating the relationship between a firm's innovation performance and its probability of bankruptcy, found R&D investment and R&D productivity demonstrate persistent significance, especially for firms in technology-intensive industries. Interestingly, despite the extensive use of dividend indicators in non-Chinese settings, we found no existing Chinese study that includes dividend information in their prediction model.

2.2.2. Non-financial indicators

Financial statements cannot provide information covering all the aspects and sometimes companies even manipulate the financial numbers to conceal the unsatisfying financial results. Therefore, to improve the financial distress prediction performance, some researchers started to include non-financial information of the companies and to search for non-financial indicators to ameliorate the prediction model (Dimitras et al., 1996; Guo et al., 2006)

According to different focuses, non-financial indicators can be classified as uncontrollable external factors such as economy, stock market information and policies, and internal factors such as internal governance. Studies have shown that macroeconomy and stock market information, such as economic development, interest rate (Zhang and Wu, 2005), and analyst ratings (Moses, 1990) also play certain roles in improving the prediction accuracy. Altman and Brenner (1981) and Atiya (2001) conducted extensive studies and confirmed Beaver's (1966) inference that market rates of return, which reflect all the sources of information available to investors, were able to provide very powerful predictability with a slight time lag.

Some previous studies included capital market-based information in the financial distress prediction. Shumway (2001) used market capitalization to access the size of a company from the capital market perspective and explained that it reflected the market opinions. Besides, volatility of stock return was also included in the model. From the valuation perspective, higher volatility of stock return reflects the higher uncertainty of free cash flows, which will further imply a higher risk of a company's not being able to meet the interest payments and dividend payout.

Campbell, Hilscher, and Szilagyi (2008) used the market value of the total asset instead of the book value and found that the market-based value had slightly better explanatory power as the market prices better reflected the investors' prospects of a company. They further took the market capitalization as the replacement of total asset to represent the size of a company and included the excess stock return in their model.

Internal factors are the underlying fundamental factors leading to financial distress. According to the agency problem, mismatching of people and positions will cause conflicts of interests, affect a company's performance, and may lead to financial distress. Bhagat and Bolton (2008), Jiang and Wang (2004) found that poor governance is more likely to result in financial distress, mainly manifested in the non-separation of the two roles of chairman and general manager, and the low proportion of independent directors in the board of directors. Lee and Yeh (2004), Deng et al. (2006) found that an overly concentrated shareholding structure does not have enough binding force on controlling shareholders, and thus those shareholders can tend to maximize their own interests. Hill (1996) proposed that independent and objective audit opinions guarantee the authenticity of financial information, and audit opinions other than the unqualified opinion reveal financial risks to a certain extent. Thus, using audit opinion as a predictor will improve the predictability.

More specifically in the Chinese setting, Wang and Ji (2006) mentioned that overdue guarantees, related guarantees, and illegal guarantees mask the explicitness of enterprises falling into financial difficulties. They also found that corporate governance is less efficient if most shares are owned by the state. Zhang et al (2010), when applying Altman's Z-score model in the Chinese setting, took into consideration that Chinese listed companies have a unique structure of equity components, which include both tradable and non-tradable shares. The tradable shares only occupy, on average, thirty percent of the total shares. Therefore, for stocks with more non-tradable shares, it is easier to manipulate the price and their volatility is potentially much higher. Thus, they calculated two ratios for market capitalization, market value of total shares (including tradable and non-tradable shares) to total liabilities and market value of tradable shares to total liabilities. Bhattacharjee and Han (2014) found that the choice of the stock exchange is related to state ownership, and size, and industry in their study on Chinese listed companies' failure prediction. The Shanghai Stock Exchange (SHSE) is dominated by larger-cap companies such as big banks and steel companies, and most former state-owned enterprises. By contrast, the majority of Shenzhen Stock Exchange (SZSE) IPOs come from successful high-tech private enterprises, small joint-ventures, and export-oriented companies seeking wider share ownership. Their results showed that companies listed on SZSE are more likely to suffer from financial distress. However, when adding corporate governance indicators into their models focusing on Chinese listed companies, Liang et al. (2016) found that the predictive performance of the model consisting of both financial indicators and corporate governance indicators is not better than the model consisting of only financial indicators in the Chinese market.

2.3. Review of the selection process of financial distress prediction indicators

Though the selection of financial distress predictors has been intensively researched, and most of them were successfully applied to the prediction model and carried out impressive results, researchers still have not come up with a standard selection process to find the most powerful indicators for financial distress prediction. Most of the predictor selection methods can be classified into two categories, the qualitative approach, and the mixture of a qualitative and quantitative approach (Dimitras et al., 1996; Sun, 2007). The method to select financial distress indicators overall is mainly evolving from the former one to the latter one mentioned above.

In the early study, because of the underdevelopment of the statistical methods, most scholars selected the prediction variables qualitatively according to their subjective judgment and experience or by simply adjusting the predictors used in previous studies (Dimitras et al., 1996; Lee et al., 2010).

Fitzpatrick (1932) firstly analyzed the significance and efficiency of financial indicators to identify the financial distress and the healthy companies based on his personal experience and comparison methods, and he found that equity to liability ratio and net profit to equity ratio work better than other financial indicators. Beaver (1966) selected 30 variables based on 3 criteria, the popularity, the prediction performance of ratios in previous studies, and the ratio defined in terms of a "cash-flow" concept firstly. Then 30 variables were categorized into 6 groups and only one variable in each group was used in the following analysis part to minimize the common elements. Ohlson (1980) simply selected six predictors which appear to be the ones most frequently mentioned in the literature with no rigorous theory and added another 3 predictors shown in previous studies according to his judgment. Yang et al. (1999) directly used predictors in Platt, Platt, and Pedersen's study (1994) as the financial distress variables in their neural network model. Jo and Han (1996) adopted two main principles to select variables. One is to use the indicators which were regarded as important in previous studies and the other is to choose financial variables frequently used by credit rating companies, banks, and insurance companies.

Several subsequent studies on corporate financial distress prediction focusing on other countries also directly referred to the indicators adopted in the previous studies or simply added or dropped several indicators based on their own cognition to construct the predictor portfolio (Lu et al., 2013; Korol, 2013; Wang and Campbell, 2010a; Wang and Campbell, 2010b).

The development of statistical methods and artificial intelligence algorithms brings a powerful way for researchers to select the predictors. They are widely used in preprocessing variables to decrease the dimension of the data while keeping the predictive power of variables to improve the performance of the models (Sun, 2007). The combination of quantitative and qualitative predictor selection methods has been the mainstream way of financial distress prediction (Lin et al., 2014).

Altman (1968) first combined the two methods in his predictor selection in bankruptcy prediction. He selected 22 potentially helpful variables and ratios, which proved significant in past studies based on their popularity in the literature and potential relevance to the study, and he also initiated a few "new" ratios. Then 5 final predictors were decided via the procedures of a statistical significance test, inter-correlation evaluation, predictive accuracy observation, and analyst judgment. Li and Sun (2011a) used the stepwise method of MDA as the filter approach to select 4 optimal features from preselected 30 financial ratios. Sun and Li (2009) selected 7 features as the predictors from 35 original financial ratios by the statistical method of stepwise discriminant analysis on the initial data set. The stepwise selection and the t-test are widely used in bankruptcy predictors selection to reduce the number of financial variables into a manageable set and to alleviate the multicollinearity and overfitting problems (Jo et al., 1997; Wu and Lu, 2001; Park and Han, 2002).

Besides, some studies also applied other quantitative techniques such as principal component analysis (PCA) on data to reduce the dimensions to filter the preselected variables (Skogsvik, 1990; Ogut et al., 2012). Furthermore, artificial intelligence algorithms are also applied in the variable selection process. Sexton et al. (2003) proposed the use of a modified genetic algorithm (MGA) as a training method to improve generalizability and to identify relevant inputs. Jeong et al. (2012) found that the application of the generalized additive model (GAM) on inputs can improve the performance of a neural network model.

2.4. Review of the models used in financial distress prediction

The development of statistical methods and algorithms stimulated the evolution of the prediction models. More advanced statistical techniques have been applied in financial distress prediction. According to the complexity, the prediction models can be classified into two categories, the models based on statistical methods and the models based on the advanced artificial intelligence algorithms (Sun et al., 2014).

Fitzpatrick (1932) pioneered to apply univariate analysis on corporate financial distress research. The research first compared the difference of financials between the financial distress and healthy companies and selected the most significant financial ratio as the ranking indicator, according to which the optimal discriminant value is determined, and companies are classified. The research further raised the equity to liability ratio and net profit to equity ratio as the most effective classifiers. In the following studies, Beaver (1966) also adopted univariate analysis and found that cash flow to total debt ratio, net income to net assets ratio, working capital to total assets ratio, etc. work well in financial distress prediction.

The most popular statistical methods are the Multivariate Discriminant Analysis (MDA) and Logistic Regression (LR). Altman (1968) argued that there existed several shortcomings in the univariate analysis as the financials of a company were closely linked with and could affect each other. Therefore, he employed the MDA method to consider multi variables, concluded an overall discriminate value, and built the famous Z-score model to predict corporate bankruptcy. Based on the Z-Score family of models, Zhang et al. (2010) focused on the Chinese market, added unique predictors to capture the unique structure of equity components of Chinese listed companies, and developed a particular model called Z_{China}-Score to support the identification of potential distressed firms in China. However, as there exist several statistical hypotheses as prerequisites, the MDA is only used in theoretical research but not popular in practice due to the poor practicality (Sun, 2007). Ohlson (1980) chose a logistic regression model to avoid the strict statistical hypotheses in MDA and brought the prediction model into practice. The LR model can directly yield the probability of financial distress. As it is more explanatory and easier to understand, LR is commonly used in classification problems. Many following studies in other countries directly applied or improved LR to increase the predictive performance (Nam and Taehong, 2000; Wu and Lu, 2001; Fedorova et al., 2013; Kovacova and Kliestik, 2017).

Besides, other statistical methods such as Linear Discriminant Analysis (Edmister, 1972), Probit Model (Zmijewski, 1984), and Linear Probability Model (Peng et al., 2008) are also developed and applied in the financial distress prediction.

The rapid development of computer science technologies stimulated the application of AI-based algorithms on financial distress prediction. Odom and Sharda (1990) firstly applied a Neural Network with five financial indicators selected by Altman (1968) to build a prediction model. The result showed 81.75% and 78.18% prediction accuracy on test sets and they concluded that the Neural Network-based model outperformed MDA in bankruptcy prediction. Several following studies also showed that Neural Networks have a strong ability to predict corporate financial distress (Zhang et al., 1999; Chen and Du, 2009; Kim et al., 2010).

Other advanced algorithms such as Genetic Algorithm (Kim and Han, 2003; Martens et al, 2010), Decision Tree (Sun and Li, 2008a; Olson, 2012), Support Vector Machine (Fan and Palaniswami, 2000; Ding, 2008; Lin et al., 2011b), etc. are also used in financial distress modeling and are proved with good predictive abilities. Some researchers also tried to combine some of these methods to build hybrid models or to improve the existing models for financial distress prediction. Laitinen and Laitinen (2000) improved the LR model with Taylor's expansion and found that the prediction accuracy of the simply LR model can be increased using the second-order and interaction terms of these ratios for the first and second years before the bankruptcy. Chen (2011) used the LR model to improve the Decision Tree to build a Logit-DT hybrid model. Kim and Upneja (2014) improved the Decision Tree (DT) model with the AdaBoosting method to overcome sensitivity problems and to make the DT model more replicable.

Though these methods somewhat show better prediction performance with fewer statistical prerequisites and improve the prediction accuracy, as these algorithms are complicated and difficult to understand, some results are hard to explain due to the black box effect, and estimating these models requires more time and computing power due to the massive calculations, the application of the advanced algorithms is limited in business practice.

2.5. Conclusion of literature review

There exist abundant studies on financial distress predictions worldwide, especially in European countries and the USA. Researchers built models for different industries over a manifold timeframe with various methodologies (Bellovary et al., 2007; Sun et al., 2014). Albeit the long and ample history of the study, limited researchers turn their attention to Chinese companies. Because of the information asymmetry due to language barriers and regulations, it is hard for researchers outside China to build a reliable model. At the same time, the increasing investment demand for the Chinese market and the immature capital market system in China further generate the need for an applicable financial distress prediction model.

Most of the studies on financial distress prediction in the Chinese market only use financial indicators to build the prediction model (Chen, 1999; Yang and Xu, 2003; Lv et al., 2004, Li, 2005; Ding et al., 2008) and only a few studies have considered non-financial indicators. Furthermore, the scope of non-financial indicators used is constrained within the capital market and corporate governance (Cao and Zeng, 2005; Wang and Ji, 2006). Whether other non-financial indicators such as macroeconomic data and external professional opinions can provide additional predicting power is still not intensively researched. Thus, to shed light on the predictive power of various financial and non-financial indicators, in this paper we meticulously selected financial and non-financial indicators based on previous studies and statistical analysis.

Moreover, most of the studies only use the financial indicators one year prior to the financial distress. However, studies showed that a company can show a trace of financial deterioration even before (Ward and Foster, 1998; Lv et al., 2004). In order to help stakeholders to detect and manage the financial distress earlier, in the study we aimed to build prediction models as earliest as 3 years prior to the happening of financial distress.

Withal, the existing models consist of both financial and non-financial indicators are outdated (Cao and Zeng, 2005; Wang and Ji, 2006). Whether the indicators maintain strong predictive power and whether there will be new indicators available remain questions. Therefore, to bridge the gap between outdated models and the demand for practical and up-to-date financial distress prediction, we build our model based on the most recent 11-year data to ensure the timeliness of the model.

Table 1. Previous studies on financial distress prediction. The table summarizes some classical studies on financial distress prediction and research focusing on the Chinese market. Author(s), the scope of the dataset, main contribution, modeling technique, determining factors, and accuracy are presented in the table.

Author(s)	Country	Work Done	Modeling Technique	Determining Factors	Accuracy (before failure)
Beaver (1966)	US	Tested that accounting data can be evaluated in terms of their utility and that utility can be defined in terms of predictive ability	Univariate Discriminant model	Cash Flow Ratios; Net Income Ratios; Debt to Total Asset Ratios; Liquid Asset to Total Asset Ratios; Liquid Asset to Current Debt Ratios; Turnover Ratios	Cash flow to total debt ratio: 1 year: 87% 2 year: 79% 3 year: 77% 4 year: 76% 5 year: 78%
Altman (1968)	US	Z-score Model	Multiple Discriminant Model	Working capital/Total assets; Retained Earnings/Total assets; Retained Earnings/Total assets; Market value equity/Book value of total debt; Market value equity/Book value of total debt	1 year: 95%
Ohlson (1980)	US	Used a logistic model to predict financial distress for US companies	Conditional Logit Model	Size of the company; Financial Structure; Performance; Current Liquidity	1 year: 85%
Skogsvik (1990)	Sweden	Tested current cost accounting ratios regarding the ability to predict business failure for Swedish companies	Probit Analysis	Profitability; Cost Structure; Capital Turnover; Liquidity; Asset Structure; Financial Structure; Growth	CCA Ratios: 1 year: 90.5% 2 year: 89.6% 3 year: 88.0% 4 year: 87.6% 5 year: 87.3% 6 year: 86.4%
Platt and Platt (1994)	US	Used financial ratios to predict financial distress for oil companies in US	Logistic Regression	Net Cash Flow/Total Asset; Total Debt/Total Assets; Exploration Expenditures/Total Reserves; Current Liabilities/Total Debt	1 year: 95%
Mario Hernandez Tinoco, Nick Wilson (2013)	UK	Offered a comparison of the classification accuracy and predictive power of three types of variables (financial statement ratios, macroeconomic indicators, and market variables)	Panel Logit Model	Accounting Ratios; Macro-Economic Variables; Market Variables	1 year: 86.7%
Chen (1999)	China	The first Chinese study using MDA to predict financial distress for Chinese listed companies	MDA	Asset/Liability; Net Profit/Total Asset; Current Ratio; Asset Turnover	1 year: 92.6%
Wu and Lu (2001)	China	Based on financial indicators of Chinese listed companies, the authors built 3 financial distress model	Fisher's Linear Decision Analysis Multiple Linear Regression Logistic Regression	Earnings Growth Index; Return on Assets; Current Ratio; Long-Term Debt/Shareholders' Equity Ratio; Working Capital/Total Assets Ratio; Asset Turnover Ratio	Fisher's linear decision: 89.93% Multiple linear regression: 89.93% Logistic regression: 93.53%
Yang and Xu (2003)	China	Built a Discriminant model - Y score model - specific for Chinese listed companies	MDA	Solvency; Profitability; Cash Flow Index; Growth	1 year: 85%
Lv, Xu and Zhou (2004)	China	Defined new financial distress definition in China. Identified that financial distress is dynamic and consists of two stage - financial distress and financial bankruptcy	Canonical Discriminate Model	Solvency; Asset-Liability Ratio; Profitability; Scale of Company	1 year: 98.1%

Author(s)	Country	Work Done	Modeling Technique	Determining Factors	Accuracy (before failure)
Li (2005)	China	Used a fuzzy neural network to predict financial distress and provide related learning algorism	Fuzzy Neural Network	Earnings Growth Rate; ROA; Current Ratio; Long-Term Debt to Shareholders' Equity Ratio; Working Capital to Total Assets Ratio; Asset Turnover Rate	1 year: 89.16%
Wang and Ji (2006)	China	Introduced non-financial indicators in financial distress prediction for Chinese listed company	Logistic Regression	Profitability; Solvency; Growth; State-Own-Shares Ratio; Audit Opinion; Related Party Transaction	1 year: 90.48%
Ding et al. (2008)	China	Applied the SVM to the prediction of financial condition of Chinese listed companies	SVM Model	Solvency; Profitability; Cash Flow Index; Growth	1 year: 83.2%
Zhang et al. (2010)	China	Z-score model for Chinese setting	MDA	Profitability; Liquidity and Solvency; Asset Management Efficiency; Growth Ability	1 year: 100% 2 year: 87% 3 year: 70% 4 year: 60% 5 year: 22%

3. Research methodology

Definition of financial distress, selection of sample companies, financial distress indicators, and prediction models are the four most important parts in the domain of company financial distress research. Firstly, this study compared different definitions of financial distress and chose the most appropriate definition, ST and *ST as the objective of the prediction model. Secondly, among a large range of Chinese financial distress companies, this paper focuses on the companies in the manufacturing industry as the sample. Thirdly, different from simply taking the most frequently used indicators and only focusing on the financial ratios, this paper also tests the prediction power of non-financial indicators from five perspectives and includes them in the prediction model to better capture the possible additional power. Fourthly, to avoid the strict statistical hypothesis of the MDA method and to ensure the model can be easily explained and applied in practice, this paper adopts the conditional logit analysis to establish the prediction model instead of using the MDA approach or advanced machine learning techniques.

The following parts of this section will further discuss in detail the financial distress definition, selected sample companies, prediction model setting, evaluation metrics of the model performance, financial and non-financial indicators as predictors, and data preprocessing.

3.1. ST/*ST and financial distress definitions

In this paper, we followed the previous studies on Chinese company financial distress prediction (Cao and Xia, 2005; Yang and Huang, 2005; Wang and Ji, 2006; Wang and Cui, 2007; Wu and Lu, 2008; Hu and Lv, 2009; Yue and Zhang, 2009; Li and Yu, 2012) and chose the Special Treatment (ST) and Delisting Risk Warning (*ST) due to financial reasons as the sign indicating the company has fallen into financial distress.

Neither the legal definition nor the comprehensive definition works well in financial distress prediction in the Chinese market. Similar to companies in western countries, a Chinese company can apply for bankruptcy, according to the Chinese bankruptcy law, when it is unable to pay off the debt after the liquidation due to poor operating performance. However, barely any listed company will apply for bankruptcy in China because a listed identity is a precious resource. A company needs to satisfy a set of strict prerequisites before getting listed on the main board in the Chinese stock market and the reviewing process by CSRC is extremely complicated, rigorous, and time-consuming. Thus, the listing qualification is a precious “shell” resource. Other companies with the demand for listing can use this “shell” and conduct reverse mergers to get listed even if a listed company is at the edge of financial distress. Thus, most of the companies facing bankruptcy choose to carry out bankruptcy reorganization or reverse merger in China.

As a result, a limited number of Chinese listed companies went through the bankruptcy procedure and declared bankrupt. Therefore, the companies meeting the bankruptcy definition widely accepted by foreign scholars seldom appear in the Chinese stock market. Since there will be limited observations with legal definitions under the Chinese setting, we believe that legal definition is not suitable for the Chinese setting.

In the meantime, we cannot directly apply the comprehensive definition proposed by Ross et al. (1995) in our study for the Chinese setting as well. As the IPO system in China is approval-based rather than registration-based as in the USA, getting listed in the Chinese stock market is more difficult, in terms of the listing procedure and the selection of listed companies. Thus, the listed companies in China shall have a good financial and operational position and enjoy a high reputation. On the other hand, CSRC further adopts a warning system that alerts investors to investment risks. After labeled with ST or *ST, the company would undergo a plummet in its share price and illiquidity in its stocks, leading to a huge loss for the shareholders even before getting delisted or bankrupt. However, being labeled with ST or *ST is not necessarily mean that the company is doomed to bankrupt. As the marks are to highlight those companies with potential risks, the companies labeled with ST or *ST are more likely to step into an early stage of financial distress, while definition in Ross et al. (1995) was proposed to detect bankrupt companies or companies at a later stage of financial distress. We aimed to predict financial distress in an early stage, which is prior to the financial distress proposed in Ross et al. (1995). With different delimitations, we believe that the comprehensive definition will not work well in the Chinese setting. Therefore, we believe that predicting ST or *ST is more meaningful in the Chinese market.

However, the comprehensive definition does provide us with a more thorough way of analyzing a company's financial condition. As discussed before, the financial distress definition proposed by Ross et al. (1995) tends to focus more on the solvency and liquidity side of a company. Compared with the comprehensive definition, the ST or *ST definitions put much emphasis on the profitability side of a company instead of liquidity and solvency. Nevertheless, among ST and *ST companies due to financial distress from 2010 to 2020, 94.2% of them have an interest coverage ratio of below 0, and 80.4% of them have a quick ratio of below 1. The results indicate that ST or *ST companies, although not explicitly stipulated in the definition, suffer from poor solvency and liquidity. That is, ST or *ST implicitly captures both the liquidation and solvency of a company.

Using ST or *ST as a benchmark against financial distress brings abundant advantages in both theoretical research and practical application. ST improves the comparability of research results. With the same definition and setting, academic researchers are able to compare their results. Furthermore, since the definition of ST is proposed by CSRC, adapting ST or *ST as the symbol of financial distress is more applicable to Chinese list companies, compared with simply reproducing models with the US setting. Practically, the financial reports of ST or *ST companies are required to be audited before releasing to the public, so the financial data are reliable in use.

3.2. Sample company selection

According to the regulation of CSRC, listed companies are obliged to disclose the company's financial status and other important information through periodical reports after each accounting quarter and year. Furthermore, the companies' annual reports are required to be audited by external professional accounting firms before they are released to the public. Therefore, these public data is reliable, standardized and they have prominent compatibility. Besides, as the financial status of listed companies in China is a leading indicator of the economy and reflects the operation of basic production activities, it is an important focus for various stakeholders including market regulators, public investors, and municipal governments. Therefore, this paper selects Chinese listed manufacturing companies as the research sample.

3.2.1. Selection of financial distress companies

As the ST or *ST companies in the manufacturing industry only take a very small proportion of the total listed companies in the Chinese stock market. We want to expand the database with more observations but also want to use the latest data to ensure timeliness. Therefore, we choose to extract all the manufacturing companies which were marked ST or *ST in the past 11 years from 2010 to 2020 from Wind Financial Terminal as the financial distress company sample to ensure the data sufficiency.

As discussed before, several reasons will lead a company to be marked with ST or *ST, but not all of them are related to the financial situation such as profitability and solvency. Some of the companies are marked with ST or *ST because of financial fraud and failure to disclose annual reports on time, etc. Therefore, a company with ST or *ST sign is not sufficiently tantamount to financial distress, so using ST or *ST sign to identify whether a company has stepped into the financial distress situation is not accurate. In this study, we only select the companies marked with ST or *ST because of negative net profit and poor operating income to make sure the selected companies best fit the definition of financial distress in the Chinese setting.

Furthermore, some companies which are previously marked with ST or *ST may be labeled again after a few years. These companies may still be in financial distress status during the two labeling time points and the problems are not actually resolved. Therefore, in order to increase the accuracy of the predicting model, a company is included in the sample data set only when it is labeled with ST or *ST for the first time. That means when a company is labeled with ST or *ST in year T, and it is still with ST or *ST in year T+1, or the label is taken off, but the company is relabeled in the following years, only the first labeling time will be selected and included in the data set.

At last, selected companies that lack required indicators are eliminated from the sample set.

3.2.2. Selection of matching financially healthy companies

Regarding the financial distress and healthy company distribution, Chinese A-share market data is imbalanced. ST or *ST companies only take up 5.14% of the total listed companies in the Chinese manufacturing industry. The proportion is much lower than that of the listed non-ST or *ST companies. The implicit optimization goal of the classification learning algorithm design is the classification accuracy on the data set, and this will cause the learning algorithm to be more biased towards the majority class with more samples on the imbalanced data. Therefore, taking the whole market data into the empirical research may lead to a model with unsatisfying discriminating ability. However, selecting a matching company sample will effectively avoid the imbalanced data problem. It can also serve as a standard group to control the irrelevant characteristics and to help to identify the indicators reflecting the characteristics of financial distress companies. Therefore, we referred to Altman (1968) and used the method of stratified sampling to collect a matching financially healthy company for each selected ST or *ST company to build the data set.

