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Corporate distress prediction in China: a machine learning approach

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Authorship Attribution Statement

This thesis contains material published in Jiang Y, and Jones S (2018) Corporate Distress Prediction in China: A Machine Learning Approach *Accounting and Finance*, 58 (4), 1063-1109. This material appears in Chapter 6 and is partially discussed in Chapters 1 and 3. I did the full data collection, literature review, Chinese institutional setting and background, and contributed significantly to the results analysis, interpretation and write up.

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Statement of Originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

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Abstract

Rapid growth and transformation of the Chinese economy and financial markets coupled with escalating default rates, rising corporate debt, and poor regulatory oversight motivates the need for more accurate distress prediction modelling in China. Given China's historical, social, and cultural intolerance towards corporate failure, this thesis examines Chinese distress based on the Special Treatment (ST) system introduced by the CSRC in 1998. Regulators can assign Special Treatment status to listed Chinese companies for poor financial performance, financial abnormality and other events. This study employs an advanced machine learning technique – gradient boosting (TreeNet®) to examine the predictive and explanatory performance of more than 90 predictor variables, including financial ratios, market returns, macroeconomic indicators, shareholder ownership/concentration, executive compensation measures, corporate governance proxies, valuation multiples, audit quality factors, corporate social responsibility metrics, and other variables.

In addition to conventional dichotomous distress modelling, this thesis also models Chinese financial distress in a multi-state setting. Unlike binary distress prediction models that are subject to oversimplification of the underlying economic reality of firms, multi-state models can better approximate the continuum of corporate financial health observable across Chinese listed companies. Based on out-of-sample tests, the binary TreeNet® model is 93.74 percent accurate in predicting distress (a Type I error rate of 6.26 percent) and 94.81 percent accurate in predicting active/healthy companies (a Type II error rate of 5.19 percent). The three-state TreeNet® model is 96.82 percent accurate in predicting active or healthy companies; 76.49 percent accurate in predicting state 1 distress (ST=1); and 73.28 percent accurate in predicting state 2 distress (ST $>$ 1). The five-state TreeNet® model is 94.47 percent accurate in predicting active or healthy companies; 61.70 percent

accurate in predicting state 1 distress (ST=1); 53.12 percent accurate in predicting state 2 distress (1$<$ ST $<$4); 62.56 percent accurate in predicting state 3 distress (ST $\geq$ 4); and 51.72 percent accurate in predicting state 4 distress (delisted).

From the analysis of the RVI metrics of the binary, three-state and five-state TreeNet® models, variables with strongest predictive value include: (i) market-price variables, particularly market capitalisation and annual market returns; (ii) executive compensation measures, such as total compensation of the top three executives and total compensation to the top three directors; (iii) macroeconomic variables, notably GDP growth, GDP per capita and unemployment rates; (iv) financial variables, particularly retained earnings to total assets, net profit margin, ROA, ROE, and market capitalisation to total debt; and (v) shareholder ownership/concentration, notably percentage of shares held by insiders. The empirical results suggest a wide range of financial and non-financial 'Western-style' bankruptcy predictors also provide good predictive and explanatory power in the Chinese context. In addition to conventional financial and market variables, some non-conventional variables such as executive compensation measures, macroeconomic variables and shareholder ownership/concentration variables are also found to be fairly predictive in the unique context of China's ST system. The diverse range of top performing predictor variables also reflects several different dimensions of corporate financial distress in China. The empirical findings imply that future research on Chinese distress prediction modelling could combine variables measuring different dimensions of corporate financial health in Chinese companies.

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Contents

Authorship Attribution Statement i

Statement of Originality ii

Abstract iii

Acknowledgements v

1 Introduction and background 1

1.1 Chapter introduction 1

1.2 Introduction and background 2

1.3 Institutional background of China 5

1.3.1 China's corporate financial reporting system 7

1.3.2 The impact of State ownership 10

1.3.3 The Special Treatment regime 12

1.4 Motivation and research objectives 16

1.5 Contributions of this research 20

1.6 Chapter conclusion 23

1.7 Organisation of this thesis 24

2 The Enterprise Bankruptcy Law of China 25

2.1 Chapter introduction 25

2.2 The history of the bankruptcy system in China . . . 26
2.3 Socialist ideology and the bankruptcy system . . . 28
2.4 The 1986 Chinese Bankruptcy Law . . . 29
2.5 The 1991 PRC Civil Procedure Law . . . 30
2.6 Some problems of the bifurcated bankruptcy system . . . 31
2.7 The new Enterprise Bankruptcy Law of China . . . 32
2.8 Inactive bankruptcy practices in China . . . 34
2.9 Reasons for inactive bankruptcy practices in China . . . 36
2.10 Chapter conclusion . . . 37