In this paper, we referred to previous studies and selected matching companies based on the industry, total asset size, and financial year (Cao and Xia, 2005; Wang and Ji, 2006; Wu and Lu,2008; Hu and Lv, 2009; Tian and Wang, 2017). First, due to different business scope and environment in different industries, the same indicator may have a different numerical range in different industries, and it may cause the trained model to be affected by extreme data, which further affects the performance of the prediction model. Second, asset size is also an important measurement economic status of a company. Even though the financial indicators of the two companies are similar to each other, the financial status and operating performance reflected by the difference in asset size are still different. Third, the macroeconomic environment in different years may vary violently with certain events, and then affects the financial status of a company. Same indicators in different years may imply different financial statuses.

Therefore, according to the rules discussed above, we first limited the range of matching companies within the same sub-industries in the manufacturing industry as the financial destress companies. Then in the same industry, we select the matching company whose asset size is within the range of ±10% of the total asset size of the matched financial distress company and whose annual reports are available in 4 years prior to the financial distress of the matched company. If there is no such sample, a healthy company with the asset size closest to the matched sample is selected. Furthermore, the data collected for the matching company and matched company should be in the same financial year. Finally, we referred to the widely used solution of the unbalanced dataset problem and selected one healthy company for each distressed company to avoid the imbalanced data set problem and to increase the ability of the model to identify the financial distress companies.

3.2.3. Selection results of sample companies

According to the sample selecting and matching rules, this paper selected 624 companies from Chinese A-share listed companies in the manufacturing industry in the past 11 years from 2010 to 2020. The sample included 312 financial distress companies marked with ST or *ST and 312 matching healthy companies. All the company data were extracted from Wind Financial Terminal. The sample distribution of each year is shown in the following *Table 2*.

Table 2. Sample distribution of financial distress companies. The table shows the distribution of our sample companies. We used the industry classification in Wind Financial Terminal, which is based on Global Industry Classification Standard (GICS). Operating in the manufacturing industry, the companies are further categorized into sub-industries, i.e., daily consumption, energy, industry, information technology, and materials. Numbers of companies labeled ST or *ST were counted for each sub-industry and each year. As each financial distress company is matched with one healthy company, the sample distribution of the matching healthy companies is not shown.

Year	Daily Consumption	Energy	Industry	Information Technology	Materials	Total
2010	0	1	13	4	7	25
2011	1	0	2	2	5	10
2012	3	0	6	1	6	16
2013	0	0	8	2	5	15
2014	2	1	13	4	7	27
2015	4	2	10	5	9	30
2016	4	5	7	5	17	38
2017	3	5	16	5	9	38
2018	5	5	11	5	9	35
2019	5	1	14	7	5	32
2020	3	1	18	11	13	46
Total	30	21	118	51	92	312

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

The table shows an increasing trend of the numbers of companies falling into financial distress in the past 11 years. As China’s economy realized relatively stable growth and no extreme external shocks or big recession happened during that time, the increase of ST or *ST companies is alongside the increasing total number of listed companies. As the CSRC gradually relaxes the requirement for a company to get listed in the stock market, the number of listed companies is expected to increase significantly, and the absolute quantity of financial distress companies will also rise accordingly. Therefore, a solid financial distress model will be of great use to identify the risk for the investors and regulators in the era of the explosive growth of the number of stocks.

3.3. Empirical model

3.3.1. Prediction horizons

According to the Stock Listing Rules issued by the CSRC, companies with abnormal financial positions will be specially treated and be labeled with ST or *ST. The time point of a company being specially treated is after the release of the annual report. As falling into financial distress is a continuous process, the company data prior to the ST or *ST date will have some predictive power of the financial deterioration. Therefore, this paper defined the year when a company was labeled with ST or *ST as year T. Accordingly, the year of the financial results which the ST or *ST decision is based on is year T-1 and the annual report of year T-1 is disclosed in year T. (For example, if a company was labeled *ST in April 2020, the *ST decision is based on the financial results of year 2019, which is available after April 2020. In this case, T equals 2020 and T-1 refers to 2019). Following this rule, the first, the second, and the third year prior to the year T are denoted as year T-1, T-2, and T-3.

The listed companies are required to publish financial reports before the end of April of the next year and the ST or *ST decision is based on the financials in the annual reports. The predicting model using annual report of year T-1 will yield extraordinarily high accuracy because of the ST mechanism, but from the practical perspective, it is of little meaning to do so as the ST or *ST result is decided without suspense once the annual results are published, and the predicting model will be useless as the risk has been priced in and reflected in the share price immediately and the investors do not have opportunities to avoid the risk.

Therefore, this paper will use financial and non-financial data accessible after the release of annual reports in year T-1, T-2, and T-3 (the annual reports of year T-2, T-3, and T-4) as three sets of samples to build three separate sets of empirical models to predict company financial distress in year T (annual results in year T-1) and thus to increase the practicality in real-life prediction.

3.3.2. Model specification

Several modeling techniques for binary classification problems can be employed to develop financial distress prediction models. As the purpose of this paper is to build a prediction model which can be simply applied by investors, companies, and regulators, considering the good predicting performance, explanatory and easy applicability, in this paper we used the Logistic Regression (LR) technique to develop the financial distress prediction model. Lo (1986) compared logit analysis and discriminate analysis and concluded that LR has good flexibility when modeling and it is more robust for purposes of parameter estimation. A direct test that compares the performance of logistic regression and other modeling techniques also showed that LR had better predicting power than neural networks (Yang, Platt and Platt, 1999). LR does not require strict statistical hypotheses like MDA. It is also simpler and straightforward to understand than many models based on advanced algorithms. Therefore, LR is easier to apply in practice and to explain, and it is more suitable for this paper.

LR is one kind of generalized linear model. Let $\boldsymbol{X_i}$ denote the independent predictor vector for the ith observation, let $\boldsymbol{\beta}$ denote the unknown parameter vector to be estimated, and let $P_i(\boldsymbol{X_i}; \boldsymbol{\beta})$ denote the probability of a company falling into financial distress status for any given $\boldsymbol{X_i}$ and $\boldsymbol{\beta}$, $0 \leq P_i \leq 1$. Logistic function is used as the probability function in the LR. Let β_j denote the jth unknown parameter and x_{ij} denote the jth independent predictor in the ith observation, and the logistic regression model is described as follow:

$$P_i(x; \beta) = \frac{1}{1 + e^{-y_i}}, \qquad where\ y_i = \beta_0 + \sum_{j=1}^{n} \beta_j\, x_{ij} = \beta_0 + \boldsymbol{\beta^T X_i} \tag{1}$$

$$logit(P_i) = ln\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \boldsymbol{\beta^T X_i} \tag{2}$$

In practice, the Maximum Likelihood Estimation (MLE) is widely used to estimate the coefficients of independent variables in the LR model. Denote:

$$P_i(Y = 1 \mid x; \beta) = P_i(x; \beta) \tag{3}$$

$$P_i(Y = 0 \mid x; \beta) = 1 - P_i(x; \beta) \tag{4}$$

These formulas above can be combined to express as follow:

$$P_i(Y \mid x; \beta) = (P_i(x; \beta))^{Y_i}(1 - P_i(x; \beta))^{1-Y_i} \tag{5}$$

The likelihood function of the parameters β is showed as below:

$$L(\beta_0, \beta_1, \dots, \beta_n) = \prod_{i=1}^{m} {P_i}^{Y_i}(1 - P_i)^{1-Y_i} \tag{6}$$

The logarithm likelihood function of parameters β is showed as below:

$$lnL(\beta_0, \beta_1, \dots, \beta_n) = \sum_{i=1}^{m} [Y_i ln(P_i) + (1 - Y_i) ln(1 - P_i)] \tag{7}$$

Therefore, the maximum likelihood estimates of β are obtained by solving:

$$\boldsymbol{max}.\, lnL(\beta_0, \beta_1, \dots, \beta_n) \tag{8}$$

Compute the partial derivatives of β_0 and β_j respectively:

$$\frac{\partial lnL(\beta_0, \beta_j)}{\partial \beta_0} = \sum_{i=1}^{m} \left(Y_i - \frac{e^{\beta_0 + \boldsymbol{\beta^T X_i}}}{1 + e^{\beta_0 + \boldsymbol{\beta^T X_i}}} \right) = 0 \tag{9}$$

$$\frac{\partial lnL(\beta_0, \beta_j)}{\partial \beta_j} = \sum_{i=1}^{m} \left(Y_i - \frac{e^{\beta_0 + \boldsymbol{\beta}^T \boldsymbol{X_i}}}{1 + e^{\beta_0 + \boldsymbol{\beta}^T \boldsymbol{X_i}}} \right) x_{ij} = 0 \tag{10}$$

The estimations of the parameters in logistic regression models are solved using an iterative method in programming language R 4.0.3.

In this paper, in order to ensure that each predictor will have strong predicting power, we further used stepwise logistic regression technique to include statistically significant predictors in and to eliminate the nonsignificant predictors from the set of predicting variables in each step, and thus to re-estimate the model coefficients using only significant predictors. To test whether the non-financial indicators will bring additional discriminating power to the prediction model and improve the prediction performance, for each predicting year, 3 models, a model with only financial indicators, a model with only non-financial indicators, and a model with both financial and non-financial indicators are estimated separately. 9 models in total are estimated in this paper.

The P_{FDi} increases with y_i. The logarithm of odds $\frac{P_{FDi}}{1-P_{FDi}}$, which means the change of the ratio of the probability of financial distress over the probability of non-financial distress, also increases with y_i. Thus, the LR model is relatively easy to interpret. Companies with higher P_i have the higher potential to fall into financial distress in the future.

3.3.3. Evaluation metrics

This paper adopted the commonly used evaluation metrics of the classification model, the overall prediction accuracy, type I error, type II error, ROC curves, and the AUC values as the evaluation criteria for financial distress prediction models. The definitions of the confusion matrix and each measurement index are shown in **Table *3***:

Table 3. Definition of the confusion matrix and each measurement index.

		Actual	
		ST/*ST Company (P)	Healthy Company (N)
Predicted	ST/*ST Company (P)	True Positive (TP)	False Positive (FP)
	Healthy Company (N)	False Negative (FN)	True Negative (TN)

$$Acuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{11}$$

$$Type\ I\ error = \frac{FP}{FP + TN} \tag{12}$$

$$Type\ II\ error = \frac{FN}{TP + FN} \tag{13}$$

The classification rule to determine whether a company is predicted to be a financial distress or a healthy company used in this paper is described as follow:

$$Predicted\ Y_i = 1\ if\ P_i(Y = 1 \mid x; \beta) \geq P^* \tag{14}$$

P^* is defined as the critical probability. A common way is to directly set the critical P^* to 0.5. A company is classified into financial distress group if the predicted P_i is larger than 0.5 and as healthy group if P_i is smaller than 0.5. However, as the cost of type I and type II error may be different, an alternative way is to set P^* based on experience and the demand of control of each kind of error. In this study, as the cost of type II error is much larger than that of type I error, we are more interned to control type II error, and thus the cutpoint P^* is set to be 0.4.

The prediction model is evaluated using both the training group and the hold-out testing group. The prediction accuracy rate is calculated based on how many data points are correctly classified by the prediction model on a given testing set. The type I error rate measures the proportion of healthy companies which the prediction model incorrectly classified as a financial distress company. Similarly, the type II error rate measures the proportion of ST or *ST companies misclassified into the healthy company group. In the financial distress prediction case, the Type II error is more critical than the average prediction accuracy. A larger Type I error rate may lead to a miss of good investment opportunities, but a larger Type II error rate will lead to significant costs when an investor invests in a financial distress company but does not realize the underlying risks.

ROC curve is also used to evaluate and compare the prediction ability of the model using only financial indicators, the model using only non-financial indicators, and models using both financial and non-financial indicators. ROC curve illustrates the diagnostic ability of a binary classifier as its discrimination threshold is varied. It is constructed by plotting the true positive rate (TPR, sensitivity) against the false positive rate (FPR, 1-specificity). Classifiers that give curves closer to the top-left corner indicate better performance. Another common part of ROC curve analysis is to calculate the area under the ROC curve (AUC). The higher AUC a model has, the better classification ability it owns. A model whose AUC equals 1 means that it is a perfect model which classifies all the data points correctly while a model with 0.5 AUC means it is a random model with no discriminate power to distinguish between ST or *ST companies and healthy companies.

3.4. Preselection of predictors

This paper follows the mainstream predictor selection procedure and combines both the quantitative and qualitative methods to select the financial and non-financial indicators as predictors. Financial indicators or ratios are directly retrieved from financial statements or calculated based on the numbers in financial statements. Non-financial indicators are related to corporate management, ownership structure, the stock market, etc.

The selection procedure of indicators includes two steps. First, we referred to previous studies with Chinese settings to include some most commonly used indicators or indicators that were proved significant, and then we also added non-financial indicators to try to capture the prediction power of the other information and to increase the prediction accuracy. Second, we proposed statistical methods such as the Kolmogorov-Smirnov test, t-test, and Mann-Whitney U test to control the multicollinearity and to filter the predictors with the strongest predicting power.

3.4.1. Financial indicators

We aimed to select financial numbers and ratios with the most powerful discriminating power to classify the potential financial distress companies and healthy companies. In this paper, we referred to financial indicators in some previous studies on Chinese companies (Ng, Wong and Zhang, 2011), and added some other indicators which we think will bring additional predicting power. 21 financial indicators covering 5 categories were selected. These 21 financial indicators capture the financial distress characteristics in solvency, profitability, operation, cash flow, and other aspects.

Solvency measures a company's ability to meet its debts and financial obligations. Solvency is an important and straightforward indicator to assess the financial health of a company, as it captures a company's liquidity and demonstrates its ability to maintain its business operation and to realize the capital circulation. Some previous research used the bankruptcy law as the definition of financial distress (Beaver, 1966; Altman, 1968; Deakin, 1972), and according to the law, a company that is not able to pay off debt is regarded as falling into financial distress. Therefore, the solvency of a company should have a strong relation to the financial condition and the prediction power to tell the difference between destressed and healthy companies.

Profit is one of the most important targets that a company pursues. The profitability of a company largely reflects the financial performance of the company during a financial period and affects the financial position. As this paper used ST or *ST as the financial distress definition, and according to the ST and *ST regulation in China, the financial distress results are strongly determined by the profitability. Therefore, the profitability index should also have strong power to discriminate the destressed and healthy companies.

Operation indexes are often used to summarize, analyze, and evaluate the sales, capital turnover, and other business operation capabilities of a company. These ratios reveal the company's capital operating turnover and reflect the efficiency of the company's management and utilization of economic resources.

Cash flow can better illustrate the quality of a company's profitability than traditional profit indicators. Accounting profits are determined on an accrual basis, and therefore profits can be manipulated through fake sales, advance confirmation of sales, expansion of credit sales, or related transactions. However, cash flow is determined based on the payment realization and thus the above profit manipulations can not affect the cash flow as no cash was received. Cash flow indicators can make up for the shortcomings of profit indicators in reflecting the company's true profitability. China’s bankruptcy law clearly stipulates that if an enterprise cannot pay off its due debts, it can declare bankruptcy. Cash flow indicator analysis can better help investors or senior managers to assess the solvency of a company and to judge the risk to fall into financial distress.

Apart from the commonly used financial indicators, this paper also includes 2 other variables, DIV and INNO, to capture the information from dividend payout and investment in research and development.

Dividend payout behavior shows that a company has strong financial performance and the ability to create free cash flow. A company with a stable dividend payout ratio is shareholder-friendly and is regarded as a good target of long-term investment. Theoretically, companies with weak financial performance are unable to pay a dividend to shareholders and therefore a company’s dividend policy can be used as an indicator to extrapolate the risk of a company falling into financial distress situation.

As technology development is relatively slow in the manufacturing industry, companies have high product homogeneity and thus the competition is severe. The Chinese manufacturing industry has excess low-efficient capacity in the last few years, which leads to decreasing profitability together with the increasing homogenous competition. In recent years, the proposal of supply-side structural reform by the government stressed the cut of low-efficient overcapacity. Only companies with competitive advantages especially in the technology aspect will survive during the capacity restricting and the industry consolidation period. Companies with outdated production capacity face harsh challenges and are more likely to go bankrupt. Therefore, investment in research and development will help a company to set up a continuous security boundary and to survive in a high-competitive environment. Besides, high R&D investment reflects that a company has a strong cash flow to support the innovation and the steering management has foresight. Furthermore, Bai and Tian (2020) studied the relationship between investment innovation and the bankruptcy probability of a company and found that companies with higher R&D investment are less likely to go bankrupt.

The preselected financial indicators and their descriptions are presented in *Table 4*. All the preselected financial indicators are tested the significance of the difference between groups and tested collinearity for the selection of predictors. Only indicators with low collinearity with each other and the best discriminating abilities will be included in the prediction models.

Table 4. Description of preselected financial indicators. The table shows the preselected financial indicators we intend to test in our model. Depending on the characteristic, the indicators are classified into 5 different categories – solvency index, profit index, operation index, cash flow index, and other financial information. The abbreviation, description, and calculations for each indicator are presented in the table.

Category	Financial indicators and calculations	
Solvency Index	CR	Current ratio = current asset / current liabilities
	QR	Quick ratio = (current asset - inventory) / current liabilities
	DAR (%)	Debt-to-asset ratio = total liabilities / total asset
	ICR	Interest cover ratio = Earnings before tax and interest / interest expense
Profit Index	OM	Operating margin = net profit / turnover
	ROE	Return on equity = net profit / shareholder's equity
	ROA	Return on asset = net profit / total asset
	CEPM	Cost expense profit margin = net profit / operation cost
	EPS	Earnings per share = net profit / total number of equity shares
Operation Index	RT	Receivable turnover = net value of sales / average receivable debt
	FAT	Fixed asset turnover = net value of sales / average fixed asset
	CAT	Current asset turnover = net value of sales / average current asset
	WC (%)	Working capital turnover = (current asset - current liabilities) / total asset
Cash Flow Index	PQ	Profit quality index = net operation cash flow / operational profit
	NOCFCL	Net operating cash flow over current liabilities = net operating cash flow / current liabilities
	NOCFL	Net operating cash flow over total liabilities = net operating cash flow / total liabilities
	CRR	Cash recovery rate = cash flow from operations / average gross assets
	SCFR	Sales cash flow ratio = net operating cash flow / turnover
	SR	Structure ratio = operating cash inflow / operating cash outflow
Other Financial Information	FAR	Fixed asset ratio = fixed asset / total asset
	DIV	Whether a company pays dividend. 1 if a company pays dividend. 0 otherwise.
	INNO	Innovation (R&D expense / revenue)

3.4.2. Non-financial indicators

Several recent studies have proved that some non-financial indicators such as corporate governance and capital market information also play a key role in predicting company financial distress (Shumway, 2001; Campbell, Hilscher, and Szilagyi, 2008; Liang et al., 2016; Bredart, 2014; Lee and Yeh, 2004; Lin, Liang, and Chu, 2010). In practice, investors do use the abnormal turnover of senior management and stock market information such as trading turnover rate and stock price volatility to identify companies may have bad operating results or internal dilemma and to avoid investment risk.

Apart from the financial indicators which are most commonly used in the company financial distress prediction, this paper also included 15 non-financial predictors covering capital market, ownership structure, corporate governance, and other external information 4 categories in the model to test whether the non-financial information can bring additional information to the financial distress prediction and can improve the prediction accuracy.

Capital market information always reflects the market opinions of the prospect of a company's development. The investors took into consideration of the available public information and traded the stock according to their understanding and judgment of a company's prospects. Therefore, the capital market indicators better capture a company's overall operating situation based on the stock market's expectations. In this paper, we included two indicators regarding market capitalization, the market value of total shares to total liabilities and market value of tradable shares to total liabilities used in a study applying Altman's Z_{China}-score model (Zhang et al., 2010). Besides, we also used some most basic stock information tested before such as stock return (Beaver, 1966) and volatility (Shumway, 2001). The stock of a company will drop drastically once it is marked with ST or *ST. In order to avoid huge losses, investors have less willingness to trade the stocks with a higher failure risk and thus the trading volume of such stocks will drop accordingly. Therefore, the trading turnover rate is also included in the model.

Zhang and Wu (2005) found that the market interest rate has additional power in predicting financial distress. The interest level significantly affects the capital liquidity in the market and the company's cost of debt. Raising money will be more difficult for a company and the company needs to bear a heavier financial burden if the interest rate increases. From the company valuation perspective, a higher interest rate will lead to a higher cost of capital can decrease the valuation. Therefore, companies may face a severer time when interest rate increases. Besides, the macroeconomic environment may also affect the operation of companies, most of the companies will suffer from the general decline of economic activity and shortage of capital in an economic recession. However, this paper did not include macroeconomic indicators in the models as the sample dataset is constructed using matched methods on the annual level and thus the macroeconomic indicators do not have discriminating power in this matched dataset.

This paper also selected some non-financial indicators from ownership structure and corporate governance aspects according to Tian and Wang's research (2017) on the financial distress prediction in China. As state-owned companies sometimes have more advantages in competition, some significant difference of treatment to their financial distress between state-owned companies and private companies has been observed. Government tends to bail out state-owned companies more than private companies. However, Wang and Ji (2006) proposed that the efficiency of state-owned companies is lower than private companies. Therefore, the percentage of state-owned shares is also included in the model. Besides, as most public funds in China tend to hold secure assets and avoid an extreme loss to retain a good reputation, the institutional investor holding rate is also expected to reflect the opinions of investment funds. Since the corporate governance operation of Chinese companies, in general, are not so mature as that of western countries, corporate governance indicators should differ significantly between the financial distress companies and the healthy companies and should have strong prediction power.

Furthermore, we also added some other non-financial indicators based on recent studies on the Chinese market such as the listing stock exchange (Bhattacharjee and Han, 2014), external audit opinions (Hill and Perry, 1996), and analyst ratings (Moses, 1990) to capture the opinions of the external professionals on a company.

The preselected non-financial indicators and their descriptions are presented in the following *Table 5*.

Table 5. Description of preselected non-financial indicators. The table shows the preselected non-financial indicators we intend to test in our model. Depending on the characteristic, the indicators are classified into 4 different categories, capital market index, ownership structure index, corporate governance index, and external non-financial information. The abbreviation, description, and calculations for each indicator are presented in the table.

Category	Non-financial indicators and definitions	
Capital Market	MVTL	Market value of total shares (all shares) / total liabilities
	MVTTL	Market value of tradable shares / total liabilities
	RE	Stock return in the year
	TR	Trading turnover rate = Trading volume of the year / average tradable shares
	VO	Volatility of the year = annualized standard deviation of daily returns
Ownership Structure	T10	Top 10 shareholder holding rate
	SOS	State-owned shares as a percentage of total shares
	II	Institutional Investor holding rate
Corporate Governance	ID	Independent directors
	CEOC	1, if a company changes its CEO; 0, otherwise.
	AC	1, if a company changes its audit company. 0, otherwise.
External Non-financial Information	SE	1, if the company is listed at SHSE; 0, otherwise.
	AO	External audit opinion. 1 if the audit company issued a standard unqualified opinion. 0 otherwise.
	AR	Analyst rating. 1 if the consensus rating is Buy or Outperform. 0 otherwise.
	ANAC	Analyst Coverage. The number of analysts covering a company's stock.

Similar to the financial indicators, all the preselected non-financial indicators are also tested the significance of the difference between groups and tested collinearity for the selection of predictors. Only indicators with low collinearity with each other and the best discriminating abilities will be included in the prediction models. Furthermore, the financial and non-financial indicators are gathered as an individual sample to rerun the selection process mentioned above to find effective indicators for the prediction model.

3.5. Data collection and preprocessing

3.5.1. Sample data collection

In this paper, for each selected company, four-year company data prior to the year when the company was marked with ST or *ST (year T) were collected. ST or *ST companies were denoted with "1" while matching healthy companies were denoted with "0". As the selected companies are within 2010 to 2020, the year range of the data is between the years 2006 and 2019.

The financial and non-financial data used in this paper were collected from Wind Financial Terminal, a few missing data from Wind were retrieved in company annual reports and filled in the data set manually. Financial ratios are calculated based on the collected financial data. The preselection of indicators is further discussed in the following section.

The selected company data is randomly divided into two groups: the training dataset and the testing dataset. As the models are used for prediction, the training dataset includes data from 2010 to 2018, corresponding to 75% of the whole dataset, and it is mainly used to select predicting indicators and to develop the predicting models. The hold-out test dataset includes the rest data from 2019 to 2020, corresponding to 25% of the whole dataset, and it is mainly used to evaluate the performance such as accuracy and sensitivity of the predicting model.

3.5.2. Data standardization

Financial indicators represent different financial meanings and economic attributes, and the data dimensions of each indicator are different. If the initial values of financial indicators are directly used in the prediction model, variables with larger dimensions will suppress other indicators and have a stronger influence on the model parameter estimations, which will lead to the ignorance of the other indicators' discriminate power in the classification. Besides, we applied the Kolmogorov-Smirnov test (K-S test) in the following chapter to identify whether an indicator satisfies the normal distribution and thus to test whether there exists a significant difference between the financial distress companies and the healthy ones, and K-S test needs the standardized data as a prerequisite to compare with the normal distribution. We also used the standardized data to re-estimate the models and to analyze the marginal effects of each continuous indicator. Therefore, in this paper, we applied Z-score standardization on the data to eliminate the influence of unit and scale differences between different indicators. The calculation of standardization is showed as follow:

$$x' = \frac{x - \bar{x}}{\sigma} \tag{15}$$

The standardized variables have zero-mean and unit variance.

4. Prediction indicator system

In this section, we aim to combine the statistical methods and the experience from previous research to filter the prediction indicators which will be finally applied in the prediction models. The final selections of indicators and the empirical model settings are shown in the variable selection results.

4.1. Prediction indicator selection

The indicator selection procedure includes 3 main steps. First, for each preselected indicator, an individual discriminating ability test is performed to judge whether there exists a significant difference between the financial distress group and the healthy group to identify the indicators with potential predicting ability. Before that, a normality test is applied for each continuous financial indicator for both the financial distress group and healthy group to determine which statistical method should be used. For normally distributed indicators, the t-test is used, while for indicators that do not satisfy the normal distribution, a nonparametric test method, Mann–Whitney U test is used. Second, as the logistic regression model is sensitive to the multicollinearity of the data, for the indicators tested to be statistically significant, a covariance matrix is calculated to evaluate the inter-correlations between the variables and to ensure that there is no multicollinearity between indicators finally used in the model. Third, for the indicators that are identified to have multicollinear problems in the second step, indicators that are most commonly used or have been tested to be significant in previous literature will be finally chosen as the predictors in the model. At least one indicator in each category is included in the prediction model to make sure the model covers different evaluation aspects of the financial position.

4.1.1. Individual discriminating ability test

Kolmogorov-Smirnov test

The first step to assess the individual discriminating ability of each indicator is to use the single-sample Kolmogorov-Smirnov test (KS test) to identify whether an indicator satisfies the normal distribution. K-S test is mainly used to test whether a single population obeys a certain theoretical distribution. The idea is to test whether two population distributions are different or whether one distribution is different from another ideal distribution based on the cumulative distribution function (CDF). As the normal distribution is an important prerequisite of the t-test, in this paper we choose the normal distribution as the benchmarking distribution of the K-S test. When the sample size is relatively large (the number of data points is larger than 50), the K-S test is the most commonly used non-parametric test when analyzing whether the distributions of two data sets are significantly different. The statistical hypothesis test is stated as follow:

H_0: The distribution of the population of indicator *i* satisfies the normal distribution.

H_1: The distribution of the population of indicator *i* does not satisfy the normal distribution.

$$D_i = \max \left| F_{n,i}(x) - F_N(x) \right| \tag{16}$$

where $F_{n,i}(x)$ represents the empirical cumulative distribution function (CDF) of indicator i and $F_N(x)$ denotes the CDF of normal distribution. D_i denotes the K-S statistic and the critical value is denoted with $D_{n,\alpha}$. The empirical CDF, $F_n(x)$ is defined as:

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I(X_i), \qquad where\ I(X_i) = \begin{cases} 1, & X_i < x \\ 0, & X_i \geq x \end{cases} \tag{17}$$

H_0 is rejected when $D_i > D_{n,\alpha}$, showing that indicator *i* does not satisfy the normal distribution, and a non-parametric test, the Mann–Whitney U test, will be used to identify the difference between the financial distress group and the healthy group. Otherwise, the t-test will be used.

Dummy variables are excluded from K-S test as obviously, they do not satisfy the normal distribution. The K-S test results of the 34 variables are shown in *Table 20, Table 21*, and *Table 22* in the Appendix.

The K-S normal distribution test results showed that on the significant level of 5%, H_0 of indicators DAR, WC, PQ, CFR, SCFR, CRR, SR, FAR, T10 for all the 3 years prior to the financial distress, LGA and II for Year T-1, NOCFL and II for Year T-2, and TR for Year T-3, cannot be rejected for both two groups, while the rest of indicators, at least for one group, in specific years appeared not to satisfy the normal distribution. Therefore, the significance of the difference between groups of indicators mentioned above in specific years will be carried out based on the t-test and the rest indicators will be tested using the Mann–Whitney U test.

T-test for variables satisfying normal distribution

T-test is widely used to test whether the means of two normally distributed populations are equal. Denote the population mean values of the financial distress and healthy groups as μ_1 and μ_2, the sample mean values of the two groups as $\bar{x}$ and $\bar{y}$, the sample standard deviations as s_1 and s_2, and the numbers of sample observations as n_1 and n_2. The statistical hypothesis test and the calculation of t statistic are stated as follow:

Under the null hypothesis, H_0: $\mu_1 - \mu_2 = 0$

and under the alternative hypothesis, H_1: $\mu_1 - \mu_2 \neq 0$

$$t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}} \tag{18}$$

H_0 is rejected when $|t| > t_{\alpha/2,df}$ where α denotes the significant level and df denotes the degree of freedom, showing that the population mean values of the two groups of an indicator are significantly different, and thus this indicator can be regarded to have discriminant ability to identify the financial distress and healthy companies.

The result of the t-test is shown in *Table 6*. The result will be further explained combined with Mann–Whitney U test in the following paragraphs.

Table 6. Results of t-test. The table shows the results of t-test for preselected indicators that are normally distributed in year T-1, T-2, and T-3. The t-test is performed on the training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in the Chinese manufacturing industry from 2010 to 2018.

	T-1		T-2		T-3	
Indicators	t statistic	p value	t statistic	p value	t statistic	p value
DAR	-9.652	0.000***	-7.956	0.000***	-8.834	0.000***
WC	9.120	0.000***	7.651	0.000***	7.992	0.000***
PQ	5.771	0.000***	4.789	0.000***	3.324	0.001***
NOCFL			6.896	0.000***		
SCFR	5.771	0.000***	4.789	0.000***	3.324	0.001***
CRR	6.581	0.000***	5.404	0.000***	3.885	0.000***
SR	5.812	0.000***	4.729	0.000***	3.438	0.001***
FAR	9.224	0.000***	7.277	0.000***	8.000	0.000***
TR					1.790	0.074*
T10	5.438	0.000***	4.762	0.000***	4.808	0.000***
II	3.591	0.000***	2.554	0.011**		

Note: * denotes significant at 10%, **denotes significant at 5% and *** denotes significant at 1%. All the company data is collected from the Wind Financial Terminal and annual reports.

Mann–Whitney U test for variables not satisfying normal distribution

Mann–Whitney U test is designed to test whether the population distributions are identical without assuming them to follow the normal distribution. The U test is based on the median values of the samples. If the samples have the same median value, then each observation x_i in financial distress group has an equal probability of being greater or smaller than each observation y_j. Denote the numbers of sample observations in each group as n_1 and n_2. Denote U_x as the number of times an observation x_i from the financial distress sample is greater than an observation y_j from the healthy sample and denote U_y as the number of times an observation x_i is smaller than y_j. Under the null hypothesis the U_x and U_y are expected to be approximately equal. The statistical hypothesis test and the calculation of U statistic are stated as follow:

Under the null hypothesis, H_0: $P(x_i > y_j) = \frac{1}{2}$

and under the alternative hypothesis, H_1: $P(x_i > y_j) \neq \frac{1}{2}$

$$U = \min(U_x, U_y) \tag{19}$$

H_0 is rejected when $U \leq U_{\alpha,n_1,n_2}$ where α denotes the significant level, showing that the population distributions of an indicator in financial distress and healthy groups are not identical and they are significantly different. Thus, this indicator is believed to have the discriminant power to classify the financial distress and healthy companies.

Table 7. Results of Mann–Whitney U test. The table shows the results of Mann–Whitney U test for preselected indicators that are not normally distributed in year T-1, T-2 and T-3. The Mann–Whitney U test is performed on the training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in the Chinese manufacturing industry from 2010 to 2018.

	T-1		T-2		T-3	
Indicators	z statistic	p value	z statistic	p value	z statistic	p value
CR	8.237	0.000***	7.229	0.000***	7.098	0.000***
QR	8.528	0.000***	7.432	0.000***	7.197	0.000***
ICR	14.215	0.000***	2.748	0.006***	6.210	0.000***
OM	16.061	0.000***	10.456	0.000***	10.220	0.000***
ROE	16.392	0.000***	8.988	0.000***	9.730	0.000***
ROA	15.839	0.000***	7.679	0.000***	9.935	0.000***
CEPM	16.181	0.000***	9.112	0.000***	9.752	0.000***
EPS	16.378	0.000***	10.984	0.000***	10.879	0.000***
RT	1.125	0.261	0.992	0.321	0.783	0.434
FAT	6.822	0.000***	6.049	0.000***	6.232	0.000***
CAT	2.911	0.004***	1.383	0.167	1.315	0.189
NOCFCL	7.306	0.000***			5.703	0.000***
NOCFL	7.471	0.000***	6.779	0.000***	5.828	0.000***
DIV	15.992	0.000***	10.087	0.000***	9.975	0.000***
INNO	3.177	0.001***	4.864	0.000***	3.143	0.002***
MVTL	5.626	0.000***	5.506	0.000***	6.693	0.000***
MVTTL	4.568	0.000***	4.433	0.000***	5.295	0.000***
RE	1.836	0.066*	0.292	0.770	0.975	0.329
TR	-1.288	0.198	0.147	0.883		
VO	-0.346	0.729	-0.217	0.828	1.361	0.174
SOS	-1.287	0.198	-1.317	0.188	-1.512	0.130
II					2.107	0.035**
ID	-1.127	0.260	0.384	0.701	0.642	0.521
CEOC	-3.850	0.000***	-1.082	0.279	-1.194	0.232
AC	-0.369	0.712	-0.094	0.925	0.000	1.000
SE	-2.412	0.016**	-2.412	0.016**	-2.412	0.016**
AO	6.485	0.000***	4.405	0.000***	4.555	0.000***
AR	7.345	0.000***	5.471	0.000***	6.118	0.000***
ANAC	8.538	0.000***	6.016	0.000***	6.103	0.000***

Note: * denotes significant at 10%, **denotes significant at 5% and *** denotes significant at 1%. All the company data is collected from the Wind Financial Terminal and annual reports.

An normal approximation of U can be used when the observation of each group is large enough (larger than 10). As the financial distress and healthy groups both have 234 observations, standardized z statistic and p value are reported in this paper for convenience.

The result of Mann–Whitney U test is shown in *Table 7*. Combined with the t-test results for normally distributed variables, we found that most of the preselected indicators showed a significant difference between the financial distress group and the healthy group.

The Chinese stock market is still under development and not mature enough. Besides, as mentioned, the listed identity is a precious resource, and a reverse merger can happen. The shell can be hyped because a financial distress listed company can be acquired by others and be on the right track through the restructure. Thus, the stock price and trading turnover of companies approaching financial distress may not always plummet since the speculate opportunity exists.

In early days, many listed companies are restructured from state-owned enterprises and the majority of the shareholders are state-owned shareholders. One major drawback of the state-owned shares domain is that the companies would operate inefficiently, thus harming the operation and leading to financial distress. Thus, in the early 21st century, the proportion of state-owned shares can be regarded as a significant indicator of predicting power (Wang and Ji, 2006). However, with the promotion of state-owned enterprise reforms such as introduce of market competition mechanism, reduce of low efficient production capacity, encourage technology innovation, and optimization of internal management, state-owned companies have improved their efficiency. Thus, nowadays, the proportion of state-owned shares is not sufficient to provide predicting power.

Besides, the significant level of some indicators increased with a company approaching the financial distress situation. Indicators CAT and CEOC only showed significance under 1% significant level 1 years prior to the financial distress. The significance of indicator II increased during the three observed years. To prevent a company to fall into financial distress in his/her tenure and to avoid a period of the shameless history of management in the career, a CEO tends to resign from a company that is highly likely to fall into a financial distress situation in the near future. When a company approaches financial distress, the characteristics of business failure become more distinct. The board of the company may realize the company is at the edge of financial distress and they may blame the CEO for his/her dereliction of duty and fire him/her. As the ST or *ST label will severely affect share price and the company reputation, when the potential of financial distress is discovered, a company has a strong tendency to reduce the operating costs and tries to adjust the net income to avoid ST or *ST, i.e., to dismiss R&D personnel because the R&D investment is long-term and is difficult to yield profit in a short term. Institutional investors own the latest company information and professional analyst team to cover stocks, therefore they are the smartest investors with advantages in the market. They make timely and instant responses to stocks when a company's operation or the business environment changes. The increasing significance level of the institutional investor holding indicator reflects the professional investors who have identified the financial distress risk and manage the risk by reducing their holdings in the stocks. The increasing trend of the significant statistics of some indicators during the three observed years also proved that financial distress is a process of a company's situation deteriorating rather than a sudden decrease of a company's operation quality.

4.1.2. Correlation analysis

The LR model is very sensitive to the collinearity of the indicators. The collinearity of the independent variables will increase the estimation error and destroy the reliability of the LR model. The estimations of the parameter in the LR model are unbiased and effective only when the degree of collinearity between the variables is very low.

As this paper adopted LR to build the prediction model, in order to ensure the accuracy and applicability of the financial distress prediction model, the correlation between predictors needs to be strictly controlled. If a serious correlation exists between any of the indicators, a method such as directly eliminating some indicators or constructing principal components should be adopted.

Models which are built with principal components as input can not be easily applied in real life with financial or non-financial ratios. As this paper intends to build a prediction model which is simple to use for investors in practice, we keep the original indicators as the input of the model and the investors can directly use this model with new data to make the prediction.

In this paper, we further conducted a correlation analysis on the indicators which were tested significance between the two groups and calculated a correlation matrix including Pearson correlation coefficients between any two preselected indicators. If a high correlation[1] between indicators is detected, the most commonly used and best-performing ones in the literature will be prioritized over other ones. Besides, to ensure that the models capture information from different aspects, we selected at least one indicator in each category and the interesting non-financial indicators in other categories and included them in the prediction models. The correlation matrix of the data in each year is shown in *Table 23, Table 24, and Table 25* in the Appendix.

Strong correlations are identified between the financial indicators within the same category. Solvency indexes except interest cover ratio are all strongly correlated. The

[1] We consider two variables highly correlated if their correlation coefficient is larger than 0.3.

debt to asset ratio is negatively correlated to the other three solvency indexes as a high debt to asset ratio indicates a high risk of solvency while the other three show the liquidity of a company and the safety of repaying the debts. After eliminating the highly correlated indicators, we keep the current ratio (CR) used in Zmijewski (1984) and the interest cover ratio (ICR) as the solvency indexes in the model. Profit indexes are all highly correlated and have heavy information overlap. This paper selected return on equity (ROE) to represent profitability. Within the three significant operation indexes, working capital over the total asset (WC) has slightly higher correlations with the other two, and correlation coefficients are beyond the 0.3 threshold. Therefore, we include the rest of the two indicators, fixed asset turnover (FAT) and current asset turnover (CAT). All cash flow indicators are significantly correlated to each other and all the correlation coefficients exceed 0.85. As the total asset cash recovery ratio (CRR) showed good performance in studies of Wang et al (2014) and Liang et al (2016), we chose CRR to represent the cash flow index in our model. Companies in the manufacturing industry generally have heavy assets and most of them are fixed assets, and the fixed assets will have a strong impact on the flexibility of a company. Thus, a company with a high fixed asset ratio may face a severer situation when unexpected shocks on operations happen and is unable to turn around immediately. However, as the fixed asset is the main and the most important mean of production, a high fixed asset ratio also indicates that a company has a strong production capacity and is easier to realize economies of scale to reduce the average fixed cost. Besides, the fixed assets also indicate the long-term solvency of a company as it can also be liquidated to repay the debt. Therefore, this paper included the fixed asset ratio (FAR) as a predictor to study its effect though it has high correlations with CR and WC. Besides, this paper also included two indicators, whether a dividend is paid (DIV) and the R&D innovation investment (INNO), in the prediction model.

Among the non-financial indicators, a few multicollinearities are also detected within each category. Only two indicators in the capital market category, the market value of total shares to total liabilities (MVTL) and the market value of tradable shares to total liabilities (MVTTL), showed a significant difference between the two groups, but they are strongly correlated with each other (correlation coefficient 0.949). We referred to studies of Altman (1968) and Lin et al (2014) and included MVTL in the prediction model to capture the capital market information. The two significant ownership structure indicators, the top 10 shareholder holding rate (T10) and institutional investor holding rate (II) are also tested correlation problems. CEO change (CEOC) is the only significant corporate governance indicator and it only showed significance in year T-2, so CEOC will only be included in the model subject to T-2. Besides, we also included three non-financial indicators providing information from external professional aspects, external audit opinion (AO), analyst rating (AR), and analyst coverage (ANAC), to capture the opinions of audits and equity research analysts on the companies.

4.2. Variable selection results

According to the variable selection procedure, this paper finally selected 9 financial indicators and 6 non-financial indicators for models of year T-1, and the same 9 financial indicators but 5 non-financial indicators (excl. CEOC) for models of year T-2 and year T-3. At least one indicator in each category is included in the models to ensure specific information from each aspect is covered in the prediction models. *Table 8* holds the summary of all the selected independent variables for 9 models. The origins and expected signs of these indicators and are also attached.

Table 8. Selection of variables. The table shows our selection of variables in each model. Except for the category and indicators, the source of indicators and expected signs are also presented. Y denotes that the indicator is included in each of the 9 models.

Category	Indicator	Source	Exp. Sign	T-1			T-2			T-3		
				(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Solvency	CR	Platt, Platt and Pedersen (1994) Wang and Ji (2006)	-	Y		Y	Y		Y	Y		Y
	ICR	Min and Lee (2005) Platt, Platt and Pedersen (1994) Lv, Xu and Zhou (2004)	-	Y		Y	Y		Y	Y		Y
Profitability	ROE	Wu and Lu (2001) Kim and Upneja (2014)	-	Y		Y	Y		Y	Y		Y
Operation	FAT	Kim and Upneja (2014) Liu, Liu and Ren (2016)	-	Y		Y	Y		Y	Y		Y
	CAT	Liu, Liu, Ren (2016) Cao, Xia (2005)	-	Y		Y						
Cash flow	CRR	Lin et al. (2014) Liang et al. (2016)	-	Y		Y	Y		Y	Y		Y
Other fin.	FAR	Li, Sun (2011)	+/-	Y		Y	Y		Y	Y		Y
	DIV	Aziz et al. (1988)	-	Y		Y	Y		Y	Y		Y
	INNO	Leshno, Spector (1996) Bai and Tian (2020)	-	Y		Y	Y		Y	Y		Y
Cap. Mkt.	MVTL	Frydman, Altman and Kao (1985) Altman (1968)	-		Y	Y		Y	Y		Y	Y
Ownership	T10	Tian and Wang (2017)	-		Y	Y		Y	Y		Y	Y
	II	Own	-		Y	Y		Y	Y		Y	Y
Governance	CEOC	Tian and Wang (2017) Gilson (1989).	+		Y	Y						
External non-fin.	AO	Wang and Ji (2006) Tian and Wang (2017) Muñoz-Izquierdo et al. (2019)	-		Y	Y		Y	Y		Y	Y
	AR	Moses (1990)	-		Y	Y		Y	Y		Y	Y
	ANAC	Own	-		Y	Y		Y	Y		Y	Y

Model (1), (4), and (7) are "financials only models" and only employ financial indicators as independent variables. Model (2), (5), and (8) are "non-financials only models" and only include non-financial indicators. Model (3), (6), and (9) are "comprehensive models" and combine both financial and non-financial indicators as predictors. As the indicator CEO change (CEOC) shows a significant difference between two groups only in year T-2, indicator CEOC is only included in models in year T-2. The empirical analysis part and the evaluation of these models are further presented in the following section.

5. Empirical analysis

5.1. Descriptive statistics

Table 9 shows the descriptive analysis of financial and non-financial indicators of both financial distress companies and healthy companies in year T-1. Overall, most indicators show a significant difference between the two groups in our sample. Consistent with Beaver (1966), the mean of CR of the financial distress group is 1.553, lower than 2.648 of the healthy companies. The mean and median ICR for financial distress companies are -6.051 and -1.321, while these ratios of healthy companies are 14.797 and 2.507. Even obviously, the mean and median of ROE for financial distress companies are negative while those for healthy companies are all positive and much higher.

Table 9. Summary statistic for all models in year T-1. This table presents summary statistics for all models, including financial ratios such as solvency index, profitability index, operation index, cash flow index, and other financial index, and non-financial ratios such as capital market, ownership structure, corporate governance, and external information in year T-1. The table covers the minimum and maximum values, the mean, median, and the standard deviation of the training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in the Chinese manufacturing industry from 2010 to 2018.

	Total Sample		Financial Distress			Healthy		
Indicator	Min	Max	Mean	Median	St. dev.	Mean	Median	St. dev.
CR	0.176	68.966	1.553	0.920	4.567	2.648	1.610	4.083
ICR	-200.755	1809.664	-6.051	-1.321	23.052	14.797	2.507	118.663
ROE	-2.650	2.879	-0.419	-0.330	0.460	0.275	0.226	0.433
FAT	0.247	5741.891	30.711	1.487	375.675	6.757	2.848	24.265
CAT	0.013	22.180	1.269	0.966	0.958	1.744	1.217	2.198
CR	-0.391	0.363	0.000	0.006	0.084	0.046	0.040	0.076
FAR	-0.460	0.971	0.292	0.272	0.232	0.486	0.482	0.222
DIV	0.000	1.000	0.030	0.000	0.170	0.751	1.000	0.432
INNO	0.000	0.430	0.022	0.004	0.049	0.028	0.019	0.036
MVTL	0.147	720.709	8.959	2.108	48.008	12.214	4.635	25.519
T10	0.000	0.956	0.486	0.477	0.159	0.563	0.564	0.146
II	0.000	0.923	0.323	0.315	0.202	0.397	0.409	0.232
CEOC	0.000	1.000	0.325	0.000	0.468	0.167	0.000	0.373
AO	0.000	1.000	0.803	1.000	0.397	0.991	1.000	0.092
AR	0.000	1.000	0.274	0.000	0.446	0.609	1.000	0.488
ANAC	0.000	29.000	1.359	0.000	2.382	4.605	2.000	5.586

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

Similar patterns can also be found in operation, cash flow, and other financial indicators, especially the median values of these indicators. The mean of MVTL of financial distress companies is only 2.108 while the mean for healthy companies is

12.214. On average, only 1.359 analysts cover each financial distress company, but 4.605 analysts cover each healthy company, indicating that most financial distress companies lack analyst coverage. A similar result also shows on AR. The median of financial distress companies is 0, indicating analysts did not issue a “buy” or “outperform” recommendation for the financial distress companies.

Table 10 shows the descriptive analysis of financial and non-financial indicators of both financial distress companies and healthy companies in year T-2. The overall difference remains large between each indicator. However, the gap narrows down compared to year T-1. The mean and median of ICR for financial distress companies are 7.129 and 1.413, and those for healthy companies are 13.932 and 2.205, respectively, indicating that the financial distress companies have poor solvency compared with healthy companies. On the profitability side, EPS for financial distress companies is also less than a third for healthy companies, regarding both mean and median.

Table 10. Summary statistic for all models in year T-2. This table presents summary statistics for all models, including financial ratios such as solvency index, profitability index, operation index, cash flow index, and other financial index, and non-financial ratios such as capital market, ownership structure, corporate governance, and external information in year T-2. The table covers the minimum and maximum values, the mean, median, and the standard deviation of the training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in the Chinese manufacturing industry from 2010 to 2018.

	Total Sample		Financial Distress			Healthy		
Indicator	Min	Max	Mean	Median	St. dev.	Mean	Median	St. dev.
CR	0.174	39.184	1.465	1.014	1.715	2.758	1.539	4.301
ICR	-29.480	1076.424	7.129	1.413	45.377	13.932	2.205	79.401
ROE	-1.030	3.360	0.101	0.040	0.253	0.347	0.230	0.440
FAT	0.244	213.521	3.835	1.721	8.143	6.257	2.931	20.941
CAT	0.009	18.904	1.412	1.044	1.028	1.700	1.219	1.972
CRR	-0.250	0.380	0.009	0.011	0.078	0.046	0.043	0.075
FAR	-0.362	0.971	0.344	0.329	0.226	0.494	0.505	0.220
DIV	0.000	1.000	0.299	0.000	0.458	0.765	1.000	0.424
INNO	0.000	0.292	0.014	0.002	0.026	0.026	0.018	0.035
MVTL	0.168	325.700	7.449	2.430	24.266	11.603	4.965	21.799
T10	0.000	0.958	0.508	0.501	0.162	0.576	0.579	0.146
II	0.000	0.923	0.319	0.307	0.209	0.372	0.382	0.242
AO	0.000	1.000	0.889	1.000	0.314	0.987	1.000	0.112
AR	0.000	1.000	0.329	0.000	0.470	0.581	1.000	0.493
ANAC	0.000	28.000	2.103	1.000	3.879	4.517	2.000	5.426

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

The same results apply to operation, cash flow and other financial indicators. In the meantime, the standard deviations of these indicators for financial distress companies are lower than those for healthy companies, suggesting that the overall financial performance for financial distress companies is stably poorer than healthy companies in year T-2. The mean and median of capital market indicators, MVTL, for financial distress companies are 7.449 and 2.430, respectively, and those for healthy companies are 11.603 and 4.965. The AR and ANAC also show substantial differences between financial distress and healthy companies. However, the mean, median and standard deviation of Ownership indicators, T10 and II, for financial distress companies do not deviate from those of healthy companies.