3 Literature Review 39

3.1 Chapter introduction . . . 39
3.2 Definition of financial distress . . . 40
3.3 The development of financial distress prediction . . . 42
3.3.1 Univariate discriminant analysis (UDA) . . . 43
3.3.2 Multivariate discriminant analysis (MDA) . . . 46
3.3.3 Logistic/Probit regression model (logit/probit) . . . 50
3.3.4 Neural network (NN) . . . 53
3.3.5 Survival analysis models . . . 56
3.3.6 The Gradient Boosting model (TreeNet®) . . . 58
3.4 Predictors of corporate distress . . . 60
3.4.1 Accounting-based versus market-price indicators . . . 61
3.4.2 Shareholder ownership/concentration variables . . . 66
3.4.3 Macroeconomic variables . . . 69
3.4.4 Executive compensation variables . . . 71
3.4.5 Corporate social responsibility variables . . . 72
3.4.6 Valuation multiples . . . 74

3.4.7 Control variables 75
3.5 Multi-class distress prediction studies 76
3.6 Chinese distress prediction studies 79
3.6.1 Late start of Chinese distress prediction studies 79
3.6.2 Issues of small distressed sample and short sample period 81
3.6.3 Machine learning versus statistical methods 82
3.6.4 The predictive power of non-financial predictors 86
3.7 Limitations of distress prediction studies in China 90
3.8 Chapter conclusion 95

4 Data, Variable definitions, and Methodology 97

4.1 Chapter introduction 97
4.2 Data and variables 97
4.2.1 Database used for data collection 98
4.2.2 Data collection procedures 98
4.2.3 Dependent and independent variables and definitions 101
4.3 The empirical framework 103
4.4 The formal TreeNet® model 107
4.4.1 The gradient boosting machine (TreeNet®) 107
4.4.2 Relative variable importances (RVIs) 110
4.4.3 Partial dependence analysis 111
4.5 Chapter conclusion 112

5 Descriptive Statistics 114

5.1 Chapter introduction 114
5.2 Distress rates 115
5.3 Descriptive statistics 122

5.4 Distress symptoms leading up to distress 129
5.5 Chapter conclusion 146

6 Empirical results – binary analysis **149**

6.1 Chapter introduction 149
6.2 RVIs of the binary TreeNet® model 150
6.3 Confusion matrix and summary of predictive performance of the binary TreeNet® model 156
6.4 Partial dependence analysis of the binary TreeNet® model 159
6.5 Chapter conclusion 178

7 Empirical results – multi-state analysis **181**

7.1 Chapter introduction 181
7.2 Empirical results of the five-state TreeNet® model 182
7.2.1 RVIs of the five-state TreeNet® model 182
7.2.2 Confusion matrix and summary of predictive performance of the five-state TreeNet® model 189
7.3 Empirical results of the three-state TreeNet® model 193
7.3.1 RVIs of the three-state TreeNet® model 194
7.3.2 Confusion matrix and summary of predictive performance of the three-state TreeNet® model 201
7.4 The binary TreeNet® model versus the multi-state TreeNet® models . . . 204
7.4.1 The RVIs of the binary versus multi-state TreeNet® models . . . 205
7.4.2 Predictive performance of the binary versus multi-state TreeNet® models 209
7.5 Chapter conclusion 212

8 Conclusions **216**

8.1 Chapter introduction 216
8.2 Summary of research setting 217
8.3 The Special Treatment regime revisited 219
8.4 Summary of research design 222
8.5 Empirical findings of this thesis 225
8.6 Summary of contributions of this thesis 231
8.7 Limitations and directions for future research 232

A Definition of Study Variables **234**

Bibliography **246**

List of Figures

4.1 Example of a binary decision-tree with two levels. 108

5.1 ROA 5 years leading up to distress (all data) 134
5.2 RE/TA 5 years leading up to distress (all data) 135
5.3 Current ratio 5 years leading up to distress (all data) 136
5.4 Debt/TA 5 years leading up to distress (all data) 137
5.5 Cash resources/TA 5 years leading up to distress (all data) 138
5.6 Sales/TA 5 years leading up to distress (all data) 139
5.7 WC/TA 5 years leading up to distress (all data) 140
5.8 State owned/total shares 5 years leading up to distress (all data) 141
5.9 Percentage of shares held by fund 5 years leading up to distress (all data) . 142
5.10 Percentage of shares held by brokers 5 years leading up to distress (all data) 143
5.11 Social contribution value per share 5 years leading up to distress (all data) 144
5.12 Annual market returns 5 years leading up to distress (all data) 145

6.1 Partial dependency plot for market capitalisation 167
6.2 Partial dependency plot for annual market returns 168
6.3 Partial dependency plot for retained earnings to total assets 169
6.4 Partial dependency plot for market capitalisation to total debt 170
6.5 Partial dependency plot for price to book ratio 171
6.6 Partial dependency plot for executive compensation (top 3 executives) . . . 172

6.7 Partial dependency plot for percentage of shares held by all insiders (supervisors) 173
6.8 Partial dependency plot for percentage of shares held by institutions (funds) 174
6.9 Partial dependency plot for state owned shares 175
6.10 Partial dependency plot for gross domestic product growth 176
6.11 Partial dependency plot for earnings management proxy 177