Table 11 shows the descriptive analysis of financial and non-financial indicators of both financial distress companies and healthy companies in year T-3. The overall difference of each indicator, except for operation, cash flow, and other financial indicators, further narrows down in year T-3, especially for solvency indicators. However, the difference in solvency indicators between financial distress companies and healthy companies remains manifest. The mean and median of ICR for financial distress companies are 3.628 and 1.157, respectively, while those for healthy companies are 10.635 and 2.683. The same applies to profitability and other financial indicators such as FAR, DIV and INNO. The results indicate that the financial distress companies are more likely to suffer from insolvency and unprofitability even 3 years ahead. When it comes to the non-financial indicators, capital market and external non-financial indicators such as AR and ANAC also show a huge difference between financial distress and healthy companies. The mean and median of MVTL for financial distress companies are 5.317 and 2.010, while those for healthy companies are 10.406 and 4.801. The mean and median of ANAC for financial distress companies are 2.389 and 1.000, and those for healthy companies are 5.162 and 3.000. However, there exists little difference of ownership indicators between the financial distress companies and healthy companies.

The three table combines to show the trends of changes of indicators for financial distress and healthy companies. Within each year, the indicators of financial distress companies are, more or less, worse than those of healthy companies. Moreover, during the three consecutive years before ST or *ST, the gap for each indicator widens when the financial distress is approaching. The mean and median of each indicator for healthy companies do not fluctuate a lot during this period but the financial numbers for financial distress companies deteriorate significantly. For healthy companies, the mean of ICR ranges from 10 to 15 and the median of ICR ranges from 2 to 3. However, when it comes to the financial distress companies, the mean of ICR is 3.638 in year T-3 and is -6.051 in year T-1, and the median of ICR is 1.157 in year T-3 and is -1.321 in year T-1. Already suffered from poorer solvency in year T-3, the financial distress companies failed to turn the tide and further sank into financial distress. The same tendency can also be found in profitability, operation, cash flow and external non-financial indicators. However, the tendency does not apply to INNO, MVTL and II. The fact that INNO increases over years may be explained by faster decreasing revenue than the R&D expense. Similarly, the liability increases faster than market value, and leads to an increase in MVTL. Seemingly counterintuitive, II for both financial distress companies and healthy companies increase over years. However, the size of fund raised by institutional investors increased by a CAGR of 20% while the growth rate of the median of II for financial distress companies only increased by 5% in year T-2 and 3% in year T-1 and the mean only increased by 8% in year T-2 and 1% in year T-1. The results suggest a relative decrease of II in financial distress companies and further explain the absolute increases.

Table 11. Summary statistic for all models in year T-3. This table presents summary statistics for all models, including financial ratios such as solvency index, profitability index, operation index, cash flow index, and other financial index, and non-financial ratios such as capital market, ownership structure, corporate governance, and external information in year T-3. The table covers the minimum and maximum values, the mean, median, and the standard deviation of the training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in the Chinese manufacturing industry from 2010 to 2018.

	Total Sample		Financial Distress			Healthy		
Indicator	Min	Max	Mean	Median	St. dev.	Mean	Median	St. dev.
CR	0.138	21.120	1.489	1.019	1.828	3.030	1.599	4.914
ICR	-213.709	381.894	3.628	1.157	36.661	10.635	2.683	28.805
ROE	-1.900	3.170	-0.060	0.030	0.506	0.393	0.272	0.508
FAT	0.015	187.280	4.010	1.783	13.215	5.999	3.095	16.082
CAT	0.028	6.657	1.444	1.066	1.097	1.782	1.207	2.391
CRR	-0.415	0.514	0.018	0.021	0.087	0.043	0.045	0.076
FAR	-2.047	0.876	0.323	0.307	0.303	0.507	0.524	0.218
DIV	0.000	1.000	0.280	0.000	0.449	0.739	1.000	0.439
INNO	0.000	0.352	0.014	0.001	0.030	0.021	0.008	0.032
MVTL	0.000	127.218	5.317	2.010	11.326	10.406	4.801	21.953
T10	0.000	1.000	0.516	0.507	0.172	0.589	0.617	0.153
II	0.000	0.831	0.294	0.292	0.221	0.340	0.332	0.248
AO	0.000	1.000	0.893	1.000	0.309	0.991	1.000	0.092
AR	0.000	1.000	0.316	0.000	0.465	0.598	1.000	0.490
ANAC	0.000	29.000	2.389	1.000	4.357	5.162	3.000	6.209

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

5.2. Logistic regression results

In this section, the empirical model results are presented and discussed. This paper intends to compare the predictive power of models with only financial indicators, models with only non-financial indicators, and comprehensive models with both financial and non-financial indicators. Besides, this paper also tried to analyze the prediction power of the models 3 consecutive years advance to the company falling financial distress and presented a theoretical analysis of the results.

The 9 models with different predictor settings mentioned in the last section are estimated based on the training data set. In the training data set, each financial distress company contributes one observation, and the matching healthy companies constitute the other half of the data set. Three years of financial and non-financial data of the companies prior to the financial distress are collected and included in the models accordingly. All the financial distress happened during the year 2010 and year 2018.

Table 12 gives the maximum likelihood estimate results of the predicting indicators for all 9 models along with the ACI statistic, McFadden's Pseudo-$R^{2,}$ and likelihood ratio test results.

Table 12. Summary of results of logistic regression for all models in year T-1, T-2, and T-3. The table reports results of logistic regression of the financial and non-financial indicator on the independent variables. Three sets of models are built based on the training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in Chinese manufacturing industry from 2010 to 2018. Models (1), (4), and (7) consist of only financial indicators, models (2), (5), and (8) consist of only non-financial indicators and models (3), (6), and (9) consists of both financial and non-financial indicators. The absolute value of z-statistics is reported in parenthesis.

Indicator	T-1			T-2			T-3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CR	0.008		-0.178*	-0.063		-0.118	-0.040		-0.156*
	(0.294)		(-1.707)	(-1.003)		(-1.466)	(-0.848)		(-1.711)
ICR	-0.006		-0.007	0.001		0.000	0.001		0.002
	(-0.537)		(-0.576)	(0.302)		(0.072)	(0.346)		(0.593)
ROE	-8.941***		-7.801***	-2.574		-1.353	-2.048**		-1.605**
	(-4.721)		(-3.843)	(-1.591)		(-0.815)	(-2.533)		(-2.079)
FAT	0.013**		0.013**	-0.013*		-0.020**	-0.009		-0.011
	(2.536)		(2.192)	(-1.679)		(-2.3)	(-1.102)		(-1.225)
CAT	-0.408***		-0.416**						
	(-2.552)		(-2.453)						
CRR	-3.522*		-3.977*	-5.716***		-5.506***	-2.998**		-2.796*
	(-1.681)		(-1.753)	(-3.499)		(-3.294)	(-2.091)		(-1.927)
FAR	-2.289***		-2.461***	-2.092***		-2.406***	-2.202***		-2.527***
	(-2.792)		(-2.636)	(-3.311)		(-3.576)	(-3.714)		(-4.017)
DIV	-3.040***		-2.936***	-1.646***		-1.423***	-1.508***		-1.253***
	(-6.296)		(-5.732)	(-6.949)		(-5.707)	(-6.436)		(-4.964)
INNO	-2.403		-2.236	-9.619**		-7.220	0.317		0.289
	(-0.702)		(-0.517)	(-2.157)		(-1.631)	(0.087)		(0.076)
MVTL		-0.002	0.021**		-0.009*	0.014		-0.028***	0.027*
		(-0.698)	(2.152)		(-1.648)	(1.327)		(-2.641)	(1.671)
T10		-1.694**	0.241		-2.003***	-0.223		-1.531**	0.320
		(-2.181)	(0.194)		(-3.027)	(-0.288)		(-2.392)	(0.433)
II		-0.216	-1.597*						
		(-0.394)	(-1.674)						
CEOC		0.867***	0.381						
		(3.243)	(0.915)						
AO		-2.588***	-1.488**		-2.096***	-1.603**		-2.263***	-1.334
		(-4.138)	(-2.07)		(-3.323)	(-2.173)		(-2.988)	(-1.5)
AR		-0.815***	-0.695*		-0.564**	-0.370		-0.757***	-0.541*
		(-3.156)	(-1.751)		(-2.353)	(-1.31)		(-3.109)	(-1.929)

Indicator	T-1			T-2			T-3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ANAC		-0.152***	-0.042		-0.065**	-0.036		-0.043*	-0.028
		(-3.580)	(-0.633)		(-2.353)	(-1.115)		(-1.797)	(-1.058)
Intercept	2.084	3.931***	4.423	2.430	3.627***	4.288	1.986	3.721***	3.502
	(4.25)	(5.425)	(4.236)	(8.334)	(5.034)	(4.951)	(7.061)	(4.513)	(3.531)
ACI	281.587	522.930	273.696	501.788	589.948	496.472	514.852	580.505	510.355
Pseudo R^2	0.597	0.219	0.631	0.254	0.109	0.278	0.234	0.124	0.257
Pr(>Chisq)			0.003			0.009			0.013
LL Ratio			21.890***			15.316***			14.497**

Note: * denotes significant at 10%, **denotes significant at 5% and *** denotes significant at 1%. All the company data is collected from the Wind Financial Terminal and annual reports.

This paper aimed to build investor-friendly financial distress prediction models which can be simply applied in real-life investment decision making. As some of the independent variables in these models are not statistically significant, we intend to apply the stepwise logistic regression method to only keep the variables with additional explanatory power and minimize the number of predictors in each model for better use in practice.

Table 13 reports the estimated coefficients of the financial distress indicators on the independent variables for all the 9 models using the stepwise logistic regression method. Almost all the significant indicators in *Table 12* are also included in the results of stepwise logistic regression except CRR in model (1), CR in model (3), MVTL in model (3) and (9)[2].

In model (1), return on equity (ROE), current asset turnover (CAT), fixed asset ratio (FAR) and dividend payout (DIV) show statistical significance at 1% level; fixed asset turnover (FAT) is statistically significant at 5% level in year T-1. The strong statistical significance of financial indicators suggests that they are efficient predictors in predicting financial distress. All the signs of the significant indicators are in coordination with what we expected except FAT. ROE shows a strong negative correlation to the financial distress probability. As the definition of financial distress in this study largely depends on the profitability level and the ROE indicator accurately captures the overall profitability of a company, ROE appears to be an important and efficient predicting indicator. Fixed asset turnover is positively correlated to the financial distress probability while the current asset turnover shows a negative correlation. Surprisingly, the positive sign of FAT is contradictory to our expectations. FAT compares revenue to fixed assets and measures a company's operating ability to generate net sales from its fixed asset investment such as property, plant, and equipment. One possible reason why the financial distress probability increases with

[2] CR in model (3), MVTL in model (3) and (9) are manually eliminated from the final models as their existence lead to multicollinearity. See also multicollinearity test in *Table 29* in the Appendix.

higher FAT is that when a company approaches financial distress, it may tend to devest fixed assets to maintain the solvency and to adjust the net profit to avoid being labeled ST or *ST. The sale of fixed assets will lead to a decrease in the average fixed asset. Therefore, though revenue decreases before the financial distress, the percentage of fixed asset decrease is larger, and thus the FAT ratio increases, leading to a positive sign of FAT indicator. The current asset turnover measures a company's ability to generate revenue through its current assets including cash, inventory, accounts receivable, etc. It is calculated as revenue divided by average current assets. A company facing financial distress has a large probability to undergo a decrease in sales, and the average current assets are also expected to increase because of sales of fixed assets, inventory overstock, and increasing accounts receivable due to weak sales ability and sales collection ability. Therefore, increasing CAT suggests a lower financial distress probability especially when a company is close to the business failing. Fixed asset ratio measures the fixed assets as a percentage of the total assets and thus indicates the flexibility of business turnaround as discussed before. The negative sign of the variable FAR suggests that the advantages of having a higher fixed assets ratio outweigh the disadvantages. For companies in the manufacturing industry, operation stability is more valued than flexibility. Companies benefit from the economies of scale and the long-term solvency resulting from a higher fixed asset ratio, and they have a lower probability to fall into financial distress. In a relatively fully developed industry, failing to pay dividends shows bad financial results. The DIV variable also displays an anticipated negative sign, where companies with dividend payout have a lower financial distress likelihood than those which cannot pay a dividend to their shareholders.

The fact that variables FAT, FAR, and DIV in model (1) also remain statistical significance in model (4), which is subject to financial distress prediction in year T-2, suggests that the retained financial indicators process high discriminating and predicting power. However, the sign of the FAT indicator appears to be negative, and it is contradictory to the result in model (1) for year T-1. When it is 2 years prior to the financial distress, the management team does not notice the risk and therefore no measure is taken to prevent the distress. Therefore, without the abnormal sales of fixed assets which will strongly affect the asset structure, the fixed asset turnover is mainly affected by the revenue when the total asset size and asset structure of companies are similar in the same industry. Companies with higher fixed asset turnover typically have higher revenue and less probability to fall into financial distress. A negative sign of the CRR variable, which represents a measure of the cash flow performance, indicates companies with higher cash flow from operations have lower financial distress likelihood. Similarly, the variable INNO displays a negative sign as expected and it indicates that companies with higher R&D investment are less likely to fall into financial distress as discussed in the prior section.

In model (7) for financial distress prediction in year T-3, indicator ROE, CRR, FAR and DIV remain statistically significant, and they have the same anticipated negative signs, showing that these 4 financial indicators have stable predicting power even the prediction is made 3 years prior the company's ST or *ST.

In the non-financial model (2), top 10 shareholder holding rate (T10), CEO change (CEOC), external audit opinion (AO), analyst rating (AR) and analyst coverage (ANAC) all showed strong statistical significance at 1% level in year T-1. The negative sign of T10 indicator indicates that the financial distress probability decreases with the ownership concentration of a company. Sun and Huang (1999) identified the ownership concentration as an important factor that affects corporate governance and thus has an impact on the corporate operating performance. Xu, Xin and Chen (2006) also concluded that a significant positive linear relationship exists between ownership concentration and operating performance. The influence of large shareholders with high ownership concentration on the company's operating performance is more of a positive incentive effect rather than a negative entrenchment effect. The reason is that the higher ownership concentration will make the large shareholders the beneficiary of and the party responsible for the company operating results, and they are more likely to maintain effective control over the company's managers to alleviate the agency problems. Besides, the marginal cost for large shareholders to hollow out listed companies is higher, which to a large extent limits the controlling shareholders' ability to pursue private interests of control and to harm the interests of all small and medium shareholders. The positive relationship between CEOC and financial distress is consistent with our expectations. The CEO change indicates the high probability of unsatisfying managing results during the CEO's tenure and shows bad financial performance with a higher likelihood to fall into financial distress. The negative sign of the AO indicator suggests that companies with standard unqualified audit opinions are less likely to fail, which is in line with our expectations and intuition. Professional external auditing companies are hired to audit the periodical reports before they can be released according to the regulation, and options other than standard unqualified audit opinions indicate that there exist violations of financial accounting regulations more or less. Analyst rating (AR) and analyst coverage (ANAC) both show a strong negative relationship with the financial distress probability, indicating that analysts have professional ability to choose company coverage and avoid companies with financial distress risks. Analysts employ the professional knowledge and skills to analyze the stocks and publish their ratings of companies to the public for all kinds of investors. They also present their analysis to institutional investors and charge from providing equity research reports. Companies with high analyst ratings such as buy and hold and with more analyst coverage have less likelihood to fall into financial distress.

Surprisingly, all the significant indicators except CEOC in model (2) also showed statistical significance in model (5) in year T-2 and model (8) in year T-3. All the signs of estimated coefficients in model (5) and (8) are the same as the signs in model (2), and they are also in line with our expectations. The comparison of results of model (2), (5) and (8) suggests that the retained non-financial indicators, T10, AO, AR, and ANAC, process high predicting power, and these non-financial indicators work throughout 3 years before financial distress. Besides, the market value of total shares over total liabilities (MVTL) showed a significant negative relationship with financial distress probability in the model (5) and (8), indicating that the capital market itself has the ability to predict financial performance and the stocks are priced with financial distress risks taken into consideration if there is only weak intended stock price manipulation on potential ST or *ST companies. Altman (1968) and Lin et al. (2014) also identified MVTL as a solvency ratio that measures the safe margin of market value decline of a company's asset before it gets insolvency. The empirical result is in line with their conclusions and shows companies with a high MVTL ratio are less likely to fail.

Model (3), (6) and (9) take both financial and non-financial indicators as the independent variables in the model setting. In model (3), some significant non-financial indicators such as T10, CEOC, and ANAC in model (2) did not further show statistical significance. However, indicator II displays a significant negative sign, which suggests companies with higher institutional investors holding rates have a lower likelihood to fall into financial distress. Institutional investors have more information sources, they can better respond to the market and they also recorded better investment performance than other small investors. They are more professional in selecting investment targets and analyzing the stock.

In the comprehensive model (6) for prediction in year T-2, some significant financial indicators in model (3) such as ROE, CAT, and II did not further show statistical significance. INNO displays a significant negative sign in model (6) but loses significance in model (9). Furthermore, in model (9), FAT and AO also lost significance, but variable ROE reappears a significant negative sign.

Besides, decreasing numbers of significant non-financial indicators were observed in the model (6) and (9) when compared with the model (3), and only one non-financial indicator, audit opinion (AO) was still kept in model (9). The decreasing numbers of significant indicators with increasing time period before the financial distress shows that the predicting power of some indicators increases when a company approaches financial distress. Comparing the decreasing numbers of financial and non-financial indicators from model (3) to model (6) and to model (9), we found that financial indicators have better predictive ability than non-financial indicators as 5 and 4 financial indicators still showed significance while only 2 and 1 non-financial indicators were included in the model (6) and (9).

Table 13. Summary of results of stepwise logistic regression for all models in year T-1, T-2, and T-3. The table reports the results of logistic regression of the financial and non-financial indicators on the independent variable. Three sets of models are built based on the training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in the Chinese manufacturing industry from 2010 to 2018, in order to test their predictive ability in addition to their discriminating power. Models (1), (4), and (7) consist of only financial indicators, models (2), (5), and (8) consist of only non-financial indicators and models (3), (6), and (9) consists of both financial and non-financial indicators. The absolute value of z-statistics is reported in parenthesis.

	T-1			T-2			T-3		
Indicator	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ROE	-9.505***		-8.499***				-2.144***		-1.853**
	(-5.369)		(-4.565)				(-2.656)		(-2.446)
FAT	0.013**		0.012**	-0.017**		-0.022**			
	(2.327)		(2.168)	(-2.131)		(-2.576)			
CAT	-0.437***		-0.401**						
	(-2.83)		(-2.477)						
CRR			-3.609*	-6.014***		-5.600***	-2.661*		-2.617*
			(-1.676)	(-3.811)		(-3.504)	(-1.917)		(-1.863)
FAR	-2.109***		-2.387***	-2.497***		-2.563***	-2.449***		-2.505***
	(-2.865)		(-2.936)	(-4.784)		(-4.79)	(-4.914)		(-4.13)
DIV	-3.069***		-2.960***	-1.761***		-1.559***	-1.497***		-1.268***
	(-6.493)		(-6.031)	(-7.827)		(-6.647)	(-6.475)		(-5.282)
INNO				-9.989**		-7.513*			
				(-2.323)		(-1.746)			
MVTL					-0.009*			-0.028***	
					(-1.648)			(-2.641)	
T10		-1.842***			-2.003***			-1.531**	
		(-2.583)			(-3.027)			(-2.392)	
II			-1.475*						
			(-1.836)						
CEOC		0.847***							
		(3.195)							
AO		-2.595***	-1.652**		-2.096***	-1.594**		-2.263***	
		(-4.153)	(-2.281)		(-3.323)	(-2.166)		(-2.988)	
AR		-0.827***	-0.767**		-0.564**	-0.592**		-0.757***	-0.671***
		(-3.208)	(-2.223)		(-2.353)	(-2.472)		(-3.109)	(-2.801)
ANAC		-0.152***			-0.065**			-0.043*	
		(-3.608)			(-2.353)			(-1.797)	
Intercept	1.942***	3.924***	4.434***	2.438***	3.627***	4.119***	1.967***	3.721***	2.302***
	(4.108)	(5.424)	(4.812)	(8.519)	(5.034)	(5.348)	(7.23)	(4.513)	(7.465)
AIC	277.244	519.252	267.095	500.153	589.948	491.319	509.195	580.505	503.775
Pseudo R^2	0.591	0.218	0.619	0.229	0.109	0.267	0.231	0.124	0.248
Pr(>Chisq)			0.001			0.002			0.010
LL Ratio			18.148***			12.828***			11.419**

Note: * denotes significant at 10%, **denotes significant at 5% and *** denotes significant at 1%. All the company data is collected from the Wind Financial Terminal and annual reports.

Table 13 also reports AIC statistics, Pseudo R^2, and likelihood ratio test results of the 9 models. AIC (Akaike Information Criterion) is used to measure model fitting. It measures the relative amount of information loss of the dependent variable using the current model setting. The smaller the AIC value, the better the model. In each year, models with only non-financial indicators recorded the highest AIC values, followed by models with only financial indicators, and the comprehensive models have the lowest AIC value. The AIC statistics indicate that the comprehensive models with both financial and non-financial indicators explain most of the information in financial distress and have the best performance. Furthermore, we also performed likelihood ratio tests on each comprehensive model based on the financial models in the same predicting year. The likelihood ratio test is a statistical test on the goodness-of-fit between two models. It provides statistical evidence on whether adding the additional non-financial variables brings a better fit to the dataset. The small p-value of the likelihood ratio test results shows that comprehensive models with added non-financial indicators are better than models with only financial variables as predictors.

Comparing the models with the same variables setting across different prediction horizons, we found that the AIC values of the model (1) and (3) in year T-1 almost double in year T-2, and further increase a bit in year T-3. We further compared McFadden's Pseudo-R^2 to identify the explanatory power of models in different years. McFadden's Pseudo-R^2 is defined as the log-likelihood value for the fitted model over the log-likelihood for the null model which includes only an intercept as the predictor. Therefore, the model with a higher McFadden's Pseudo-R^2 value is often more desirable. The Pseudo-R^2 of all the 3 models decrease drastically from year T-1 to year T-2 but do not change a lot from year T-2 to year T-3. The increasing pattern of AIC value and the decreasing pattern of McFadden's Pseudo-R^2 both shows that the discriminating and predicting power of models dropped drastically in year T-2 but do not further decrease a lot between year T-2 and year T-3, indicating that predicting financial distress becomes more difficult when extending the predicting period from 1 year before the financial distress to 2 years. The main reason why the huge gap exists between year T-1 and year T-2 is that falling in financial distress is a dynamic process with vicious circulation and the accumulation of bad operating performance finally results in the burst of financial distress (Lv et al., 2004).

5.3. Marginal effects and changes in predicted probabilities

In many previous studies that used binary response models, only the final overall predicting results are presented and analyzed. However, compared with linear models, the overall results of binary response models hardly provide enough information on the individual level because of the non-linear feature. In a non-linear model, the average behavior of individuals differs from the behavior of the average individual. For financial distress prediction, the average marginal effect, or the marginal effect at a certain representative value, is usually more meaningful.

In this section, we referred to Tinoco and Wilson's study (2013) on financial distress and bankruptcy prediction among the UK listed companies and presented the results of marginal effects of the indicators included in our model to interpret the individual effects of the indicators on the predicting results. For each indicator, this paper first estimated the marginal effects estimated at each observation in the training dataset and then computed the average of individual marginal effects at each observation to obtain the overall marginal effects. Besides, we standardized the continuous variables and re-estimated the 9 models. Marginal effects of continuous variables on their standardized values are also presented in *Table 14* to improve the comparability.

Furthermore, predicted financial distress probabilities were calculated and plotted in *Figure 1.* The range of each focused indicator is from its approximate minimum to the maximum observed value in the training dataset and all the other covariates were kept constant at their mean values.

The marginal effects presented in *Table 14* reflect to what extent the indicators have an impact on the result. Model (1), (4) and (7) consist of only financial indicators. The result of the financial model subjected to year T-1 is mostly affected by ROE, FAT and DIV, while CAT and FAR appear to have the smallest impacts. In year T-2, DIV still shows a large impact on the predicted financial distress. CRR and FAR have significant marginal effects while indicator FAT shows the smallest impact on the predicting model. One more year ahead, in year T-3, DIV and FAR have the largest impact on the predicting model while CRR only slightly influences the prediction results. The marginal effects of all the indicators decrease from year T-1 to year T-3 except FAR. Consistent with the logistic regression results, the marginal effect of FAT contraries in year T-1 and T-2.

Model (2), (5) and (8) consist of only non-financial indicators. In year T-1, AO has the largest impact on the model, followed by AR, while ANAC has the smallest impact followed by T10. The results of marginal effects in year T-1 still hold in year T-2 and T-3. No clear developing trend of the marginal effects of each indicator is observed in the non-financial models over years.

Model (3), (6) and (9) consist of both financial and non-financial indicators. In year T-1, financial indicators ROE, FAT and DIV have significantly larger marginal effects on the prediction results while CRR and II have the smallest impact. In year T-2, FAR and AO have the most significant marginal effects in financial and non-financial indicators, respectively. In year T-3, FAR remains the largest impact on the financial indicators but DIV replaces AO and shows the largest marginal effect in non-financial indicators. In both year T-2 and year T-3, FAT and CRR record small marginal effects. Same as in the financial models, the marginal effect of FAT in the model (3) and (6) also contraries in year T-2 and T-3. The marginal effects of FAR and AR increase over the years, while the marginal effects of other indicators fluctuate.

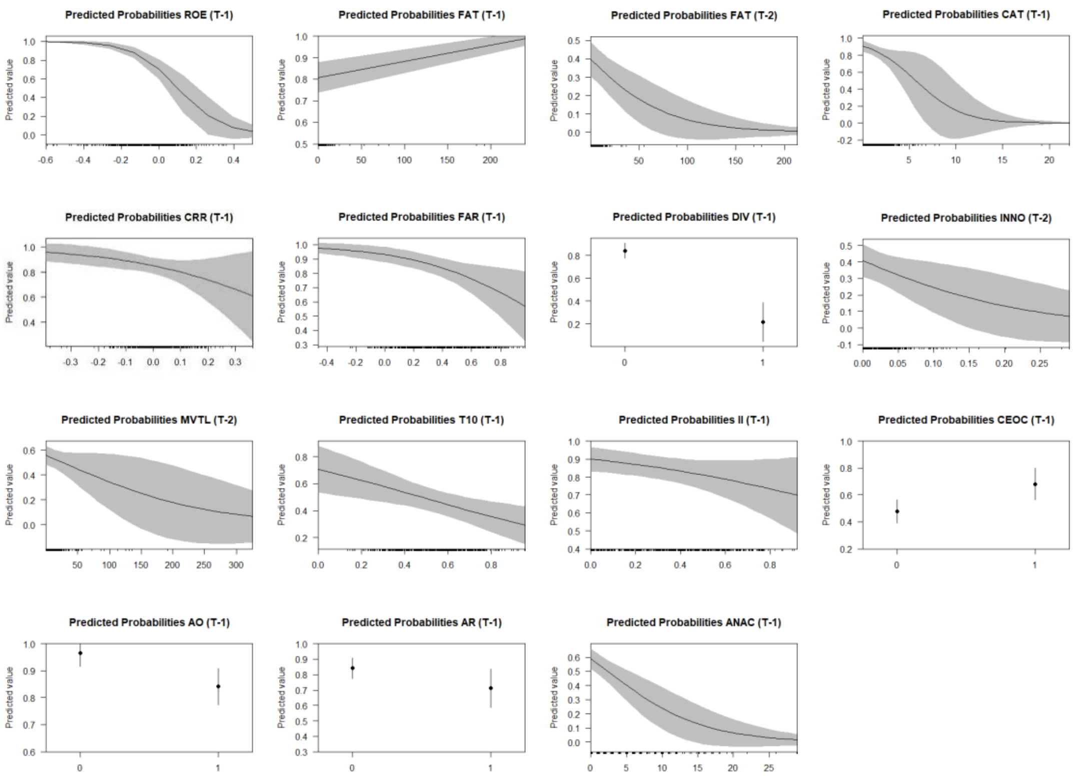
Table 14. Summary of marginal effects. The table reports the marginal effects for each variable in the 9 models. Panel A presents the marginal effects of variables on their absolute values and Panel B presents the marginal effects of continuous variables on standardized values to improve the comparability. Models (1), (4), and (7) consist of only financial indicators, models (2), (5), and (8) consist of only non-financial indicators and models (3), (6), and (9) consists of both financial and non-financial indicators. The marginal effect calculation is performed on training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in Chinese manufacturing industry from 2010 to 2018. The marginal effects are intended to measure the expected instantaneous changes in the response variable as a result of a change in a specific predictor variable. The marginal effect of each indicator is computed as the average of individual marginal effect at each observation in the training dataset.

	T-1			T-2			T-3		
Indicator	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Marginal effects of variables on absolute values									
ROE	-0.818		-0.680				-0.382		-0.321
FAT	0.001		0.001	-0.003		-0.004			
CAT	-0.038		-0.032						
CRR			-0.289	-1.039		-0.940	-0.474		-0.415
FAR	-0.182		-0.191	-0.431		-0.430	-0.437		-0.468
DIV	-0.412		-0.362	-0.361		-0.262	-0.312		-0.268
INNO				-1.725		-1.261			
MVTL					-0.002			-0.006	
T10		-0.340			-0.431			-0.323	
II			-0.118						
CEOC		0.157							
AO		-0.406	-0.129		-0.381	-0.268		-0.392	
AR		-0.163	-0.065		-0.126	-0.099		-0.169	-0.118
ANAC		-0.028			-0.014			-0.009	
Panel B: Marginal effects of continuous variables on standardized values									
ROE	-0.258		-0.215				-0.088		-0.074
FAT	in		0.264	-0.046		-0.059			
CAT	-0.064		-0.055						
CRR			-0.024	-0.082		-0.074	-0.039		-0.034
FAR	-0.045		-0.047	-0.102		-0.101	-0.122		-0.131
INNO				-0.054		-0.040			
MVTL					-0.044			-0.104	
T10		-0.055			-0.083			-0.062	
II			-0.026						

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

Figure 1 shows the behavior of the predicted probabilities for financial distress at different values of some financial and non-financial indicators. We found that the predicted financial distress probabilities are negatively correlated with most of the financial indicators including ROE, FAT, CAT, CRR, FAR, DIV and INNO. Consistent with the results in the regression models, FAT shows a contrary impact on the predicting result in T-1 and T-2. While having a positive influence on the result in year T-1, FAT has a negative influence on the result in T-2. Similarly, there exists a negative relationship between the predicted probability and most of the non-financial indicators, including MVTL, T10, II, AO, AR and ANAC. However, CEOC has a positive correlation with the predicted result. All the marginal effects of indicators accord with the results presented in the previous regression analysis. Except for some indicators with different signs of marginal effects between year T-1 and year T-2, all the indicators have similar marginal effects in year T-2 and year T-3, and therefore only figures in year T-1 were presented.

Figure 1. Predicted probabilities when financial distress occurs with 95% confidence limits. The figures show the changes in predicted probabilities for both financial and non-financial indicators. The predicted probabilities are calculated using a training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in the Chinese manufacturing industry from 2010 to 2018. The figure plots the vectors reflecting changes in predicted probabilities at different levels of ROE, FAT, CAT, CRR, FAR, DIV, INNO, MVTL, T10, II, CEOC, AO, AR and ANAC in the training dataset.



Note: All the company data is collected from the Wind Financial Terminal and annual reports.

5.4. Evaluation of the models

This section shows the financial distress predicting power of the 9 models during the 2 evaluation periods with training dataset from 2010 to 2018 and hold-out test dataset from 2019 to 2020. The most important objective is to identify which model has the best predicting power to classify financial distress companies and healthy companies. The 9 models will be evaluated from the overall prediction accuracy, type I error and type II error perspectives. ROC curves and AUC values are also used as an evaluation criterion. Besides, the models are also further tested on different cutpoints and sub-datasets.

5.4.1. Model accuracy

Table 15 summarizes the results of different evaluation metrics of the 9 models. The results show that the models with only financial indicators have strong predicting power with classification accuracy up to 88.5% in year T-1 when the model is evaluated on the training dataset. Similar high predicting accuracy of 87.2% is also shown on the hold-out test dataset. However, when the financial models are compared across 3 prediction horizons, the accuracy of models with only financial indicators dropped sharply to 72.9% in prediction year T-2 and further decreased by 1.7% to 71.2% in the year T-3 on the training dataset. A same trend of the decreasing accuracy in year T-2 can also be observed on the evaluation using the hold-out test dataset. The accuracy decreased drastically from 87.2% to 70.5% in prediction year T-2 but increased by 4.8% to 76.3% in the year T-3. As discussed in the previous section, the cost of type II error is much severer than type I error, and therefore we paid more attention to the type II error. The type I error of model (1) on the training dataset is 18.4%, which is higher than the type II error of 4.7%. Similar results of type I and type II errors were found on the test dataset, but the difference converges. The type I and type II error of model (1) reported 15.4% and 10.3%. Compared with the numbers drawn on the training dataset, the type I error dropped while the type II error increased a bit on the test dataset from 2019 to 2020. Consistent with the accuracy, higher type I error and type II error of models with only financial indicators were observed in year T-2 and year T-3. These two metrics increase significantly between year T-1 and T-2 but do not show a further increasing trend in the second and the third year before the financial distress. The prediction performance even shows improvement in year T-3 on the hold-out test dataset.

The prediction models with only non-financial indicators and comprehensive models with both financial and non-financial indicators both show similar results when compared across the 3 predicting years. The accuracy metrics of these models decrease while the sensitivity and specificity increase sharply on both the training dataset and the hold-out test dataset from year T-1 to year T-2 but do not display significant change between year T-2 and year T-3.

When compared with the calculated accuracy, sensitivity and specificity based on the training dataset, these overall performance metrics on the hold-out test dataset in years T-2 are less satisfying but still acceptable. However, the prediction performance of model (7) and (9) is even better on the hold-out test dataset in year T-3.

Through the comparison of models with similar predictor settings across three years, interestingly, we found that the predicting power of all the three models dropped sharply between year T-1 and T-2 but did not show a significant further decrease between year T-2 and T-3. The results further indicated that characteristics of financial distress become increasingly obvious when it approaches the distress, and the significance of the features jumped to a much higher level in 1 year prior to the actual financial distress.

Comparing the financial model, the non-financial model, and the comprehensive model in the same predicting period T-1, unsurprisingly, we found that the comprehensive model (3), though marginally, overperforms model (1) on both training and hold-out test datasets. Model (2) with only non-financial indicators performed the worst with only 69.9% and 64.1% accuracy, type I error up to 44.0% and 56.4%, and type II error of 16.2% and 15.4% based on the training and hold-out test datasets. The accuracy of model (2) is much lower than the accuracy of model (1) and model (3), and the two types of error were also significantly larger.

In prediction year T-2, similar results of comparison of 3 different models were observed though the performance of all the models was not as good as their performance in year T-1. The financial model and comprehensive model perform much better and are more reliable than non-financial models from accuracy, type I error, and type II error perspectives. The comprehensive model (6) shows the best prediction performance on prediction accuracy, type I error, and type II error, followed by the financial model (5). In the prediction year T-3, model (8) with only non-financial indicators continues to perform the worst among the 3 models. However, interestingly, the comprehensive model still ranks the first based on the evaluation on the training dataset, but its prediction performance does not surpass the financial model anymore on the hold-out testing dataset. The accuracy of model (7) on the test dataset records 76.3%, which is higher than the 73.1% accuracy of model (9). Though the type II error decreases by 2.6% after the introduction of non-financial indicators but the type I error increases sharply by 10.9%, leading to the overall decrease of prediction accuracy.

The results of comparing different model settings in the same year show that comprehensive models with both financial and non-financial indicators have the best overall prediction performance except the evaluation on hold-out test dataset in year T-3, followed by the financial models, and both 2 types of models significantly surpassed the models with only non-financial indicators. The non-financial models with low accuracy and high type I and type II errors are concluded not to have enough predicting power themselves to classify the financial distress and healthy companies. Furthermore, though the financial models solely have been proved to have good predictive power, the predictive ability of the financial models is enhanced with additional non-financial indicators based on the overall evaluation on accuracy and type I and type II errors in year T-1 and year T-2. However, in predicting year T-3, incorporating non-financial indicators in model (7) does not improve the prediction performance anymore, and in the contrary, it even deteriorates the prediction power of the financial model. The reason will be further tested and analyzed in the robustness test section.

Table 15. Summary of model performance evaluation. This table reports model performance measures, AUC value, overall accuracy, Type I Error and Type II Error on both training dataset and hold-out test dataset. Three sets of models are evaluated, respectively. Model (1), (4) and (7) consist of only financial indicators, model (2), (5) and (8) consist of only non-financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators. Panel A represents the performance of models based on a training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in the Chinese manufacturing industry from 2010 to 2018. Panel B represents the performance of models based on a hold-out test dataset consisting of 78 financial distress listed companies and 78 healthy listed companies in the Chinese manufacturing industry from 2019 to 2020.

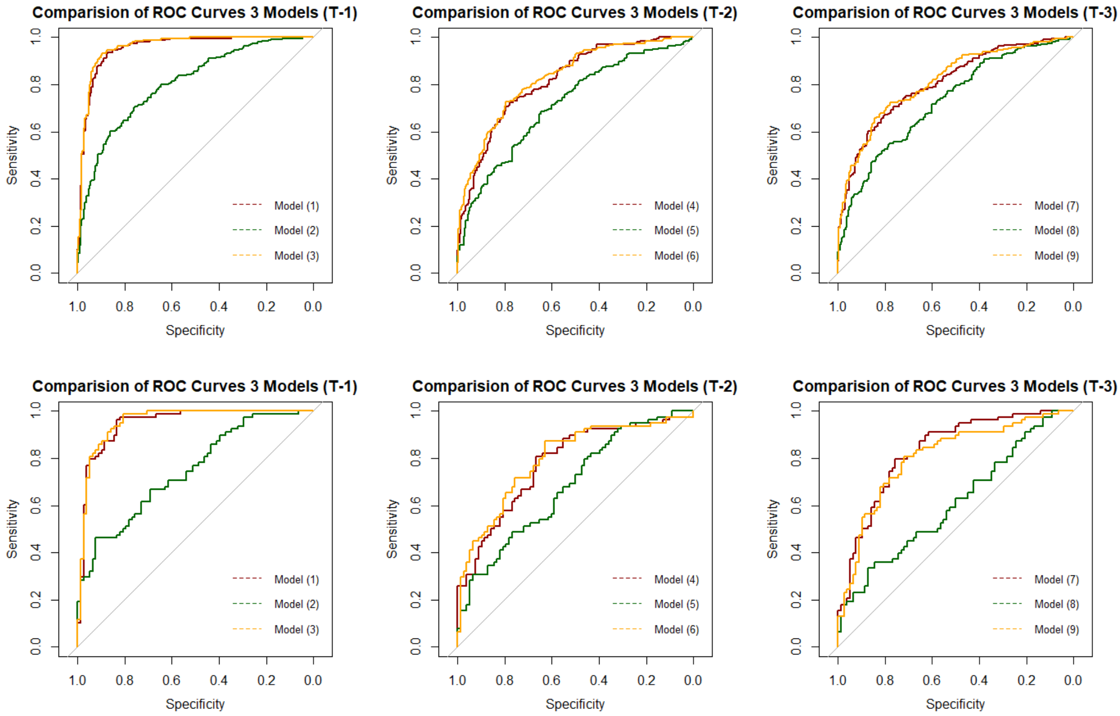
	T-1			T-2			T-3		
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: models' performance on the training dataset (biased)									
AUC	0.954	0.803	0.959	0.822	0.716	0.829	0.805	0.728	0.815
Accuracy	0.885	0.699	0.894	0.729	0.645	0.739	0.712	0.650	0.718
Type I Error	0.184	0.440	0.165	0.342	0.526	0.325	0.338	0.491	0.355
Type II Error	0.047	0.162	0.047	0.201	0.184	0.197	0.239	0.209	0.209
Panel B: models' performance on the hold-out test dataset (unbiased)									
AUC	0.947	0.745	0.954	0.779	0.682	0.796	0.829	0.607	0.791
Accuracy	0.872	0.641	0.891	0.705	0.609	0.731	0.763	0.596	0.731
Type I Error	0.154	0.564	0.115	0.256	0.526	0.244	0.244	0s82	0.333
Type II Error	0.103	0.154	0.103	0.333	0.256	0.295	0.231	0.423	0.205

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

5.4.2. ROC curves

ROC curves are also used as an evaluation criterion to compare the predicting performance. *Figure 2* shows the comparison of ROC curves of models with 3 different predictor settings in each of the 3 predicting years based on the training dataset from 2010 to 2018 and the hold-out test dataset from 2019 to 2020. The figure derived from both datasets demonstrates that financial models and comprehensive models significantly outperformed the non-financial models in terms of discriminative power. Comprehensive models with additional non-financial indicators, though marginally, improve the overall predicting power of the models with only financial indicators in prediction year T-1 and T-2 according to this measure. Besides, another statistic stated in *Table 15*, the AUC values, the area under the ROC curves, also verified the conclusion that the contribution of incorporating non-financial indicators to the performance of financial models is positive. However, corresponding to the last graph in *Figure 2*, the AUC value decreases by 0.038 on the hold-out test dataset in the year T-3, entailed by the inclusion of additional non-financial indicators.

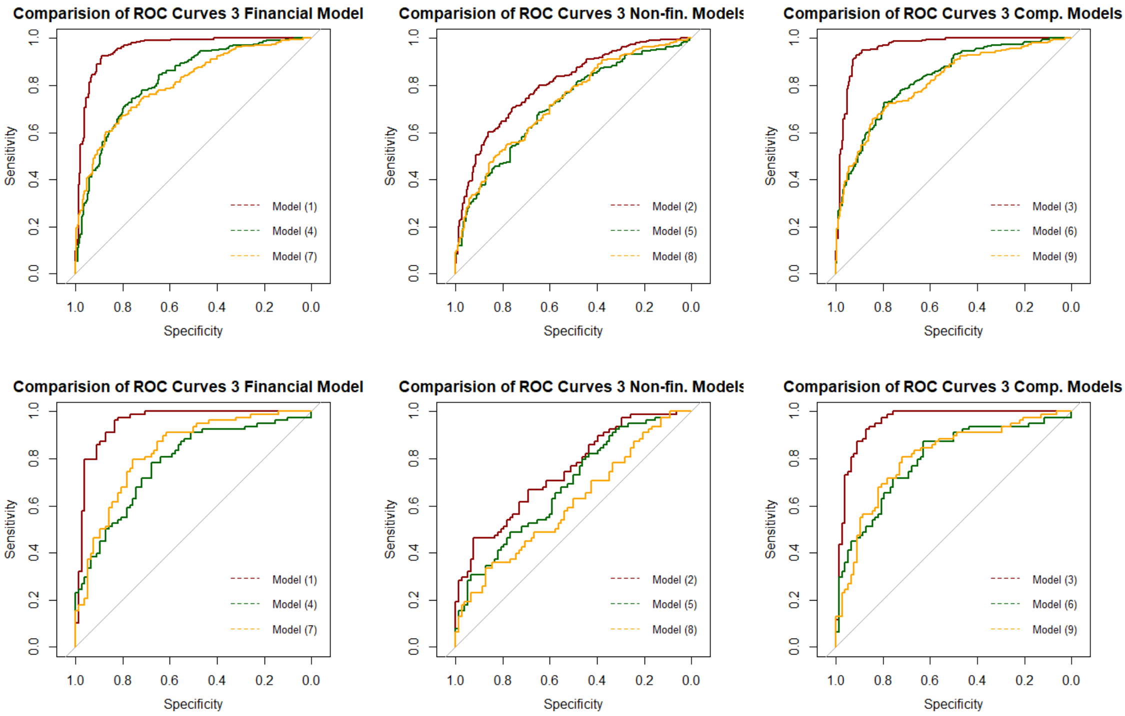
Figure 2. Comparison of ROC curves over year T-1, T-2, and T-3. Each figure shows the ROC curve for three models in each year. The first row is ROC curves based on the training dataset and the second row is ROC curves based on the hold-out test dataset. Model (1), (4) and (7) consist of only financial indicators, model (2), (5) and (8) consist of only non-financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators. The first row shows the figures for training data and the second row shows the figures for test data.



Note: All the company data is collected from the Wind Financial Terminal and annual reports.

Figure 3 further showed the comparison of ROC curves of each kind of model with similar independent variables in different predicting years based on training dataset from 2010 to 2018 and hold-out test dataset from 2019 to 2020. Almost all the figures showed that there are significant decreases of the predicting performance when we advanced the predicting year from year T-1 to year T-2, but only small decreases or even a slight increase of prediction performance is observed from year T-2 to year T-3. Consistent with the ROC curves, almost all the AUC values of each model show a sharp decrease from year T-1 to year T-2 but do not display considerable change when the prediction horizon is advanced from year T-2 to year T-3. The ROC curves and AUC values of each model further confirmed the conclusion that the change of financial distress characteristic is not linear and the level of predicting difficulty increases sharply from year T-1 to year T-2 but remains high between year T-2 and year T-3.

Figure 3. Comparison of ROC curves for different models. Each figure shows the ROC curve for the same model in year T-1, T-2, and T-3. The first role is ROC curves based on the training dataset and the second role is ROC curves based on the hold-out test dataset. Model (1), (4) and (7) consist of only financial indicators, model (2), (5) and (8) consist of only non-financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators. The first row shows the figures for training data and the second row shows the figures for test data.



Note: All the company data is collected from the Wind Financial Terminal and annual reports.

5.4.3. Classification cutpoints analysis

As discussed in the previous section, a lot of prior research on classification problems using LR model set the classification cutpoint as 0.5 since 0.5 is the middle point of the range of the predicted event probabilities (from 0 to 1) and the logistic function is asymmetry with 0.5. In this paper, we further considered the cost of misclassification and set the cutpoint as 0.4 because the cost of misclassifying a distressed company as a healthy company exceeds the cost of misclassifying a healthy company as a distressed company. In another word, we value the specificity over the sensitivity of the model. In this section, we test the prediction results on the accuracy, type I error and type II error based on the hold-out test dataset by setting the cutpoints to be 0.3. 0.4, and 0.5, respectively. This analysis is also important and useful for risk managers or investors to develop a better understanding of the model's performance at different cutpoints.

Table 16 showed the evaluation metrics of 9 models with cutpoints as 0.3, 0.4 and 0.5. Most of the prediction performance rankings of 3 sets of models still hold with different cutpoints. The financial models and comprehensive models are comparably good overall, but the performance of non-financial models is not acceptable. In prediction year T-3, the comprehensive model displays a slightly better accuracy than financial models with a cutpoint of 0.5. The reason is that the increase the type II error of the model (7) is larger than the model (9) but the decrease of type I error of the model (7) is smaller. Comparing the accuracy and the two types of error showed in *Table 16*, we found that the overall accuracy of the 3 models did not change a lot with different cutpoints in each year. However, the type I errors decreased, and the type II errors of the models increased correspondingly with the cutpoint increasing from 0.3 to 0.4 and further to 0.5 in each prediction year. Therefore, different cutpoints around 0.5 do not significantly influence the accuracy of the model but may have an impact on the sensitivity and specificity of the models in this paper. The selection of cutpoints is a trade-off between type I error and type II error. We further found that the cutpoint of 0.4 seems to well balance these two kinds of error, though under this circumstance the result tends to control the type II error. However, it is reasonable since the cost of type II error is more expensive than the type I error. We further verified that our selection of 0.4 as the cutpoint in this paper is reasonable and will lead to good classification results.

Table 16. Classification accuracy tables with different cutpoints. Classification accuracy tables with different cutpoints. The table shows the models' performance on the hold-out test dataset with different cutpoints. Panel A shows the performance on the hold-out test dataset with a cutpoint of 0.3. Panel B shows the performance on the hold-out test dataset with a cutpoint of 0.4. Panel C shows the models' performance on the hold-out test dataset with a cutpoint of 0.5. Accuracy, Type I Error and Type II Error are presented for each model. The hold-out test dataset consists of 78 financial distress listed companies and 78 healthy listed companies in the Chinese manufacturing industry from 2019 to 2020. Model (1), (4) and (7) consist of only financial indicators, model (2), (5) and (8) consist of only non-financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators.

	T-1			T-2			T-3		
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: models' performance on the hold-out test dataset, cutpoint 0.3									
Accuracy	0.872	0.731	0.891	0.718	0.590	0.724	0.763	0.551	0.692
Type I Error	0.167	0.192	0.154	0.372	0.769	0.346	0.346	0.744	0.462
Type II Error	0.090	0.346	0.064	0.192	0.051	0.205	0.128	0.154	0.154
Panel B: models' performance on the hold-out test dataset, cutpoint 0.4									
Accuracy	0.872	0.641	0.891	0.705	0.609	0.731	0.763	0.596	0.731
Type I Error	0.154	0.564	0.115	0.256	0.526	0.244	0.244	0.382	0.333
Type II Error	0.103	0.154	0.103	0.333	0.256	0.295	0.231	0.423	0.205
Panel C: models' performance on the hold-out test dataset, cutpoint 0.5									
Accuracy	0.872	0.641	0.872	0.692	0.603	0.692	0.731	0.558	0.744
Type I Error	0.128	0.487	0.128	0.231	0.308	0.179	0.192	0.256	0.218
Type II Error	0.128	0.231	0.128	0.385	0.487	0.436	0.346	0.628	0.295

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

5.4.4. Model validation

In order to further validate the model performance, the whole training dataset was divided into 3 sub-periods, 2010 to 2012, 2013 to 2015 and 2016 to 2018. The reason why we chose 2012 and 2015 as the cutpoints are because, at the end of 2012 and the end of 2015, the CSRC improved the delisting regulation and introduced some additional rules for forced delisting due to unsatisfying financial performance. The “full” financial models and the “full” comprehensive models were applied to the sub-datasets to test whether the predicting performance remains acceptable as measured by the AUC, accuracy, type I error, and type II error. Additionally, financial models and comprehensive models in each year are tested to confirm the conclusion that including non-financial indicators will improve the predicting performance in year T-1 and T-2.