List of Tables

3.1 Tabular representation of selected Chinese distress prediction studies . . . 94

5.1 Distribution of active and distressed firm-year observations 116

5.2 Distribution of active and distressed firms 116

5.3 Distribution of distressed firm-year observations by distress states 118

5.4 Distribution of distressed firm-year observations by industry 120

5.5 Distribution of distressed firm-year observations by year 121

5.6 Descriptive statistics and independent sample t-tests for equality of means between active and distress firm years 128

6.1 RVIs of the binary TreeNet® Model – All Data 153

6.2 Confusion matrix – test sample (binary model) 158

6.3 Summary of predictive performance of the binary TreeNet® model 159

7.1 RVIs of the five-state TreeNet® Model – All Data 185

7.2 Confusion matrix – test sample (five-state model) 192

7.3 Summary of predictive performance for the five-state TreeNet® model . . 193

7.4 RVIs of the three-state TreeNet® Model – All Data 198

7.5 Confusion matrix – test sample (three-state model) 203

7.6 Summary of predictive performance for the three-state TreeNet® model . 204

7.7 Confusion matrix – test sample by joining state 1 to state 4 (five-state model) 211

7.8 Confusion matrix – test sample by joining state 1 and state 2 (three-state model) 212

List of Abbreviations

ST	**Special Treatment**
GFC	**Global financial crisis**
GDP	**Gross domestic product**
SOE	**State owned enterprise**
SSE	**The Shanghai Stock Exchange**
SZSE	**The Shenzhen Stock Exchange**
IFRS	**International Financial Reporting Standards**
GAAP	**Generally Accepted Accounting Principles**
CPA	**Certified Public Accountant**
CSRC	**China Securities Regulatory Commission**
U.S.	**The United States of America**
CSR	**Corporate social responsibility**
RVI	**Relative variable importance**
MDA	**Multivariate discriminant analysis**
Logit	**Logistic regression**
NN	**Neutral network**
SVM	**Support vector machine**
GB	**Gradient boosting**
CSMAR	**China Stock Market & Accounting Research Database**
NYSE	**The New York Stock Exchange**
NASDAQ	**The Nasdaq Stock Exchange**
AIM	**The London Stock Exchange**
NPL	**Non-performing loan**
SOCB	**State-owned commercial bank**
AI	**Artificial intelligence**
MSVM	**Multi-class support vector machine**
OVSVM	**Ordinal multi-class support vector machine**
OPP	**Ordinal pairwise partitioning**
OVAPES	**One-vs-All aggregative model with parallel ensemble strategy**
OVAHES	**One-vs-All aggregative model with hierarchical ensemble strategy**
OVOAM	**One-vs-One aggregative model**
DT	**Decision tress**
RS	**Rough set**
SAT	**Single attribute test**
D-S	**Dempster-Shafer**

DEA	**Data envelopment analysis**
TE	**Technical efficiency**
PTE	**Pure technical efficiency**
SE	**Scale efficiency**
VRS	**Variable returns to scale**
ROC	**Receiver operating characteristic**
AUC	**Area under curve**
ROA	**Return on asset**
ROE	**Return on equity**
EPS	**Earnings per share**

Chapter 1

Introduction and background

1.1 Chapter introduction

This chapter introduces the topic of corporate financial distress prediction in China. Section 1.2 provides an introduction and background of this thesis. Aspects of the institutional background of China are described in Section 1.3, including features of the corporate financial reporting system (Section 1.3.1), the impact of state ownership and control (Section 1.3.2), and the origin of the Special Treatment (ST) system (Section 1.3.3). The ST system provides a unique opportunity and distressed sample for Chinese distress prediction modelling. Section 1.4 presents the motivation and research objectives of this thesis, and Section 1.5 explores the contributions of this research. Section 1.6 provides a summary of this chapter and Section 1.7 provides an overview of organisation of this thesis.

1.2 Introduction and background

Over the past two decades, the world has gone through several spates of corporate bankruptcies, including the Asian Financial Crisis of 1997, the Dot.com bubble of 2000–2002, the more recent Global financial crisis (GFC) of 2007-2008 and the most recent Russian financial crisis of 2014–2017. Global economies have become cautious with credit risks, especially after the demise of giant organisations like Enron and Worldcom (Aziz and Dar, 2006). With the breakout of the Global Financial Crisis (GFC), a large number of corporations have incurred great losses or even become bankrupt. China as an export-driven economy also suffered a great loss as a result of weakened external demand during the GFC period (Zhang, 2009). High profile corporate bankruptcies can impose significant economic and social costs. For example, the top 10 GFC bankruptcies in the U.S. alone totalled more than $1.4 trillion (Jones and Johnstone, 2012). On a global scale, corporate bankruptcy can also cause wider social and political impacts through economic downturns and recessions. Corporate bankruptcy can destabilise the economic system in important (and often subtle) ways, such as increasing the unemployment rate, depriving investors and creditors of livelihoods and even increasing the crime rate (Mbat and Eyo, 2013). The often catastrophic consequences of corporate bankruptcy has intensified academic research to develop models to better predict failure (Jones and Hensher, 2008b). As the market capitalisation of firms and stock exchanges have increased dramatically, the implications of business failure, and the destruction of wealth that failure involves, has taken on even greater significance (Chen et al., 2006).