Table 17. Model validation. The table shows the prediction performance of two sets of models on sub-datasets in year T-1, T-2 and T-3. Model (1), (4) and (7) consist of only financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators. Panel A shows the models’ performance based on a sub-dataset of training data consisting of 102 companies from 2010 to 2012. Panel B shows the models’ performance based on a sub-dataset of training data consisting of 144 companies from 2013 to 2015. Panel C shows the models’ performance based on a sub-dataset of training data consisting of 222 companies from 2016 to 2018. The AUC value, overall accuracy, Type I Error and Type II Error are presented.

	T-1		T-2		T-3	
Measure	(1)	(3)	(4)	(6)	(7)	(9)
Panel A: models' performance on sub-dataset 1 from 2010 to 2012, n=102						
AUC	0.948	0.950	0.816	0.838	0.780	0.784
Accuracy	0.843	0.853	0.706	0.755	0.667	0.667
Type I Error	0.255	0.235	0.451	0.392	0.471	0.490
Type II Error	0.059	0.059	0.137	0.098	0.196	0.176
Panel B: models' performance on sub-dataset 2 from 2013 to 2015, n=144						
AUC	0.976	0.976	0.841	0.842	0.790	0.818
Accuracy	0.938	0.907	0.736	0.743	0.667	0.708
Type I Error	0.097	0.097	0.306	0.292	0.375	0.333
Type II Error	0.028	0.090	0.222	0.222	0.292	0.250
Panel C: models' performance on sub-dataset 3 from 2016 to 2018, n=222						
AUC	0.943	0.951	0.814	0.816	0.828	0.828
Accuracy	0.869	0.878	0.734	0.730	0.761	0.748
Type I Error	0.207	0.180	0.315	0.315	0.252	0.306
Type II Error	0.054	0.063	0.216	0.225	0.225	0.198

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

As showed in *Table 17*, the overall performance of models based on 3 validation datasets remains satisfying. AUC values of financial and comprehensive models on the validation datasets are as good as those on the whole training dataset. Only the accuracy of model (7) and (9) show decreases on the sub-dataset 1 and sub-dataset 2, while other models remain similar accuracy levels in each year. Type II errors are also well controlled with the cutpoint of 0.4. In most of the cases, type I errors are also at the similar level as the results on the whole dataset in general. The type I errors of both the models on sub-dataset 1 are slightly higher in year T-2 and T-3, but the result is still acceptable as sensitivities are sacrificed for higher specificities. Both financial and the comprehensive models remain high predicting performance across the 3 years overall.

5.5. Robustness test

Several potential issues may influence the estimation of the logistic regression model and then affect the robustness of the model performance and the predicting results. In this section, model stability test, outlier test and multicollinearity test were performed to test the robustness of the prediction model.

5.5.1. Model stability test

In the previous model evaluation section, we found that the comprehensive models have slightly better prediction performance than financial models on both the training dataset and hold-out test dataset in year T-1 and year T-2, indicating that incorporating non-financial indicators in the financial models improves the models' predictive ability. However, the comprehensive model overperforms the financial model on the training dataset but adding non-financial indicators deteriorates the prediction power of the financial model on the hold-out test dataset in year T-3. In order to understand the disappearing improvement on the prediction performance of incorporating non-financial indicators on the test dataset in year T-3, we further re-estimated the 9 models using the same predictors as in *Table 13* based on the hold-out test dataset and checked whether the significant non-financial indicators still hold. 3 out of 5 indicators

As shown in *Table 18*, all the 9 models experience losses of statistically significant indicators when estimated on the hold-out dataset. In model (3) and model (6), there is still one non-financial indicator AO showing weak significance, but the only non-financial indicator AR in model (9) does not show statistical significance. Furthermore, the likelihood ratio test shows that the financial model (3) and (6) with non-financial indicator AO are better than the model (1) and (4) with only financial variables as predictors. However, the likelihood ratio test of model (9) shows there does not exist a significant improvement of the model (7). The result further suggests that the model (3) and (6) with non-financial indicator AO are relatively stable in year T-1 and year T-2 and incorporating non-financial indicators in the financial model (1) and (4) brings additional predictive power, but the model (9) is not stable as significant indicator AR on training dataset is not significant on the test dataset and adding non-financial indicators cannot improve the predictive ability of the financial model (7).

Table 18. Summary of stability test results for all models in year T-1, T-2, and T-3. The table reports results of logistic regression of the financial and non-financial indicators on the independent variable. The models were computed for 3 periods. Three sets of models are built based on the hold-out test dataset to test the stability of each model. The hold-out dataset consists of 78 financial distress listed companies and 78 healthy listed companies in the Chinese manufacturing industry from 2019 to 2020. Models (1), (4), and (7) consist of only financial indicators, models (2), (5), and (8) consist of only non-financial indicators and models (3), (6), and (9) consists of both financial and non-financial indicators. The absolute value of z-statistics is reported in parenthesis.

	T-1			T-2			T-3		
Indicator	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ROE	-5.304**		-4.363*				-0.854		-1.009
	(-2.487)		(-1.949)				(-0.551)		(-0.628)
FAT	0.042		0.026	0.010		0.010			
	(1.626)		(1.341)	(0.816)		(0.766)			
CAT	-0.561*		-0.409						
	(-1.645)		(-1.102)						
CRR			-4.765	-5.276*		-5.837**	-11.331***		-11.406***
			(-1.591)	(-1.89)		(-1.988)	(-3.088)		(-3.109)
FAR			-3.320**	-3.608***		-4.060***	-2.714***		-2.606***
			(-2.404)	(-3.808)		(-3.959)	(-2.884)		(-2.727)
DIV	-3.538***		-3.231***	-1.292***		-1.046**	-1.450***		-1.526***
	(-5.639)		(-4.562)	(-3.252)		(-2.533)	(-3.284)		(-3.363)
INNO	-5.390			-4.978		-2.500			
	(-1.226)			(-1.18)		(-0.577)			
MVTL					-0.018			-0.022*	
					(-1.464)			(-1.894)	
T10		-2.404*			-2.191*			-2.643*	
		(-1.892)			(-1.918)			(-2.343)	
II			-0.716						
			(-0.479)						
CEOC		0.250							
		(0.583)							
AO		-3.308***	-2.012*		-2.224**	-2.028*		-1.537	
		(-3.164)	(-1.694)		(-2.056)	(-1.736)		(-1.378)	
AR		0.635	0.190		0.037	-0.672		0.239	0.419
		(1.013)	(0.286)		(0.086)	(-1.51)		(0.55)	(0.979)
ANAC		-0.223**			-0.102**			-0.032	
		(-2.151)			(-2.054)			(-0.628)	
Intercept	1.808***	4.426***	4.470***	2.552***	3.773***	4.860***	2.387***	3.147**	2.132***
	(3.074)	(3.519)	(2.816)	(4.713)	(3.09)	(3.711)	(4.613)	(2.494)	(3.711)
ACI	106.412	181.726	103.936	178.174	206.561	175.720	164.835	212.042	165.857
Pseudo R^2	0.563	0.215	0.607	0.232	0.100	0.261	0.284	0.075	0.289
Pr(>Chisq)			0.050			0.040			0.324
LL Ratio			9.482**			6.457**			0.972

Note: * denotes significant at 10%, **denotes significant at 5% and *** denotes significant at 1%. All the company data is collected from the Wind Financial Terminal and annual reports.

5.5.2. Outliers and influential values

The values of outliers in the dataset deviate from normal values and their existence will lead to the higher corresponding statistical analysis error and then decrease the inaccurate estimation of coefficients in the prediction model. Therefore, we first tested the outliers using Cook's distance. The higher the Cook's distance, the higher likelihood the observation is an influential outlier. As shown in *Figure 4* in the Appendix, in each model, some outliers were identified with high Cook's distance. However, not all outliers are influential observations. To check whether the data of each model contain potential influential observations, we further inspected and plotted the standardized residual error of each observation. Data points with an absolute standardized residual above 3 indicate possible influential outlier and may need further attention. *Figure 5* in the Appendix showed that all the data points have absolute standardized residuals lower than 3, indicating no significant influential value exists in these models.

Table 19. Comparison of the performance of models estimated on the winsorized and original training dataset. The table shows the prediction performance of models based on both training and hold-out dataset, respectively. Panel A and B show the performance of the winsorized models based on the training dataset and hold-out test dataset, respectively. Panel C and D show the performance of the original models based on the training dataset and hold-out test dataset. Both AUC and accuracy are presented in the table. Model (1), (4) and (7) consist of only financial indicators, model (2), (5) and (8) consist of only non-financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators.

	T-1			T-2			T-3		
Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: models' performance on training dataset, models trained on winsorized dataset									
AUC	0.953	0.827	0.957	0.844	0.748	0.847	0.828	0.756	0.834
Accuracy	0.889	0.722	0.893	0.778	0.673	0.778	0.748	0.688	0.744
Panel B: models' performance on hold-out test dataset, models trained on winsorized dataset									
AUC	0.935	0.765	0.940	0.693	0.714	0.700	0.749	0.643	0.737
Accuracy	0.859	0.673	0.872	0.654	0.680	0.654	0.744	0.596	0.724
Panel C: models' performance on training dataset, models trained on original dataset									
AUC	0.954	0.803	0.959	0.822	0.716	0.829	0.805	0.728	0.815
Accuracy	0.885	0.699	0.894	0.729	0.645	0.739	0.712	0.650	0.718
Panel D: models' performance on hold-out test dataset, models trained on original dataset									
AUC	0.947	0.745	0.954	0.779	0.682	0.796	0.829	0.607	0.791
Accuracy	0.872	0.641	0.891	0.705	0.609	0.731	0.763	0.596	0.731

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

In order to double-check that the outliers do not influence the quality of the logistic regression model. We further performed the winsorize process on the continuous variables in the sample dataset. We first identified the data points which fall below the

1% quantile or above the 99% quantile of the data as the outliers, and then substituted the lowest 1% and the highest 1% outliers with the data just falling on the 1% quantile and the 99% quantile of the dataset. The winsorized training dataset is used to estimate the models and the results including AUC and accuracy metrics were compared with the performance of models estimated on the original sample dataset. *Table 19* showed that there exists no significant difference between the performance of models trained on the winsorized dataset and the original dataset. The comparison further indicated that the outliers do significantly affect the quality of the predicting models.

5.5.3. Multicollinearity

Logistic regression models are sensitive to the multicollinearity problem. This paper considered the multicollinearity issues and cautiously considered which indicator should be included in the model using the covariance matrices to control the multicollinearity of the models. In this section, we further test multicollinearity by examining Variance Inflation Factors (VIF). VIF of an independent variable represents how well the variable is explained by other covariates and it quantifies the severity of multicollinearity. The higher the VIF, the more serious the effect of multicollinearity. A rule of thumb is that the multicollinearity of the model is problematic if a VIF value exceeds 5 and some authors suggest a more conservative level of 2.5. The VIF test results are present in *Table 29* in the Appendix and it shows that most models have VIF values lower than 1.5, but the VIF of CR and MVTL in the model (3) and (9) are higher than 2.5 and there exist multicollinearity in the model (3) and (9). Thus, we eliminated the CR and MVTL variables in these 2 models and estimated the models again. We further tested the VIF values of adjusted model (3) and (9) and found that the VIF values of them are lower than 1.5 after adjustment. Therefore, we concluded that our predicting models are not materially affected by multicollinearity.

6. Conclusions

This study aims to build timely and practical financial distress prediction models specific to the Chinese manufacturing industry traced back as earliest as 3 years prior to the financial distress. Besides, this paper also proposes to test the predictive power of non-financial indicators and whether incorporating non-financial indicators in the financial distress prediction models with only financial indicators can bring additional predictive power and improve the prediction performance.

To address the research questions, this paper first defined the financial distress in the Chinese market and then collected both financial data and non-financial data of financial distress companies as well as matching healthy companies from 2010 to 2020. The financial data covers solvency, profitability, operation, cash flow, and other financial information such as fixed asset ratio, dividend payout, and innovation investment. Non-financial data includes capital market, ownership structure, corporate governance, and external non-financial information such as listed stock exchange, external audit opinion, and analyst coverage. Then this paper applied statistical methods to identify indicators with strong discriminating power and to control collinearity, and finally selected 9 financial indicators and 7 non-financial indicators as the independent variables of the predicting models. This paper further used stepwise logistic regression to build 3 sets of models, financial models with only financial indicators, non-financial models with only non-financial indicators, and comprehensive models with both financial and non-financial indicators for each of the 3 prediction horizons. Finally, the prediction performance of the 3 models is compared in each year to identify the predictive power of non-financial indicators and to conclude whether incorporating non-financial indicators can bring additional predictive power and improve the prediction performance.

Through the theoretical and empirical analysis, this paper drew 4 conclusions.

First, non-financial indicators show significant differences between financial distress and healthy companies and show statistical significance in the logistic regression models on the training dataset from 2010 to 2018. The results indicate that companies with a higher market value of total shares over total liabilities, top 10 shareholder holding rate, institutional investor holding rate, analyst rating, have a lower likelihood of falling into financial distress. Companies with standard unqualified audit opinions, more analyst coverage and without CEO change are less likely to fall into financial distress.

Second, incorporating non-financial indicators in the financial models improves the predictive performance in year T-1 and year T-2, but does not work in year T-3. Non-financial indicators bring additional predictive power to the financial models in year T-1 and year T-2, but the comprehensive model with the only non-financial indicator analyst rating (AR) is not stable in year T-3 as the variable AR does not show significance on the hold-out test dataset.

Third, this paper successfully built effective financial distress prediction models in year T-1, T-2, and T-3. The prediction model in year T-1 is a comprehensive model with financial indicators ROE, FAT, CAT, CRR, FAR, DIV and non-financial indicators II, AO, AR as independent variables. The prediction model in year T-2 is also a comprehensive model with financial indicators FAT, CRR, FAR, DIV, INNO and non-financial indicators AO, AR as independent variables. The prediction model in year T-3 is a financial model with only financial indicators ROE, CRR, FAR, DIV as independent variables. All the variables have negative signs in each model except FAT. The prediction accuracy on the hold-out dataset record 89.1%, 73.1% and 76.3% in year T-1, T-2, and T-3.

Forth, most indicators in foreign studies also work well in the Chinese market though the definitions of financial distress are different. Traditional financial indicators such as ROE, FAT, CRR and FAR, and non-financial indicators MVTL, T10, CEOC, and AO in previous studies also show effective predictive abilities in this study. Besides, DIV used by Dietrich and Kaplan (1982), INNO used by Bai and Tian (2020), AR used by Moses (1990) on the US market also display significance in Chinese market. Furthermore, we also found that non-financial indicators institutional holding ratio (II) and analyst coverage (ANAC) also show predictive power in this study.

This paper contributes to the existing literature in 3 aspects.

First, unlike other studies on Chinese market which directly used ST or *ST as financial distress, this study delved into the definitions and found the relationship between the financial distress definition in China and definitions widely used in other countries. We found that the legal definition of financial distress is not applicable in China due to limited bankruptcy cases. Besides, directly applying the definition in Ross et al. (1995) does not work well neither because their definition is more on company bankruptcy while this study focused on the financial distress. Though ST and *ST focus more on the profitability, we found that most ST or *ST companies also suffer from illiquidity and insolvency, which are emphasized in the comprehensive definition. By linking the definition of ST and *ST with the comprehensive definition, we further underpin the rationale of using the ST and *ST as financial distress in Chinese studies.

Second, this study successfully built well-performing and easily applicable financial distress prediction models focusing on companies in the Chinese manufacturing industry as earliest as 3 years prior to the happening of financial distress. The models with the latest and well-rounded data can yield accurate predicting results and provide a solid reference for investors to avoid company financial distress risks in practice. The model is also easy to use as the logistic regression model will directly yield a value which can be interpreted as probability of financial distress. These models can also be used by rating companies in credit or corporate bond ratings. Government or regulators can also take advantage of these models to better set boundaries and limitations to capital market operations of companies with higher financial distress risk and to alert the financial distress risk to protect private investors.

Third, previous studies in the field of financial distress prediction targeting on Chinese market usually directly relied on the independent variables used in previous research works without any explanation. However, this study combined the practical experience with the previous research to preselect independent variables with a wide coverage of solvency, profitability, operation, cash flow and capital market, ownership structure, corporate governance, etc. Then it applied statistical procedure to select the independent variables with the highest contribution to the overall performance of the models. Furthermore, unlike most studies before, this study explained the reasons for using each retained variable in the final models.

We acknowledge that study has some limitations. First, as our study is based on a sample of Chinese manufacturing companies from 2010 to 2020 and same value of indicators in different industries can have totally different meanings, the prediction models are only applicable to Chinese manufacturing companies and the generalization ability of the models to other industries is limited. Second, as annual reports have the most complete information, in this paper, all the financial and non-financial data are collected based on annual reports. However, as Chinese listed companies release the annual reports around the April of the following year, only last year's annual reports can be used in prediction. Thus, the data may have problems in lagging to reflect the latest information. Third, since this study is designed to use matched dataset on the annual level, the macroeconomic indicators are not appropriate to be included in the predicting models and thus we did not analyze the predictive power of macroeconomic indicators. Fourth, although this paper built well-performed prediction models with prediction accuracy up to 89.1% and AUC up to 0.954 on hold-out test dataset in year T-1, this paper did not try to apply the selected indicators with other modeling techniques such as MDA, support vector machine and neural network to analyze whether the prediction performance can be significantly improved.

We also have numerous suggestions for further studies within the field of financial distress prediction. First, data from quarterly reports can be adopted in building prediction models as quarterly data will bring timely information. Besides, as the financial distress prediction may be required anytime, using the latest quarterly data may bring better results than using annual data. Second, as some studies have concluded that macroeconomic information also plays certain roles in improving the prediction performance (Zhang and Wu, 2005; Tinoco and Wilson, 2013), future studies on the Chinese market can also include new macroeconomic indicators in the prediction models. Third, modeling techniques other than logistic regression can also be applied with the selected indicators to test whether the conclusion that non-financial indicators can improve the prediction performance in year T-1 and T-2 still holds in different models. Fourth, we identified a sharp drop in prediction accuracy between year T-1 and year T-2 and that the prediction performance of models changes in a nonlinear pattern. Analysis of the changing pattern of prediction performance will also be an interesting topic.

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Appendix

Table 20. Results of Kolmogorov-Smirnov (K-S) test. The table shows the result of K-S test for all preselected indicators on the cumulative distribution function (CDF) of normal distribution based on the training dataset in year T-1. The training dataset consists of 234 financial distress listed companies and 234 healthy listed companies in Chinese manufacturing industry from 2010 to 2018.

	Financial Distress Companies		Healthy Companies	
Indicator	D Statistic	P value	D Statistic	P value
CR	0.141	0.000***	0.141	0.000***
QR	0.159	0.000***	0.129	0.001***
DAR	0.063	0.304	0.045	0.722
ICR	0.128	0.001***	0.167	0.000***
OM	0.148	0.000***	0.126	0.001***
ROE	0.122	0.002***	0.149	0.000***
ROA	0.053	0.532	0.091	0.042**
CEPM	0.149	0.000***	0.136	0.000***
EPS	0.074	0.153	0.132	0.001***
RT	0.17	0.000***	0.186	0.000***
FAT	0.168	0.000***	0.119	0.003***
CAT	0.131	0.001***	0.101	0.016**
WC	0.069	0.213	0.068	0.23
PQ	0.072	0.181	0.076	0.138
NOCFCL	0.055	0.488	0.114	0.004***
NOCFL	0.065	0.275	0.105	0.011**
SCFR	0.072	0.181	0.075	0.139
CRR	0.045	0.74	0.045	0.731
SR	0.058	0.401	0.07	0.202
FAR	0.067	0.244	0.046	0.708
INNO	0.235	0.000***	0.175	0.000***
MVTL	0.199	0.000***	0.172	0.000***
MVTTL	0.217	0.000***	0.157	0.000***
RE	0.097	0.023**	0.074	0.151
TR	0.087	0.057*	0.118	0.003***
VO	0.091	0.04**	0.124	0.002***
T10	0.042	0.794	0.045	0.737
SOS	0.167	0.000***	0.235	0.000***
II	0.055	0.475	0.069	0.212
ID	0.246	0.000***	0.309	0.000***
ANAC	0.258	0.000***	0.205	0.000***

Note: * denotes significant at 10%, **denotes significant at 5% and *** denotes significant at 1%. All the company data is collected from the Wind Financial Terminal and annual reports.

Table 21. Results of Kolmogorov-Smirnov (K-S) test. The table shows the result of K-S test for all preselected indicators on the cumulative distribution function (CDF) of normal distribution based on the training dataset in year T-2. The training dataset consists of 234 financial distress listed companies and 234 healthy listed companies in Chinese manufacturing industry from 2010 to 2018.

	Financial Distress Companies		Healthy Companies	
Indicator	D Statistic	P value	D Statistic	P value
CR	0.145	0.000***	0.14	0.000***
QR	0.135	0.000***	0.147	0.000***
DAR	0.053	0.535	0.043	0.782
ICR	0.166	0.000***	0.173	0.000***
OM	0.107	0.01**	0.123	0.002***
ROE	0.186	0.000***	0.119	0.003***
ROA	0.103	0.014**	0.096	0.026**
CEPM	0.148	0.000***	0.207	0.000***
EPS	0.215	0.000***	0.222	0.000***
RT	0.17	0.000***	0.19	0.000***
FAT	0.166	0.000***	0.143	0.000***
CAT	0.138	0.000***	0.114	0.005***
WC	0.05	0.614	0.049	0.627
PQ	0.083	0.081*	0.061	0.358
NOCFCL	0.071	0.185	0.09	0.044**
NOCFL	0.053	0.52	0.074	0.15
SCFR	0.083	0.081*	0.06	0.36
CRR	0.041	0.83	0.043	0.777
SR	0.063	0.306	0.051	0.567
FAR	0.054	0.506	0.047	0.676
INNO	0.257	0.000***	0.277	0.000***
MVTL	0.176	0.000***	0.177	0.000***
MVTTL	0.157	0.000***	0.154	0.000***
RE	0.128	0.001***	0.115	0.004***
TR	0.112	0.006***	0.119	0.003***
VO	0.096	0.026**	0.102	0.015**
T10	0.044	0.767	0.055	0.489
SOS	0.162	0.000***	0.225	0.000***
II	0.064	0.298	0.085	0.069*
ID	0.309	0.000***	0.29	0.000***
ANAC	0.279	0.000***	0.203	0.000***

Note: * denotes significant at 10%, **denotes significant at 5% and *** denotes significant at 1%. All the company data is collected from the Wind Financial Terminal and annual reports.

Table 22. Results of Kolmogorov-Smirnov (K-S) test. The table shows the result of K-S test for all preselected indicators on the cumulative distribution function (CDF) of normal distribution based on the training dataset in year T-3. The training dataset consists of 234 financial distress listed companies and 234 healthy listed companies in Chinese manufacturing industry from 2010 to 2018.

	Financial Distress Companies		Healthy Companies	
Indicator	D Statistic	P value	D Statistic	P value
CR	0.152	0.000***	0.168	0.000***
QR	0.155	0.000***	0.149	0.000***
DAR	0.053	0.515	0.058	0.42
ICR	0.074	0.151	0.205	0.000***
OM	0.122	0.002***	0.077	0.124
ROE	0.152	0.000***	0.057	0.436
ROA	0.112	0.006***	0.061	0.357
CEPM	0.124	0.001***	0.126	0.001***
EPS	0.116	0.004***	0.119	0.003***
RT	0.154	0.000***	0.192	0.000***
FAT	0.165	0.000***	0.129	0.001***
CAT	0.134	0.000***	0.103	0.014**
WC	0.055	0.485	0.072	0.178
PQ	0.088	0.055*	0.054	0.504
NOCFCL	0.058	0.414	0.108	0.009***
NOCFL	0.059	0.383	0.121	0.002***
SCFR	0.088	0.055*	0.054	0.505
CRR	0.058	0.403	0.046	0.708
SR	0.068	0.223	0.074	0.152
FAR	0.054	0.508	0.066	0.259
INNO	0.26	0.000***	0.295	0.000***
MVTL	0.183	0.000***	0.153	0.000***
MVTTL	0.17	0.000***	0.156	0.000***
RE	0.112	0.005***	0.078	0.119
TR	0.089	0.05*	0.085	0.069*
VO	0.097	0.025**	0.101	0.018**
T10	0.036	0.919	0.077	0.129
SOS	0.212	0.000***	0.263	0.000***
II	0.094	0.032**	0.113	0.005***
ID	0.293	0.000***	0.295	0.000***
ANAC	0.288	0.000***	0.195	0.000***

Note: * denotes significant at 10%, **denotes significant at 5% and *** denotes significant at 1%. All the company data is collected from the Wind Financial Terminal and annual reports.

Table 23. Correlation matrix. The table shows the correlation matrix of all the preselected variables in year T-1. It includes financial indicators including solvency index, profitability index, operation index, cash flow index and other financial index, and non-financial indicators including capital market index, ownership index, governance index and external non-financial index.

T-1	CR	QR	DAR	ICR	OM	ROE	ROA	CEPM	EPS	FT	CAT	WC	PQ	NOCFCL	NOCFL	SCFR	CRR	SR	FAR	DIV	INNO	MVTL	MVTTL	GDP	IAV	LPR	T10	II	CEOC	AO	AR	ANAC
CR	1	0.933	-0.793	0.162	0.343	0.406	0.281	0.353	0.386	0.281	-0.357	0.929	0.031	0.124	0.115	0.031	0.013	0.031	0.792	0.358	0.279	0.682	0.643	-0.101	-0.082	-0.041	0.124	-0.074	-0.055	0.178	0.047	0.033
QR	0.933	1	-0.756	0.177	0.381	0.416	0.316	0.394	0.396	0.27	-0.286	0.851	0.093	0.175	0.161	0.093	0.071	0.092	0.729	0.381	0.275	0.634	0.597	-0.121	-0.105	-0.064	0.149	-0.058	-0.066	0.162	0.075	0.052
DAR	-0.793	-0.756	1	-0.191	-0.395	-0.486	-0.301	-0.397	-0.445	-0.117	0.171	-0.751	-0.167	-0.235	-0.245	-0.167	-0.159	-0.174	-0.911	-0.36	-0.224	-0.733	-0.679	0.135	0.125	0.073	-0.14	0.061	0.121	-0.199	-0.061	-0.056
ICR	0.162	0.177	-0.191	1	0.738	0.728	0.809	0.751	0.706	0.306	0.202	0.182	0.276	0.317	0.321	0.276	0.313	0.283	0.139	0.619	0.03	0.108	0.072	0.025	0.028	0.011	0.153	0.094	-0.179	0.181	0.288	0.326
OM	0.343	0.381	-0.395	0.738	1	0.82	0.875	0.95	0.795	0.378	0.22	0.337	0.359	0.393	0.394	0.359	0.369	0.358	0.337	0.674	0.085	0.243	0.19	0.053	0.072	0.083	0.245	0.156	-0.171	0.22	0.346	0.399
ROE	0.406	0.416	-0.486	0.728	0.82	1	0.891	0.84	0.907	0.361	0.138	0.461	0.311	0.368	0.372	0.311	0.358	0.321	0.43	0.699	0.102	0.278	0.221	0.039	0.054	0.053	0.269	0.159	-0.178	0.278	0.356	0.427
ROA	0.281	0.316	-0.301	0.809	0.875	0.891	1	0.897	0.86	0.36	0.218	0.299	0.347	0.421	0.427	0.347	0.41	0.356	0.253	0.682	0.056	0.187	0.143	0.079	0.094	0.087	0.205	0.145	-0.174	0.256	0.361	0.418
CEPM	0.353	0.394	-0.397	0.751	0.95	0.84	0.897	1	0.814	0.361	0.187	0.351	0.345	0.381	0.381	0.345	0.36	0.353	0.354	0.661	0.112	0.271	0.219	0.027	0.048	0.066	0.234	0.134	-0.185	0.251	0.353	0.395
EPS	0.386	0.396	-0.445	0.706	0.795	0.907	0.86	0.814	1	0.368	0.112	0.423	0.28	0.353	0.358	0.28	0.329	0.291	0.39	0.698	0.108	0.326	0.269	0.027	0.041	0.049	0.214	0.107	-0.156	0.277	0.345	0.453
FT	0.281	0.27	-0.117	0.306	0.378	0.361	0.36	0.361	0.368	1	0.206	0.372	-0.062	0	0.018	-0.062	0.002	-0.084	0.087	0.289	0.016	0.14	0.127	0.07	0.08	0.064	0.081	0.004	-0.018	0.095	0.183	0.161
CAT	-0.357	-0.286	0.171	0.202	0.22	0.138	0.218	0.187	0.112	0.206	1	-0.371	0.148	0.238	0.231	0.148	0.291	0.137	-0.192	0.076	-0.304	-0.269	-0.291	0.159	0.158	0.204	0.082	0.151	-0.057	0.041	0.044	0.126
WC	0.929	0.851	-0.751	0.182	0.337	0.461	0.299	0.351	0.423	0.372	-0.371	1	0.021	0.097	0.096	0.021	0.004	0.019	0.762	0.37	0.287	0.604	0.57	-0.083	-0.065	-0.034	0.152	-0.057	-0.045	0.226	0.091	0.073
PQ	0.031	0.093	-0.167	0.276	0.359	0.311	0.347	0.345	0.28	-0.062	0.148	0.021	1	0.86	0.846	1	0.88	0.985	0.109	0.235	0.07	0.031	0.008	0.04	0.027	-0.02	0.113	0.07	-0.104	0.078	0.115	0.16
NOCFCL	0.124	0.175	-0.235	0.317	0.393	0.368	0.421	0.381	0.353	0	0.238	0.097	0.86	1	0.98	0.86	0.915	0.855	0.17	0.322	0.06	0.109	0.077	0.037	0.026	0.011	0.146	0.055	-0.164	0.127	0.147	0.192
NOCFL	0.115	0.161	-0.245	0.321	0.394	0.372	0.427	0.381	0.358	0.018	0.231	0.096	0.846	0.98	1	0.846	0.92	0.843	0.189	0.33	0.077	0.127	0.09	0.036	0.025	0.011	0.154	0.048	-0.171	0.126	0.152	0.189
SCFR	0.031	0.093	-0.167	0.276	0.359	0.311	0.347	0.345	0.28	-0.062	0.148	0.021	1	0.86	0.846	1	0.88	0.985	0.109	0.235	0.07	0.031	0.008	0.04	0.027	-0.02	0.113	0.07	-0.104	0.078	0.115	0.16
CRR	0.013	0.071	-0.159	0.313	0.369	0.358	0.41	0.36	0.329	0.002	0.291	0.004	0.88	0.915	0.92	0.88	1	0.877	0.114	0.284	0.043	0.027	0	0.065	0.047	-0.001	0.134	0.079	-0.149	0.101	0.163	0.2
SR	0.031	0.092	-0.174	0.283	0.358	0.321	0.356	0.353	0.291	-0.084	0.137	0.019	0.985	0.855	0.843	0.985	0.877	1	0.117	0.243	0.076	0.031	0.007	0.027	0.014	-0.037	0.121	0.073	-0.107	0.08	0.116	0.162
FAR	0.792	0.729	-0.911	0.139	0.337	0.43	0.253	0.354	0.39	0.087	-0.192	0.762	0.109	0.17	0.189	0.109	0.114	0.117	1	0.339	0.233	0.675	0.626	-0.08	-0.071	-0.023	0.137	-0.072	-0.124	0.228	0.034	0.041
DIV	0.358	0.381	-0.36	0.619	0.674	0.699	0.682	0.661	0.698	0.289	0.076	0.37	0.235	0.322	0.33	0.235	0.284	0.243	0.339	1	0.176	0.215	0.156	-0.067	-0.058	-0.005	0.233	0.142	-0.156	0.245	0.327	0.335
INNO	0.279	0.275	-0.224	0.03	0.085	0.102	0.056	0.112	0.108	0.016	-0.304	0.287	0.07	0.06	0.077	0.07	0.043	0.076	0.233	0.176	1	0.204	0.159	-0.37	-0.341	-0.172	0.131	-0.076	-0.064	0.156	0.176	0.091
MVTL	0.682	0.634	-0.733	0.108	0.243	0.278	0.187	0.271	0.326	0.14	-0.269	0.604	0.031	0.109	0.127	0.031	0.027	0.031	0.675	0.215	0.204	1	0.949	-0.211	-0.224	-0.268	0.011	-0.112	-0.057	0.084	0.043	-0.003
MVTTL	0.643	0.597	-0.679	0.072	0.19	0.221	0.143	0.219	0.269	0.127	-0.291	0.57	0.008	0.077	0.09	0.008	0	0.007	0.626	0.156	0.159	0.949	1	-0.174	-0.191	-0.265	-0.184	-0.174	-0.032	0.06	0.011	-0.045
GDP	-0.101	-0.121	0.135	0.025	0.053	0.039	0.079	0.027	0.027	0.07	0.159	-0.083	0.04	0.037	0.036	0.04	0.065	0.027	-0.08	-0.067	-0.37	-0.211	-0.174	1	0.978	0.644	-0.057	-0.077	0.001	-0.057	-0.097	0.104
IAV	-0.082	-0.105	0.125	0.028	0.072	0.054	0.094	0.048	0.041	0.08	0.158	-0.065	0.027	0.026	0.025	0.027	0.047	0.014	-0.071	-0.058	-0.341	-0.224	-0.191	0.978	1	0.743	-0.047	-0.055	0.018	-0.059	-0.077	0.113
LPR	-0.041	-0.064	0.073	0.011	0.083	0.053	0.087	0.066	0.049	0.064	0.204	-0.034	-0.02	0.011	0.011	-0.02	-0.001	-0.037	-0.023	-0.005	-0.172	-0.268	-0.265	0.644	0.743	1	0.012	-0.068	0.076	-0.055	-0.013	0.124
T10	0.124	0.149	-0.14	0.153	0.245	0.269	0.205	0.234	0.214	0.081	0.082	0.152	0.113	0.146	0.154	0.113	0.134	0.121	0.137	0.233	0.131	0.011	-0.184	-0.057	-0.047	0.012	1	0.454	-0.095	0.127	0.168	0.257
II	-0.074	-0.058	0.061	0.094	0.156	0.159	0.145	0.134	0.107	0.004	0.151	-0.057	0.07	0.055	0.048	0.07	0.079	0.073	-0.072	0.142	-0.076	-0.112	-0.174	-0.077	-0.055	-0.068	0.454	1	0.017	0.085	0.153	0.272
CEOC	-0.055	-0.066	0.121	-0.179	-0.171	-0.178	-0.174	-0.185	-0.156	-0.018	-0.057	-0.045	-0.104	-0.164	-0.171	-0.104	-0.149	-0.107	-0.124	-0.156	-0.064	-0.057	-0.032	0.001	0.018	0.076	-0.095	0.017	1	-0.175	0.027	-0.001
AO	0.178	0.162	-0.199	0.181	0.22	0.278	0.256	0.251	0.277	0.095	0.041	0.226	0.078	0.127	0.126	0.078	0.101	0.08	0.228	0.245	0.156	0.084	0.06	-0.057	-0.059	-0.055	0.127	0.085	-0.175	1	0.108	0.126
AR	0.047	0.075	-0.061	0.288	0.346	0.356	0.361	0.353	0.345	0.183	0.044	0.091	0.115	0.147	0.152	0.115	0.163	0.116	0.034	0.327	0.176	0.043	0.011	-0.097	-0.077	-0.013	0.168	0.153	0.027	0.108	1	0.534
ANAC	0.033	0.052	-0.056	0.326	0.399	0.427	0.418	0.395	0.453	0.161	0.126	0.073	0.16	0.192	0.189	0.16	0.2	0.162	0.041	0.335	0.091	-0.003	-0.045	0.104	0.113	0.124	0.257	0.272	-0.001	0.126	0.534	1

Table 24. Correlation matrix. The table shows the correlation matrix of all the preselected variables in year T-2. It includes financial indicators including solvency index, profitability index, operation index, cash flow index and other financial index, and non-financial indicators including capital market index, ownership index, governance index and external non-financial index.

T-2	CR	QR	DAR	ICR	OM	ROE	ROA	CEPM	EPS	FT	CAT	WC	PQ	NOCFCL	NOCFL	SCFR	CRR	SR	FAR	DIV	INNO	MVTL	MVTTL	GDP	IAV	LPR	T10	II	CEOC	AO	AR	ANAC
CR	1.000	0.915	-0.796	-0.037	0.410	0.172	0.139	0.397	0.256	0.265	-0.453	0.931	-0.036	0.106	0.114	-0.036	-0.060	-0.048	0.803	0.215	0.274	0.702	0.636	-0.070	-0.064	-0.048	0.149	-0.026	-0.133	0.148	0.039	0.017
QR	0.915	1.000	-0.758	-0.007	0.416	0.198	0.172	0.403	0.284	0.255	-0.363	0.847	-0.015	0.139	0.147	-0.015	-0.017	-0.015	0.749	0.242	0.309	0.660	0.591	-0.068	-0.068	-0.049	0.165	-0.034	-0.143	0.151	0.071	0.052
DAR	-0.796	-0.758	1.000	-0.075	-0.440	-0.149	-0.159	-0.413	-0.263	-0.092	0.242	-0.745	-0.095	-0.227	-0.251	-0.095	-0.082	-0.103	-0.918	-0.240	-0.227	-0.785	-0.711	0.038	0.045	0.018	-0.142	0.036	0.158	-0.189	-0.021	-0.006
ICR	-0.037	-0.007	-0.075	1.000	0.391	0.470	0.481	0.448	0.429	0.086	0.138	-0.007	0.144	0.157	0.151	0.144	0.147	0.148	0.033	0.233	-0.032	0.031	0.023	0.144	0.164	0.156	0.044	0.073	-0.026	0.060	0.119	0.224
OM	0.410	0.416	-0.440	0.391	1.000	0.707	0.714	0.827	0.723	0.243	-0.087	0.409	0.278	0.342	0.350	0.278	0.243	0.277	0.394	0.467	0.103	0.412	0.353	0.115	0.124	0.109	0.227	0.052	-0.097	0.194	0.294	0.358
ROE	0.172	0.198	-0.149	0.470	0.707	1.000	0.881	0.751	0.870	0.268	0.099	0.193	0.250	0.318	0.330	0.250	0.277	0.245	0.136	0.422	0.033	0.185	0.138	0.194	0.218	0.202	0.202	0.095	-0.010	0.084	0.311	0.415
ROA	0.139	0.172	-0.159	0.481	0.714	0.881	1.000	0.754	0.805	0.228	0.162	0.142	0.271	0.351	0.364	0.271	0.302	0.272	0.138	0.391	0.005	0.188	0.150	0.204	0.228	0.238	0.149	0.048	-0.002	0.103	0.245	0.360
CEPM	0.397	0.403	-0.413	0.448	0.827	0.751	0.754	1.000	0.757	0.145	-0.200	0.400	0.241	0.295	0.308	0.241	0.197	0.231	0.382	0.418	0.187	0.412	0.370	0.049	0.064	0.082	0.177	0.047	-0.077	0.142	0.225	0.286
EPS	0.256	0.284	-0.263	0.429	0.723	0.870	0.805	0.757	1.000	0.274	0.073	0.290	0.230	0.316	0.331	0.230	0.252	0.230	0.248	0.541	0.163	0.191	0.118	0.124	0.155	0.152	0.305	0.143	-0.028	0.154	0.333	0.421
FT	0.265	0.255	-0.092	0.086	0.243	0.268	0.228	0.145	0.274	1.000	0.150	0.378	-0.057	0.000	0.028	-0.057	0.014	-0.081	0.075	0.141	0.035	0.156	0.122	0.033	0.057	0.059	0.100	-0.013	-0.003	0.122	0.125	0.142
CAT	-0.453	-0.363	0.242	0.138	-0.087	0.099	0.162	-0.200	0.073	0.150	1.000	-0.464	0.173	0.252	0.237	0.173	0.333	0.190	-0.274	0.028	-0.263	-0.280	-0.297	0.170	0.201	0.195	0.062	0.091	0.051	0.049	0.068	0.143
WC	0.931	0.847	-0.745	-0.007	0.409	0.193	0.142	0.400	0.290	0.378	-0.464	1.000	-0.074	0.051	0.068	-0.074	-0.088	-0.090	0.770	0.228	0.282	0.636	0.572	-0.025	-0.019	0.000	0.178	-0.048	-0.119	0.140	0.067	0.052
PQ	-0.036	-0.015	-0.095	0.144	0.278	0.250	0.271	0.241	0.230	-0.057	0.173	-0.074	1.000	0.869	0.855	1.000	0.886	0.982	0.027	0.197	-0.004	0.067	0.048	0.093	0.085	0.055	0.111	0.031	-0.045	0.121	0.125	0.139
NOCFCL	0.106	0.139	-0.227	0.157	0.342	0.318	0.351	0.295	0.316	0.000	0.252	0.051	0.869	1.000	0.976	0.869	0.907	0.867	0.166	0.264	0.025	0.170	0.132	0.076	0.083	0.070	0.140	0.055	-0.100	0.123	0.158	0.211
NOCFL	0.114	0.147	-0.251	0.151	0.350	0.330	0.364	0.308	0.331	0.028	0.237	0.068	0.855	0.976	1.000	0.855	0.912	0.851	0.201	0.272	0.061	0.205	0.170	0.077	0.079	0.075	0.122	0.027	-0.104	0.131	0.160	0.201
SCFR	-0.036	-0.015	-0.095	0.144	0.278	0.250	0.271	0.241	0.230	-0.057	0.173	-0.074	1.000	0.869	0.855	1.000	0.886	0.982	0.027	0.197	-0.004	0.067	0.048	0.093	0.085	0.055	0.111	0.031	-0.045	0.121	0.125	0.139
CRR	-0.060	-0.017	-0.082	0.147	0.243	0.277	0.302	0.197	0.252	0.014	0.333	-0.088	0.886	0.907	0.912	0.886	1.000	0.882	0.029	0.225	-0.009	0.044	0.024	0.105	0.100	0.082	0.093	0.034	-0.051	0.112	0.151	0.184
SR	-0.048	-0.015	-0.103	0.148	0.277	0.245	0.272	0.231	0.230	-0.081	0.190	-0.090	0.982	0.867	0.851	0.982	0.882	1.000	0.033	0.209	0.012	0.071	0.047	0.085	0.072	0.051	0.123	0.039	-0.049	0.126	0.143	0.147
FAR	0.803	0.749	-0.918	0.033	0.394	0.136	0.138	0.382	0.248	0.075	-0.274	0.770	0.027	0.166	0.201	0.027	0.029	0.033	1.000	0.224	0.235	0.726	0.659	0.006	0.002	0.037	0.154	-0.045	-0.178	0.172	-0.007	-0.002
DIV	0.215	0.242	-0.240	0.233	0.467	0.422	0.391	0.418	0.541	0.141	0.028	0.228	0.197	0.264	0.272	0.197	0.225	0.209	0.224	1.000	0.212	0.107	0.027	-0.093	-0.071	-0.033	0.301	0.231	-0.066	0.185	0.324	0.330
INNO	0.274	0.309	-0.227	-0.032	0.103	0.033	0.005	0.187	0.163	0.035	-0.263	0.282	-0.004	0.025	0.061	-0.004	-0.009	0.012	0.235	0.212	1.000	0.133	0.079	-0.364	-0.341	-0.233	0.189	0.097	-0.041	0.134	0.201	0.059
MVTL	0.702	0.660	-0.785	0.031	0.412	0.185	0.188	0.412	0.191	0.156	-0.280	0.636	0.067	0.170	0.205	0.067	0.044	0.071	0.726	0.107	0.133	1.000	0.938	0.014	-0.033	-0.063	0.041	-0.093	-0.160	0.095	0.030	-0.034
MVTTL	0.636	0.591	-0.711	0.023	0.353	0.138	0.150	0.370	0.118	0.122	-0.297	0.572	0.048	0.132	0.170	0.048	0.024	0.047	0.659	0.027	0.079	0.938	1.000	0.002	-0.051	-0.096	-0.179	-0.142	-0.134	0.061	-0.025	-0.070
GDP	-0.070	-0.068	0.038	0.144	0.115	0.194	0.204	0.049	0.124	0.033	0.170	-0.025	0.093	0.076	0.077	0.093	0.105	0.085	0.006	-0.093	-0.364	0.014	0.002	1.000	0.965	0.800	0.017	-0.209	-0.029	0.000	-0.048	0.063
IAV	-0.064	-0.068	0.045	0.164	0.124	0.218	0.228	0.064	0.155	0.057	0.201	-0.019	0.085	0.083	0.079	0.085	0.100	0.072	0.002	-0.071	-0.341	-0.033	-0.051	0.965	1.000	0.853	0.036	-0.179	-0.051	-0.005	-0.028	0.123
LPR	-0.048	-0.049	0.018	0.156	0.109	0.202	0.238	0.082	0.152	0.059	0.195	0.000	0.055	0.070	0.075	0.055	0.082	0.051	0.037	-0.033	-0.233	-0.063	-0.096	0.800	0.853	1.000	0.049	-0.179	-0.036	-0.024	-0.023	0.087
T10	0.149	0.165	-0.142	0.044	0.227	0.202	0.149	0.177	0.305	0.100	0.062	0.178	0.111	0.140	0.122	0.111	0.093	0.123	0.154	0.301	0.189	0.041	-0.179	0.017	0.036	0.049	1.000	0.312	-0.008	0.068	0.241	0.238
II	-0.026	-0.034	0.036	0.073	0.052	0.095	0.048	0.047	0.143	-0.013	0.091	-0.048	0.031	0.055	0.027	0.031	0.034	0.039	-0.045	0.231	0.097	-0.093	-0.142	-0.209	-0.179	-0.179	0.312	1.000	0.054	0.026	0.189	0.231
CEOC	-0.133	-0.143	0.158	-0.026	-0.097	-0.010	-0.002	-0.077	-0.028	-0.003	0.051	-0.119	-0.045	-0.100	-0.104	-0.045	-0.051	-0.049	-0.178	-0.066	-0.041	-0.160	-0.134	-0.029	-0.051	-0.036	-0.008	0.054	1.000	-0.022	-0.040	-0.028
AO	0.148	0.151	-0.189	0.060	0.194	0.084	0.103	0.142	0.154	0.122	0.049	0.140	0.121	0.123	0.131	0.121	0.112	0.126	0.172	0.185	0.134	0.095	0.061	0.000	-0.005	-0.024	0.068	0.026	-0.022	1.000	0.075	0.084
AR	0.039	0.071	-0.021	0.119	0.294	0.311	0.245	0.225	0.333	0.125	0.068	0.067	0.125	0.158	0.160	0.125	0.151	0.143	-0.007	0.324	0.201	0.030	-0.025	-0.048	-0.028	-0.023	0.241	0.189	-0.040	0.075	1.000	0.562
ANAC	0.017	0.052	-0.006	0.224	0.358	0.415	0.360	0.286	0.421	0.142	0.143	0.052	0.139	0.211	0.201	0.139	0.184	0.147	-0.002	0.330	0.059	-0.034	-0.070	0.063	0.123	0.087	0.238	0.231	-0.028	0.084	0.562	1.000

Table 25. Correlation Matrix. The table shows the correlation matrix of all the preselected variables in year T-3. It includes financial indicators including solvency index, profitability index, operation index, cash flow index and other financial index, and non-financial indicators including capital market index, ownership index, governance index and external non-financial index.