The literature on corporate financial distress prediction dates back to at least the 1930s (see e.g., Ramser (1931) and Fitzpatrick (1932)). The ongoing development of conceptually sound and more accurate forecasting models is of considerable interest to academics, practitioners, corporate regulators and financial economists over the last five decades

(Shumway, 2001; Altman, 2002; Jones and Hensher, 2008b). With the globalisation of the world economy, competition has become one of the basic mechanisms of the market (Sun and Li, 2009). Due to the uncertainty of business environment and fierce competition, companies with any exisiting management deficiency and a lack of innovation may fail to survive. Even companies with sound operation mechanisms could be subject to various crises, such as a marketing crisis, human resource crisis, credit crisis, and innovation crisis, which may subsequently lead to financial distress and even bankruptcy (Sun and Li, 2009). The significance of corporate financial distress prediction studies is rather 'obvious'. Whether companies' financial distress can be predicted effectively and in a timely manner not only relates to the development of the company, but business failure also affects many internal and external stakeholders of the company such as management, employees, shareholders, creditors, suppliers, clients, the government, the broader economy, and even the order of the capital market (Shumway, 2001; Sun and Li, 2008).

One of the motivations for the large number of empirical studies in corporate distress prediction modelling can be explained by a relatively direct link between the research outputs (corporate financial distress prediction models) and practical decision-making in a variety of contexts. According to Jones, Johnstone, and Wilson (2017, p. 4) 'distress forecasts are now also widely used in a number of accounting, finance and regulatory contexts, such as monitoring the solvency of financial institutions, assessment of corporate and consumer loan security by banks and other financial institutions, estimating fair value of interest rates on loans, going concern evaluations by corporate auditors and measurement of portfolio risk and the pricing of defaultable credit derivatives and other financial instruments exposed to credit risk' (Altman, 1980; Serrano-Cinca, 1997; Atiya, 2001; Shumway, 2001; Duffie and Singleton, 2012).

To date, much of the extant literature on corporate bankruptcy prediction has been undertaken using samples drawn from Western reporting jurisdictions (mainly the United States and Europe) (Jones and Hensher, 2008a; Zhou, Lai, and Yen, 2012). There have been comparatively few distress prediction studies based on Chinese listed company samples. Arguably, Chinese distress prediction modelling has been 'under-researched' and largely remains a novel field of exploration. China provides a unique context for financial distress prediction modelling for at least two important reasons. First, rapid economic growth and globalisation have transformed China into the world's second biggest economy with the fourth largest financial system and the second biggest stock market in terms of market capitalisation. China is the largest developing country, with a long history of a planned economic system, and is continuing to transform itself into a free market economy, leading investors and creditors to face rising corporate debt levels and escalating default rates. Given the increasing exposure to rising corporate bond defaults, bank defaults, and the rapid growth of the Chinese shadow banking sector, corporate distress prediction modelling is of the utmost importance in the Chinese context.

Second, despite some recent bankruptcy reforms, the Chinese bankruptcy regime is considerably new and less developed than that of other Western economies such as the United States. In contrast to the Western notion of bankruptcy, China as a socialist economy is more concerned with maintaining social stability and employment (Jiang, 2014). Given China's historical, social and cultural intolerance towards corporate failure, there have been few bankruptcies and liquidations. To protect domestic and overseas investors' interests, the 'Chinese equivalent of U.S. Chapter 11' – Special Treatment (ST) system was introduced in 1998 with an aim to identify distressed companies and provide investors and creditors with an early warning system. Despite the implementation of the ST system, the annual average delisting rate of China's stock market is only 2 percent, which is significantly lower than the delisting rate of 6 percent on NYSE (The New York Stock Exchange), 8 percent on NASDAQ (The Nasdaq Stock Exchange), and 12 percent on AIM (The London Stock Exchange) (Cheng, 2014). In addition, there is also a series of other problems underlying China's recently established stock market, such as insider trading, financial fraud, market manipulation, and excessive speculation (Cheng, 2014).

Given China's growing importance in the world economy and the relevance of distress prediction in the Chinese context, this study has four main research objectives. First, it attempts to develop a class of accurate distress prediction models based on China's unique Special Treatment system using a large sample of Chinese corporate financial distress data. Second, in addition to the conventional dichotomous distress modelling, this study also aims to model Chinese financial distress in a multi-state setting including a three-state model and a five-state model. Third, this study also aims to examine the predictive and explanatory power of a wide range of financial and non-financial variables, including accounting-based variables, market-price indicators, shareholder ownership/concentration variables, corporate governance proxies, macroeconomic variables, executive compensation variables, corporate social responsibility (CSR) variables, industry background and other variables. Finally, following the approach of Jones (2017), this study employs an advanced machine learning technique – the gradient boosting (GB) model to examine the predictive performance of a large number of different input variables. A commercial version of the GB model known as the TreeNet Gradient Boosting Machine (TreeNet®) will be applied.

1.3 Institutional background of China

It is necessary to understand the institutional background of China in order to grasp the broader context of corporate distress in China, including features of the corporate financial reporting system, characteristics of share ownership and control, and the origin of the ST system.

After the People's Republic of China was founded in 1949 by the Communist Party, China began to imitate the Soviet's centrally planned economic model to promote economic recovery and growth by establishing state-owned enterprises (SOEs). Before the introduction of Chinese economic reform in 1978, China's industrial sector was dominated exclusively by SOEs (Kam, Citron, and Muradoglu, 2005). No real capital market existed when China was a socialist state-directed economy, so funds were centrally administered and allocated to SOEs (Hu, 2011). One of the key characteristics of such a system was that national banks lent money to SOEs freely to ensure maximum employment rate, regardless of the borrowing company's efficiency and financial strength (Palmer and Rapisardi, 2009). As a result, the economy of China was filled with inefficient companies and overwhelmed by 'non-performing loans' ('NPLs') ranging from $410 million to $815 million as of mid-2003, with the amount of NPLs gradually increasing each year (Palmer and Rapisardi, 2009).

Starting from the late 1970s, reform and opening up of China's economy promoted the emergence of China's capital market (Bian, 2014). In the process of financial liberalisation from a planned economy to a market oriented economy, China's share issue privatisation of SOEs catalysed the development of its two stock exchanges, namely the Shanghai Securities Exchange (SSE) and Shenzhen Stock Exchange (SZSE) in 1990 and 1991 respectively (Kam, Citron, and Muradoglu, 2005). The number of listed companies surged from 14 in 1990 to 2489 by the end of 2013 (Zhang, 2015). With the evolution of China's market economy, the demand for more market-oriented resource allocation increased, leading to the gradual establishment and development of China's capital market. Nonetheless, the march toward a market-based economy in China revealed the change from a socialist state-directed economy to a type of 'market socialism', a more pragmatic market-driven model that still features strong centralised control over the economy and government (Palmer and Rapisardi, 2009). Unlike NYSE which was founded in 1908 and has a long history of development and trading, the Chinese stock market has been established for a relatively short period; it was formally set up in 1990 and 1991 under the guidelines of Deng Xiaoping Theory[1] after the economic reform and opening-up. Therefore, the Chinese stock market remains at a preliminary stage.

1.3.1 China's corporate financial reporting system

China started its economic reform in 1978 with an aim to transform itself from a centrally planned economy to a fully-fledged market-oriented economy (Ding and Su, 2008; Jones, 2016). One of the most important and critical components of the economic reform was to restructure SOEs to prevent their widespread losses (Lee, 2001). In fact, a majority of the listed companies were SOEs before going public (Chen, Chen, and Su, 2001). Before the economic reforms, the main purpose of accounting in China was to serve centralised state macro-economic planning (Chen, Chen, and Su, 2001; Ding and Su, 2008). According to Lee (2001), at that time, China was using the Soviet-style cash-based fund accounting system and the role of accounting in SOEs had little more than a book-keeping function. The Soviet-style macroeconomy oriented fund accounting system was adopted by China in the 1950s (Chen, Chen, and Su, 2001). The Soviet-style accounting system was rule-based as opposed to principle-based (Walter and Howie, 2011). A complete code of extremely specific accounting treatments were developed for almost every situation, so

[1]Deng Xiaoping Theory, also known as Dengism, is the series of political and economic ideologies first developed by Chinese leader Deng Xiaoping. Deng led China through a series of market-economy reforms and opening up.

accountants in China at that time were only required to place the item in the right 'box' (Walter and Howie, 2011).

As one of the main purposes of the economic reform was to establish an open financial market and let market mechanisms guide production and investment decisions, some practices adopted under the socialist planned economic system became obsolete (Lee, 2001). Rapid economic development and globalisation in China, combined with the need to attract domestic and international capital to maintain sustainable economic growth, compelled the Chinese government to make significant changes to its accounting system (Peng et al., 2008). These fundamental changes to the Chinese accounting system came into practice after the establishment of the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) in the early 1990s (Chen, Sun, and Wang, 2002). In 1992, the Chinese government issued *Accounting Regulation for Experimental Listed Companies* in response to China's newly opened stock market (Chen, Sun, and Wang, 2002). The 1992 accounting regulation marked a new era of accounting in China, as it finally abandoned the fund-based Soviet accounting model and started to incorporate the Anglo-Saxon style accrual-based financial accounting system (Lee, 2001; Chen, Sun, and Wang, 2002). Since the 1992 accounting regulation, China began to incorporate many features of Western accounting practices as reflected in International Accounting Standards (Chen, Sun, and Wang, 2002).