T-3	CR	QR	DAR	ICR	OM	ROE	ROA	CEPM	EPS	FT	CAT	WC	PQ	NOCFCL	NOCFL	SCFR	CRR	SR	FAR	DIV	INNO	MVTL	MVTTL	GDP	IAV	LPR	T10	II	CEOC	AO	AR	ANAC
CR	1.000	0.920	-0.778	0.120	0.438	0.288	0.319	0.466	0.333	0.317	-0.386	0.944	-0.045	0.087	0.102	-0.045	-0.083	-0.038	0.789	0.286	0.251	0.699	0.619	-0.075	-0.059	-0.010	0.214	-0.095	-0.036	0.217	0.030	-0.041
QR	0.920	1.000	-0.752	0.105	0.415	0.286	0.320	0.438	0.338	0.276	-0.319	0.854	-0.008	0.127	0.142	-0.008	-0.036	0.006	0.748	0.299	0.278	0.666	0.580	-0.067	-0.050	0.009	0.232	-0.106	-0.027	0.181	0.056	-0.013
DAR	-0.778	-0.752	1.000	-0.177	-0.473	-0.290	-0.360	-0.464	-0.370	-0.113	0.204	-0.759	-0.076	-0.229	-0.250	-0.076	-0.068	-0.084	-0.936	-0.310	-0.180	-0.781	-0.706	0.026	0.019	0.001	-0.202	0.088	0.051	-0.268	-0.048	-0.029
ICR	0.120	0.105	-0.177	1.000	0.580	0.666	0.662	0.625	0.617	0.181	0.122	0.175	0.141	0.166	0.158	0.141	0.176	0.144	0.148	0.388	0.011	0.123	0.053	0.140	0.151	0.030	0.192	0.092	-0.022	0.239	0.314	0.306
OM	0.438	0.415	-0.473	0.580	1.000	0.813	0.850	0.907	0.830	0.286	-0.066	0.476	0.321	0.358	0.360	0.321	0.268	0.318	0.446	0.541	0.143	0.409	0.293	0.043	0.076	0.030	0.336	0.078	-0.053	0.323	0.391	0.362
ROE	0.288	0.286	-0.290	0.666	0.813	1.000	0.936	0.839	0.914	0.344	0.098	0.351	0.242	0.309	0.313	0.242	0.277	0.250	0.273	0.553	0.126	0.304	0.186	0.155	0.192	0.081	0.358	0.129	-0.031	0.248	0.436	0.426
ROA	0.319	0.320	-0.360	0.662	0.850	0.936	1.000	0.866	0.893	0.334	0.108	0.377	0.285	0.367	0.372	0.285	0.312	0.291	0.330	0.545	0.118	0.353	0.236	0.160	0.192	0.100	0.333	0.087	-0.037	0.267	0.429	0.401
CEPM	0.466	0.438	-0.464	0.625	0.907	0.839	0.866	1.000	0.835	0.266	-0.126	0.503	0.256	0.306	0.309	0.256	0.212	0.260	0.461	0.514	0.199	0.440	0.335	0.081	0.117	0.087	0.330	0.051	-0.064	0.296	0.377	0.310
EPS	0.333	0.338	-0.370	0.617	0.830	0.914	0.893	0.835	1.000	0.333	0.053	0.402	0.224	0.293	0.294	0.224	0.235	0.229	0.347	0.628	0.191	0.318	0.195	0.067	0.110	0.035	0.382	0.163	-0.040	0.271	0.468	0.441
FT	0.317	0.276	-0.113	0.181	0.286	0.344	0.334	0.266	0.333	1.000	0.161	0.411	-0.072	0.005	0.029	-0.072	0.002	-0.080	0.120	0.178	0.047	0.153	0.117	0.026	0.054	0.025	0.094	-0.035	0.023	0.128	0.104	0.075
CAT	-0.386	-0.319	0.204	0.122	-0.066	0.098	0.108	-0.126	0.053	0.161	1.000	-0.404	0.131	0.255	0.238	0.131	0.329	0.148	-0.222	0.075	-0.167	-0.258	-0.283	0.114	0.123	0.040	0.045	0.168	0.071	0.061	0.136	0.209
WC	0.944	0.854	-0.759	0.175	0.476	0.351	0.377	0.503	0.402	0.411	-0.404	1.000	-0.056	0.049	0.067	-0.056	-0.094	-0.056	0.783	0.307	0.247	0.648	0.572	-0.041	-0.026	-0.005	0.230	-0.095	-0.031	0.260	0.061	-0.002
PQ	-0.045	-0.008	-0.076	0.141	0.321	0.242	0.285	0.256	0.224	-0.072	0.131	-0.056	1.000	0.858	0.848	1.000	0.885	0.981	0.045	0.171	0.024	0.027	0.001	0.029	0.026	-0.016	0.106	0.039	0.029	0.128	0.159	0.178
NOCFCL	0.087	0.127	-0.229	0.166	0.358	0.309	0.367	0.306	0.293	0.005	0.255	0.049	0.858	1.000	0.982	0.858	0.908	0.859	0.172	0.264	0.028	0.173	0.123	0.031	0.034	-0.003	0.141	0.050	0.006	0.146	0.206	0.198
NOCFL	0.102	0.142	-0.250	0.158	0.360	0.313	0.372	0.309	0.294	0.029	0.238	0.067	0.848	0.982	1.000	0.848	0.912	0.851	0.199	0.267	0.039	0.194	0.140	0.042	0.041	-0.009	0.146	0.027	0.015	0.140	0.198	0.192
SCFR	-0.045	-0.008	-0.076	0.141	0.321	0.242	0.285	0.256	0.224	-0.072	0.131	-0.056	1.000	0.858	0.848	1.000	0.885	0.981	0.045	0.171	0.024	0.027	0.001	0.029	0.026	-0.016	0.106	0.039	0.029	0.128	0.159	0.178
CRR	-0.083	-0.036	-0.068	0.176	0.268	0.277	0.312	0.212	0.235	0.002	0.329	-0.094	0.885	0.908	0.912	0.885	1.000	0.886	0.035	0.203	-0.015	0.019	-0.021	0.073	0.066	-0.018	0.107	0.060	0.033	0.141	0.189	0.213
SR	-0.038	0.006	-0.084	0.144	0.318	0.250	0.291	0.260	0.229	-0.080	0.148	-0.056	0.981	0.859	0.851	0.981	0.886	1.000	0.054	0.189	0.047	0.033	0.002	0.024	0.022	-0.024	0.120	0.048	0.017	0.131	0.178	0.194
FAR	0.789	0.748	-0.936	0.148	0.446	0.273	0.330	0.461	0.347	0.120	-0.222	0.783	0.045	0.172	0.199	0.045	0.035	0.054	1.000	0.292	0.190	0.741	0.674	0.007	0.016	0.027	0.214	-0.092	-0.032	0.276	0.036	-0.003
DIV	0.286	0.299	-0.310	0.388	0.541	0.553	0.545	0.514	0.628	0.178	0.075	0.307	0.171	0.264	0.267	0.171	0.203	0.189	0.292	1.000	0.246	0.187	0.058	-0.106	-0.092	-0.092	0.371	0.185	-0.065	0.215	0.388	0.348
INNO	0.251	0.278	-0.180	0.011	0.143	0.126	0.118	0.199	0.191	0.047	-0.167	0.247	0.024	0.028	0.039	0.024	-0.015	0.047	0.190	0.246	1.000	0.159	0.089	-0.432	-0.376	-0.161	0.213	0.067	0.073	0.075	0.162	0.000
MVTL	0.699	0.666	-0.781	0.123	0.409	0.304	0.353	0.440	0.318	0.153	-0.258	0.648	0.027	0.173	0.194	0.027	0.019	0.033	0.741	0.187	0.159	1.000	0.923	0.009	0.030	0.062	0.144	-0.072	-0.054	0.084	0.055	0.041
MVTTL	0.619	0.580	-0.706	0.053	0.293	0.186	0.236	0.335	0.195	0.117	-0.283	0.572	0.001	0.123	0.140	0.001	-0.021	0.002	0.674	0.058	0.089	0.923	1.000	-0.009	0.004	0.079	-0.094	-0.083	-0.084	0.031	-0.025	-0.020
GDP	-0.075	-0.067	0.026	0.140	0.043	0.155	0.160	0.081	0.067	0.026	0.114	-0.041	0.029	0.031	0.042	0.029	0.073	0.024	0.007	-0.106	-0.432	0.009	-0.009	1.000	0.954	0.589	-0.003	-0.301	-0.047	0.054	-0.074	0.022
IAV	-0.059	-0.050	0.019	0.151	0.076	0.192	0.192	0.117	0.110	0.054	0.123	-0.026	0.026	0.034	0.041	0.026	0.066	0.022	0.016	-0.092	-0.376	0.030	0.004	0.954	1.000	0.633	0.005	-0.242	-0.055	0.046	-0.037	0.054
LPR	-0.010	0.009	0.001	0.030	0.030	0.081	0.100	0.087	0.035	0.025	0.040	-0.005	-0.016	-0.003	-0.009	-0.016	-0.018	-0.024	0.027	-0.092	-0.161	0.062	0.079	0.589	0.633	1.000	-0.057	-0.210	-0.028	-0.027	-0.067	-0.055
T10	0.214	0.232	-0.202	0.192	0.336	0.358	0.333	0.330	0.382	0.094	0.045	0.230	0.106	0.141	0.146	0.106	0.107	0.120	0.214	0.371	0.213	0.144	-0.094	-0.003	0.005	-0.057	1.000	0.248	0.097	0.109	0.255	0.274
II	-0.095	-0.106	0.088	0.092	0.078	0.129	0.087	0.051	0.163	-0.035	0.168	-0.095	0.039	0.050	0.027	0.039	0.060	0.048	-0.092	0.185	0.067	-0.072	-0.083	-0.301	-0.242	-0.210	0.248	1.000	0.005	0.059	0.313	0.381
CEOC	-0.036	-0.027	0.051	-0.022	-0.053	-0.031	-0.037	-0.064	-0.040	0.023	0.071	-0.031	0.029	0.006	0.015	0.029	0.033	0.017	-0.032	-0.065	0.073	-0.054	-0.084	-0.047	-0.055	-0.028	0.097	0.005	1.000	-0.034	-0.129	-0.042
AO	0.217	0.181	-0.268	0.239	0.323	0.248	0.267	0.296	0.271	0.128	0.061	0.260	0.128	0.146	0.140	0.128	0.141	0.131	0.276	0.215	0.075	0.084	0.031	0.054	0.046	-0.027	0.109	0.059	-0.034	1.000	0.135	0.127
AR	0.030	0.056	-0.048	0.314	0.391	0.436	0.429	0.377	0.468	0.104	0.136	0.061	0.159	0.206	0.198	0.159	0.189	0.178	0.036	0.388	0.162	0.055	-0.025	-0.074	-0.037	-0.067	0.255	0.313	-0.129	0.135	1.000	0.571
ANAC	-0.041	-0.013	-0.029	0.306	0.362	0.426	0.401	0.310	0.441	0.075	0.209	-0.002	0.178	0.198	0.192	0.178	0.213	0.194	-0.003	0.348	0.000	0.041	-0.020	0.022	0.054	-0.055	0.274	0.381	-0.042	0.127	0.571	1.000

Table 26. Confusion matrix of 9 models on the training dataset and hold-out test dataset. Panel A shows the confusion matrix of models based on training dataset consisting of 234 financial distress listed companies and 234 healthy listed companies in Chinese manufacturing industry from 2010 to 2018. Panel B shows the confusion matrix of models based on hold-out test dataset consisting of 78 financial distress listed companies and 78 healthy listed companies in Chinese manufacturing industry from 2019 to 2020.

T-1			T-2			T-3		
Panel A: models' performance on training dataset (biased)								
(1)	Actual		(4)	Actual		(7)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	191	11	0	154	47	0	155	56
1	43	223	1	80	187	1	79	178
Accuracy		0.885	Accuracy		0.729	Accuracy		0.712
Type I Error		0.184	Type I Error		0.342	Type I Error		0.338
Type II Error		0.047	Type II Error		0.201	Type II Error		0.239
(2)	Actual		(5)	Actual		(8)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	131	38	0	111	43	0	119	49
1	103	196	1	123	191	1	115	185
Accuracy		0.699	Accuracy		0.645	Accuracy		0.650
Type I Error		0.440	Type I Error		0.526	Type I Error		0.491
Type II Error		0.162	Type II Error		0.184	Type II Error		0.209
(3)	Actual		(6)	Actual		(9)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	197	11	0	158	46	0	151	49
1	39	223	1	76	188	1	83	185
Accuracy		0.894	Accuracy		0.739	Accuracy		0.718
Type I Error		0.165	Type I Error		0.325	Type I Error		0.355
Type II Error		0.047	Type II Error		0.197	Type II Error		0.209
Panel B: models' performance on hold-out test dataset (unbiased)								
(1)	Actual		(4)	Actual		(7)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	66	8	0	58	26	0	59	18
1	12	70	1	20	52	1	19	60
Accuracy		0.872	Accuracy		0.705	Accuracy		0.763
Type I Error		0.154	Type I Error		0.256	Type I Error		0.244
Type II Error		0.103	Type II Error		0.333	Type II Error		0.231
(2)	Actual		(5)	Actual		(8)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	34	12	0	37	20	0	42	33
1	44	66	1	41	58	1	26	45
Accuracy		0.641	Accuracy		0.609	Accuracy		0.596
Type I Error		0.564	Type I Error		0.526	Type I Error		0.382
Type II Error		0.154	Type II Error		0.256	Type II Error		0.423
(3)	Actual		(6)	Actual		(9)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	69	8	0	59	23	0	52	16
1	9	70	1	19	55	1	26	62
Accuracy		0.891	Accuracy		0.731	Accuracy		0.731
Type I Error		0.115	Type I Error		0.244	Type I Error		0.333
Type II Error		0.103	Type II Error		0.295	Type II Error		0.205

Note: All the company data is collected from the Wind Financial Terminal and annual reports.

Table 27. Confusion matrix of 9 models on hold-out test dataset with cutpoints of 0.3 and 0.5. Panel A shows the confusion matrix for 9 models with cutpoint of 0.3. Panel B shows the confusion matrix for 9 models with cutpoint of 0.5. The hold-out test dataset consists of 78 financial distress listed companies and 78 healthy listed companies in Chinese manufacturing industry from 2019 to 2020.

T-1			T-2			T-3		
Panel A: models' performance on the hold-out test dataset, cutpoint 0.3								
(1)	Actual		(4)	Actual		(7)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	65	7	0	49	15	0	51	10
1	13	71	1	29	63	1	27	68
Accuracy		0.872	Accuracy		0.718	Accuracy		0.763
Type I Error		0.167	Type I Error		0.372	Type I Error		0.346
Type II Error		0.090	Type II Error		0.192	Type II Error		0.128
(2)	Actual		(5)	Actual		(8)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	63	27	0	18	4	0	20	12
1	15	51	1	60	74	1	58	66
Accuracy		0.731	Accuracy		0.590	Accuracy		0.551
Type I Error		0.192	Type I Error		0.769	Type I Error		0.744
Type II Error		0.346	Type II Error		0.051	Type II Error		0.154
(3)	Actual		(6)	Actual		(9)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	66	5	0	51	16	0	42	12
1	12	73	1	27	62	1	36	66
Accuracy		0.891	Accuracy		0.724	Accuracy		0.692
Type I Error		0.154	Type I Error		0.346	Type I Error		0.462
Type II Error		0.064	Type II Error		0.205	Type II Error		0.154
Panel B: models' performance on the hold-out test dataset, cutpoint 0.5								
(1)	Actual		(4)	Actual		(7)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	68	10	0	60	30	0	63	27
1	10	68	1	18	48	1	15	51
Accuracy		0.872	Accuracy		0.692	Accuracy		0.731
Type I Error		0.128	Type I Error		0.231	Type I Error		0.192
Type II Error		0.128	Type II Error		0.385	Type II Error		0.346
(2)	Actual		(5)	Actual		(8)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	40	18	0	54	38	0	58	49
1	38	60	1	24	40	1	20	29
Accuracy		0.641	Accuracy		0.603	Accuracy		0.558
Type I Error		0.487	Type I Error		0.308	Type I Error		0.256
Type II Error		0.231	Type II Error		0.487	Type II Error		0.628
(3)	Actual		(6)	Actual		(9)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	68	10	0	64	34	0	61	23
1	10	68	1	14	44	1	17	55
Accuracy		0.872	Accuracy		0.692	Accuracy		0.744
Type I Error		0.128	Type I Error		0.179	Type I Error		0.218
Type II Error		0.128	Type II Error		0.436	Type II Error		0.295

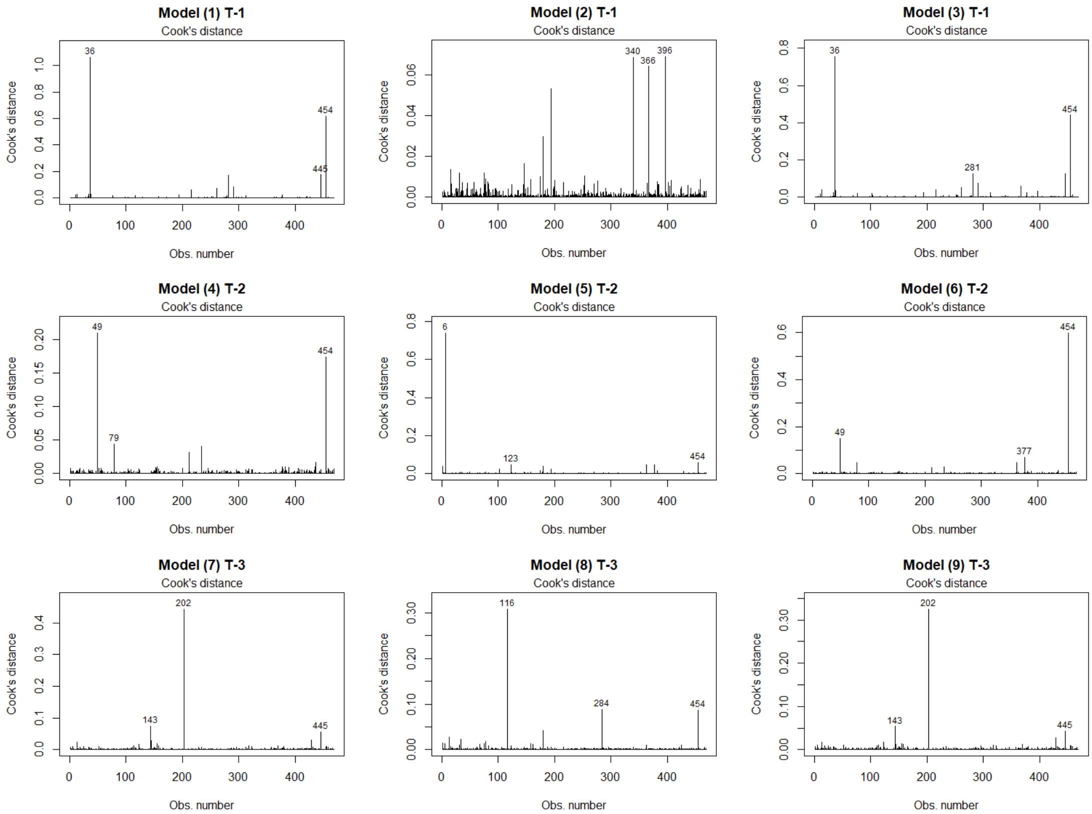
Note: All the company data is collected from the Wind Financial Terminal and annual reports.

Table 28. Confusion matrix of 9 models on sub-dataset of training dataset from 2010 to 2012, 2013 to 2015 and 2016 to 2018. Panel A shows the confusion matrix of each model based on a sub-dataset of training data consisting of 102 companies from 2010 to 2012. Panel B shows the confusion matrix of each model based on a sub-dataset of training data consisting of 144 companies from 2013 to 2015. Panel C shows the confusion matrix of each model based on a sub-dataset of training data consisting of 222 companies from 2016 to 2018.

T-1			T-2			T-3		
Panel A: models' performance on sub-dataset 1 from 2010 to 2012, n=102								
(1)	Actual		(4)	Actual		(7)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	38	3	0	28	7	0	27	10
1	13	48	1	23	44	1	24	41
Accuracy		0.843	Accuracy		0.706	Accuracy		0.667
Type I Error		0.255	Type I Error		0.451	Type I Error		0.471
Type II Error		0.059	Type II Error		0.137	Type II Error		0.196
(3)	Actual		(6)	Actual		(9)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	39	3	0	31	5	0	26	9
1	12	48	1	20	46	1	25	42
Accuracy		0.853	Accuracy		0.755	Accuracy		0.667
Type I Error		0.235	Type I Error		0.392	Type I Error		0.490
Type II Error		0.059	Type II Error		0.098	Type II Error		0.176
Panel B: models' performance on sub-dataset 2 from 2013 to 2015, n=144								
(1)	Actual		(4)	Actual		(7)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	65	2	0	50	16	0	45	21
1	7	70	1	22	56	1	27	51
Accuracy		0.938	Accuracy		0.736	Accuracy		0.667
Type I Error		0.097	Type I Error		0.306	Type I Error		0.375
Type II Error		0.028	Type II Error		0.222	Type II Error		0.292
(3)	Actual		(6)	Actual		(9)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	65	7	0	51	16	0	48	18
1	7	71	1	21	56	1	24	54
Accuracy		0.907	Accuracy		0.743	Accuracy		0.708
Type I Error		0.097	Type I Error		0.292	Type I Error		0.333
Type II Error		0.090	Type II Error		0.222	Type II Error		0.250
Panel C: models' performance on sub-dataset 3 from 2016 to 2018, n=222								
(1)	Actual		(4)	Actual		(7)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	88	6	0	76	24	0	83	25
1	23	105	1	35	87	1	28	86
Accuracy		0.869	Accuracy		0.734	Accuracy		0.761
Type I Error		0.207	Type I Error		0.315	Type I Error		0.252
Type II Error		0.054	Type II Error		0.216	Type II Error		0.225
(3)	Actual		(6)	Actual		(9)	Actual	
Predict	0	1	Predict	0	1	Predict	0	1
0	91	7	0	76	25	0	77	22
1	20	104	1	35	86	1	34	89
Accuracy		0.878	Accuracy		0.730	Accuracy		0.748
Type I Error		0.180	Type I Error		0.315	Type I Error		0.306
Type II Error		0.063	Type II Error		0.225	Type II Error		0.198

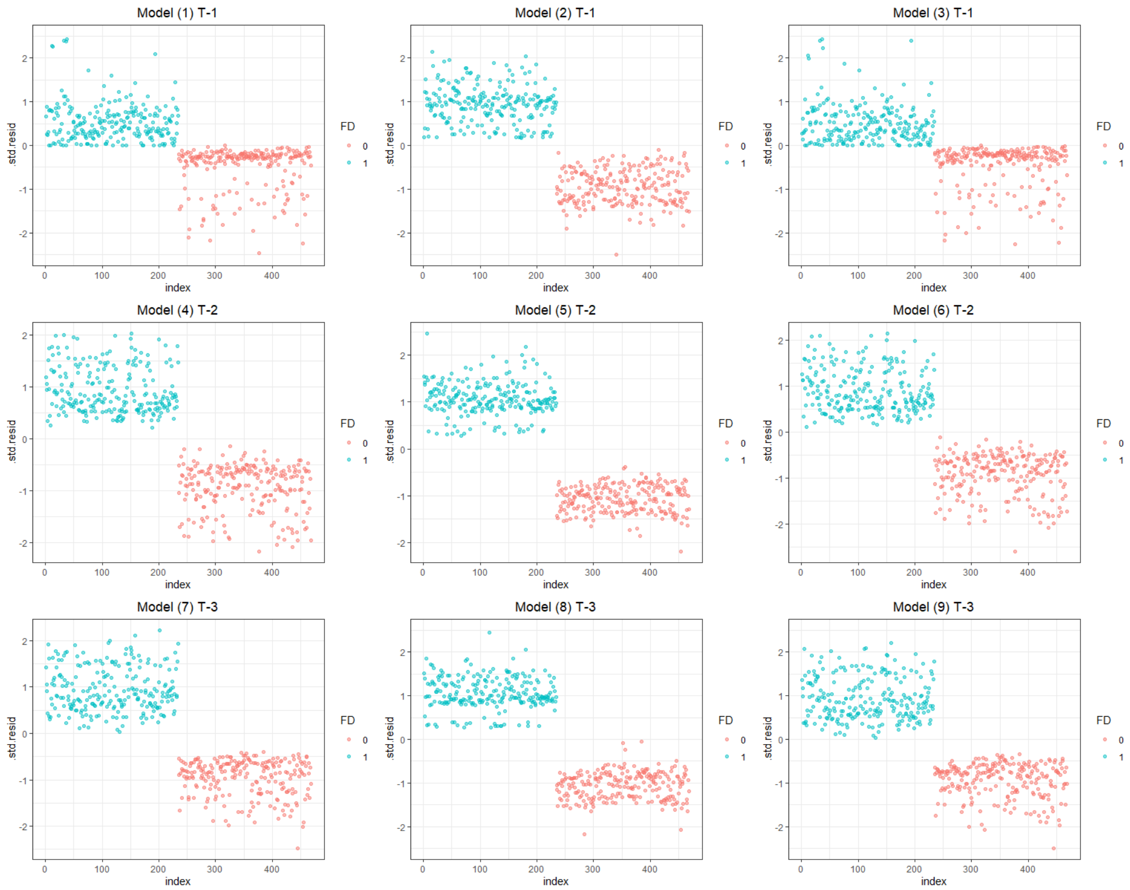
Note: All the company data is collected from the Wind Financial Terminal and annual reports.

Figure 4. Cook's distance. These figures show the cook's distance for each model in year T-1, T-2 and T-3 based on the training dataset from 2010 to 2018. The Cook's distance indicates the most extreme values in the data. The top 3 largest values are labeled with number. Model (1), (4) and (7) consist of only financial indicators, model (2), (5) and (8) consist of only non-financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators.



Note: All the company data is collected from the Wind Financial Terminal and annual reports.

Figure 5. Standardized residuals. These figures show the absolute standardized residuals for each model in year T-1, T-2 and T-3 based on the training dataset from 2010 to 2018. The standardized residual indicates whether the data contains potential influential observations. Model (1), (4) and (7) consist of only financial indicators, model (2), (5) and (8) consist of only non-financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators.



Note: All the company data is collected from the Wind Financial Terminal and annual reports.

Table 29. Multicollinearity test. The table shows results from multicollinearity test for all the 9 models by calculating the variance inflation factor (VIF) of each independent variable. Model (1), (4) and (7) consist of only financial indicators, model (2), (5) and (8) consist of only non-financial indicators and model (3), (6) and (9) consist of both financial and non-financial indicators. As discussed in section 5.5.3., VIF value exceeding 5 suggests the multicollinearity of the model if problematic. Some researchers suggest a more conservative level of 2.5.

Model (1)		Model (2)		Model (3)		Adj. Model (3)	
	VIF		VIF		VIF		VIF
ROE	1.297	T10	1.037	CR	6.950	ROE	1.355
FAT	1.155	CEOC	1.033	ROE	1.369	FAT	1.206
CAT	1.158	AO	1.005	FAT	1.226	CAT	1.229
FAR	1.101	AR	1.377	CAT	1.247	CRR	1.078
DIV	1.225	ANAC	1.412	CRR	1.118	FAR	1.161
				FAR	1.316	DIV	1.240
				DIV	1.282	II	1.052
				II	1.060	AO	1.008
				AO	1.007	AR	1.059
				AR	1.085		
				MVTL	6.830		

Model (4)		Model (5)		Model (6)	
	VIF		VIF		VIF
FAT	1.013	MVTL	1.005	FAT	1.127
CRR	1.037	T10	1.042	CRR	1.040
FAR	1.052	AO	1.002	FAR	1.091
DIV	1.009	AR	1.429	DIV	1.067
INNO	1.057	ANAC	1.435	INNO	1.083
				AO	1.125
				AR	1.115

Model (7)		Model (8)		Model (9)		Adj. Model (9)	
	VIF		VIF		VIF		VIF
ROE	1.135	MVTL	1.021	CR	4.476	ROE	1.128
CRR	1.038	T10	1.076	ROE	1.127	CRR	1.044
FAR	1.017	AO	1.002	CRR	1.055	FAR	1.060
DIV	1.111	AR	1.453	FAR	1.434	DIV	1.158
		ANAC	1.481	DIV	1.168	AR	1.157
				AR	1.162		
				MVTL	4.239		

Note: All the company data is collected from the Wind Financial Terminal and annual reports.