To date, the Chinese government has issued four sets of accounting regulations (in 1992,1998, 2001, and 2006), with each new regulation replacing the previous one, with the aim to eliminate discrepancies between Chinese Generally Accepted Accounting Principles (Chinese GAAP) and International Financial Reporting Standards (IFRS) and harmonise China's accounting system with IFRS (Chen, Sun, and Wang, 2002; Peng et al., 2008). In fact, China's new accounting standards of 2006 have become substantively convergent with IFRS (Ding and Su, 2008). From 2007, the new IFRS-convergent accounting standards became mandatory for Chinese publicly listed companies (Liu et al., 2011).

The type of accounting regulations applicable to a particular listed company depends on the type of shares issued (Peng et al., 2008). Listed companies in China fall under three primary categories: A shares, B shares and H shares. While A shares can only be purchased and traded by Chinese domestic investors, foreign investors can buy and trade B shares, which are denominated in U.S. dollars in the SSE and Hong Kong dollars in the SZSE (Chen, Chen, and Su, 2001). H shares are listed in the stock exchange of Hong Kong and are quoted in Hong Kong dollars. Companies that issue A shares are required to comply with Chinese GAAP, while companies that issue B shares are required to comply with IFRS (Peng et al., 2008). If a listed company issues both A and B shares, then two sets of financial statements are compulsory; one based on Chinese GAAP and the other on IFRS (Peng et al., 2008). The Chinese GAAP-based financial statement is usually audited by a local CPA firm, while the IFRS-based financial statement is audited by another CPA firm, which is usually one of the Big 5 auditors (Chen, Chen, and Su, 2001). It has been argued that such requirements by the Chinese government are to ease overseas investors' concerns regarding accounting quality (Chen, Sun, and Wang, 2002) and to improve financial reporting comparability (Liu et al., 2011) and value relevance of accounting information in China (Chen, Chen, and Su, 2001).

The Chinese economy was greatly influenced by the closed regulatory culture inherited from the former Soviet Union, where the market was mainly disciplined by regulators rather than market mechanisms (Ding and Su, 2008). As IFRS was developed based on

Western economic practices, it is important to discuss the effect of IFRS-convergent accounting standards in China, where there exists significant differences in terms of institutional, cultural, legal, economic, and political environments to Western economies. After examining accounting quality for the period 2005 to 2008 with firms mandated to follow the new IFRS-convergent standards, Liu et al. (2011) conclude that the quality of accounting has improved significantly with decreased earnings management and increased value relevance of accounting measures in China. Empirical evidence also reveals that the value relevance of reported earnings has increased while earnings smoothing has decreased following the mandatory adoption of IFRS-convergent standards in China (Liu et al., 2011). Therefore there appears to be good empirical evidence that IFRS-convergent standards exert a positive effect on accounting quality in China.

1.3.2 The impact of State ownership

One of the distinct characteristics of China's listed companies is that the state remains in control of restructured SOEs. Shares of a listed company in China are split into state shares, legal-entity shares, and tradable shares, with the restriction that state and legal-entity shares cannot be publicly traded (CSRC, 2008). A considerable number of shares issued by listed companies are held by the state or 'legal persons' such as enterprises and institutions and cannot be traded in the same way as shares held by individual investors (Chen, Chen, and Su, 2001). A split share structure exists in China's stock market where there are a large volume of non-tradable state-owned and legal person shares and only one-third of tradable shares (Yu, 2013). Despite China's initiation of the Split Share Structure Reform during 2005 to 2006 to reduce the volume of non-tradable shares on the stock market, state ownership still remains high in 'strategically important industries such as the oil, natural gas and mining sector and the publishing, broadcasting and media sector' (Yu, 2013, p. 76). Unlike individual investors who rely on publicly available information, institutional shareholders in China usually have direct access to insider information (Chen, Chen, and Su, 2001). As such, listed companies in China with a large number of institutional shareholders may have fewer incentives to produce high quality financial statements, which in turn affects the reliability of accounting information in China (Chen, Chen, and Su, 2001). Generally speaking, other features of typical Chinese listed companies include concentrated ownership structure, limited disclosure, poor investor protection, and reliance on China's banking system (Yu, 2013).

Although China's economic reform broke ground regarding the emergence of the nation's capital markets, the initial purpose of establishing domestic stock exchanges was to provide SOEs with more capital raising opportunities rather than a thorough reform towards a market-based economy (Hu, 2011; Guo and Ma, 2015; Zhang, 2015). Hence, a great number of listed companies were originally SOEs, with on average only 30% of share capital actively traded on the SSE and SZSE (Zhang, Altman, and Yen, 2010). By the end of 2012, the state remains as a controlling shareholder in nearly half of Chinese listed companies (Zhang, 2015). The reason for the high concentration of state ownership in Chinese listed companies is because during the economic reform the Chinese government privatised a large number of small and medium sized SOEs and corporatised large SOEs (Yu, 2013). Due to the high concentration of state owned and other non-tradable shares on the stock exchanges, the volatility of Chinese stocks is potentially much higher than those in western economies (Zhang, Altman, and Yen, 2010). One problem associated with China's listed companies, especially SOEs, is that the controlling shareholder often has a dominating influence (Cheng, 2014) that can raise major governance concerns. Excessive authority in the hands of the controlling shareholder can be dangerous as all of the company's important decisions are made exclusively by one person. In practice, false information disclosure, insider trading, and malicious manipulation of the market are often observed in listed companies with a controlling shareholder (Cheng, 2014).

1.3.3 The Special Treatment regime

Following the establishment of the SSE and SZSE, the governing body of the securities market – the China Securities Regulatory Commission (CSRC), was instituted in 1992. The main function of the CSRC is to oversee China's nationwide centralised securities supervisory system (CSRC, 2008). As required by the CSRC, the SSE and SZSE launched the Special Treatment (ST) system on 22$^{\text{nd}}$ April 1998 to differentiate firms in abnormal financial conditions (CSRC, 2008). The ST system is designed to identify and single out poorly performing stocks as an early warning signal to investors and creditors (Kim, Ma, and Zhou, 2016). According to the rules governing the listing of stocks on the Chinese stock exchange, a listed company would be placed under Special Treatment for financial abnormality and other reasons if it faces the risks of being terminated from listing or if its investors' interests would likely be impaired due to difficulties in judging its prospects.

A Special Treatment can either be classified as a delisting risk warning (as represented by putting '*ST' before the stock name) or other kind of Special Treatment (as represented by putting 'ST' before the stock name). The Exchange issues a delisting risk warning (*ST) on stocks upon the occurrences of any of the following circumstances:

> (1) the company has been in the red in the most recent two consecutive years based on the audited net profits disclosed in financial statements;
> (2) after correcting the serious errors or falsehoods in its financial report either on its own initiative or by the order of the CSRC, the company adjusts its previous financial reports retroactively and as a result, the company goes

into the red for the most recent two consecutive years;

(3) the company has been ordered by the CSRC to correct the serious errors or falsehoods in its financial report but fails to address these issues within the specified time limit, and the company's stocks have been suspended from trading for two months;

(4) the company fails to disclose its annual report or interim report within the statutory period and the company's stocks have been suspended from trading for two months;

(5) the company is likely to be dissolved;

(6) the court has accepted the company's application for reorganisation, settlement or bankruptcy liquidation;

(7) as equity changes renders the company unsuitable for listing, the company submits to the Exchange a plan for addressing the equity structure problem and obtains approval from the Exchange;

(8) other circumstances as recognised by the Exchange.

The Exchange issues the other kind of Special Treatment (ST) upon the occurrence of any of the following circumstances:

(1) the audit results for the most recent financial year show that shareholders' equity is negative;

(2) the company's financial report for the latest financial year is issued a disclaimer of opinion or adverse opinion by a CPA firm;

(3) after the company applies to the Exchange for lifting the delisting risk warning and obtains the approval, the audit results for the most recent financial year reveal abnormal operation of its principal business activities, or a negative net profit after deducting non-recurring gains and losses;

(4) the company's production and business activities are seriously affected and not likely to return to normal within three months;

(5) principal bank account of the company is frozen;

(6) board of directors is unable to convene meetings and reach a resolution;

(7) the funds of the company are misappropriated by its controlling shareholder or the controlling shareholder's related parties for non-operating purposes, or the company provides external guarantees in breach of the prescribed decision-making process, and the circumstance is serious;

(8) other circumstances as determined by the CSRC or the Exchange.

The Exchange acts to suspend the listing of the stocks of a listed company if the audit results for the most recent financial year show that the company remains in the red after it was issued a delisting risk warning (*ST) as a result of two consecutive years' losses or if the company fails to follow the order of the Exchange after it was issued a delisting risk warning (*ST). The Exchange terminates the listing of stocks of a listed company if after the company's stocks were suspended from listing, the latest annual report disclosed by the company during the statutory period shows that the company is still in the red or the company fails to release its latest annual report within the statutory period since its stocks were suspended from listing and all other circumstances as determined by the Exchange. Bai, Liu, and Song (2004) note that around 94% of Chinese listed companies are given ST labels as a result of either making two years of losses or shareholder's equity being lower than registered capital. Zheng and Yanhui (2007) also state that most ST companies in China are the result of financial abnormality.

Companies with ST status face a two-way street: they must either remove the ST status and return to normal listing by turning to profit, or they will be de-listed as a result of persistent financial distress. However, in reality, it is quite rare for delisting to be carried out in the Chinese stock market (Tan and Wang, 2007). Most of the ST stocks are able to improve their financial health and retrieve their listing positions, often with aid from the government (Zhang, 2015). Furthermore, ST firms will often adopt a series of restructuring or reorganisation programs to improve their financial health. According to Kim, Ma, and Zhou (2016), on average a ST firm retains Special Treatment status for 3.66 years until a final resolution is reached. Based on their sample of ST firms listed on either SSE or SZSE from 1998 to 2011, Kim, Ma, and Zhou (2016) find that 65 percent of ST firms return to normal trading status. As also evidenced by Green, Czernkowski, and Wang (2009), a majority of ST companies have their ST status removed by the third year after the initial ST designation. They also find that in comparison with non-ST companies, ST companies are more likely to engage in practices indicating earnings manipulation to remove the ST designation (Green, Czernkowski, and Wang, 2009).

However, there are several reasons why ST companies can continue in the distressed state, even re-entering ST status several times. First, as the majority of listed companies have parent SOEs, ST companies are usually rescued by their parent company who can access cheap loans from state-run banks (Cheung et al., 2009). Second, the Chinese government tends to subsidise and rescue ST companies for political and economic purposes, e.g., if the ST company is the backbone of a particular industry (Zhang, 2015). Third, the listing status is in itself very valuable in China. Competitors are also motivated to help ST companies to recover, because they perceive the value of troubled firms not only in terms of their fundamental value but also a ‘shell’ value. The ‘shell’ value represents the valuable stock listing right subject to a highly competitive Initial Public Offering (IPO) listing regime (Kim, Ma, and Zhou, 2016). A number of capital hungry companies wishing to be publicly listed find ST firms more attractive because acquiring those ST firms through merger or acquisition might lead to the probability of accessing a liquid capital market (Kim, Ma, and Zhou, 2016).

1.4 Motivation and research objectives

Against China's unique institutional background, this research aims to develop a class of corporate financial distress prediction models utilising a large sample of Chinese corporate financial distress data based on China's unique Special Treatment (ST) system. The sample of this study includes all listed companies on both the Shanghai and Shenzhen stock exchanges from 1998 to 2016. Despite being the world's second largest economy after the U.S., corporate financial distress prediction in China has garnered fairly limited research attention, with the majority of research emerging only in recent years (Zhang, Altman, and Yen, 2010). Most empirical studies on corporate financial distress prediction are based on Western economies. Adaption of these models to assess distress potentials of Chinese companies could be both theoretically and practically questionable, because representative bankruptcy predictors may vary according to nation, industry, or even company specific factors (Liang and Wu, 2005). As suggested by Grice and Dugan (2001), bankruptcy prediction models should be applied more cautiously, as applying prediction models to time periods and industries other than those used to compute the original models may result in a significant decline in prediction accuracies and other potential problems. Applying existing models to other time periods and different industries can be questionable, let alone applying models from developed countries to the case of China. This is because there exist distinct differences between China and Western countries in terms of institutional, economic, socio-political, and regulatory background, which makes extant prediction techniques less compatible.

Despite some recent reforms of the Chinese bankruptcy legislation, the bankruptcy regime in China is considerably less developed than other major industrialised nations such as the U.S. In fact, there have been comparatively few bankruptcies and liquidations in China. For example, in 2009, bankruptcy filings totalled 1,473,675 in the United

States while the number of accepted bankruptcy applications in China reached only 2,434 (Jiang, 2014). The main reason for the inactiveness of bankruptcy is because the Communist government of China prioritises the maintenance of social stability, taking collectivist approaches over private or individual concerns, and allocating more power to the courts and government in such disputes (Jiang, 2014). Given China's historical, social and cultural intolerance towards corporate failure the 'Chinese equivalent of U.S. Chapter 11' – Special Treatment (ST) system was introduced in 1998 to provide investors and creditors with a measure of protection by identifying companies in the early stages of distress as well as providing a regulatory mechanism by which struggling companies can improve their performance and return to normal listing status. Arguably, the ST system provides a unique opportunity and distressed sample to evaluate and model Chinese financial distress.

In the financial distress prediction literature, most studies to date have modelled financial distress in terms of a simplistic binary classification outcome (i.e., bankruptcy and non-bankrupt). As discussed by Hensher, Jones, and Greene (2007), the conventional 'two-state' model frequently applied in the literature remains skeptical on a number of theoretical and pragmatic grounds. For example, the legal concept of bankruptcy defined in many studies may not always reflect the underlying economic reality of corporate failure (Jones and Hensher, 2007). In fact, some companies might abuse the bankruptcy law and employ 'strategic bankruptcy' (Delaney, 1992) to avoid financial obligations to creditors. Law-suits and union problems are also important factors that could result in companies filing for bankruptcy as a result of strategic management decisions (Grice and Dugan, 2001). In addiction, bankruptcy is not always solely the result of financial distress. It is usually the outcome of a joint result of financial distress and other events that precipitate legal action (Grice and Dugan, 2001). In practice, the full spectrum of financial distress is not always captured by outright failure (Hensher, Jones, and Greene, 2007).

Some financially distressed firms might reduce or eliminate dividend payments, or even default on loans. Financial failure is a necessary but not sufficient condition of corporate bankruptcy (Karels and Prakash, 1987). That is to say firms might experience financial distress, but they do not necessarily enter into bankruptcy as a result of financial distress.

Although the relevance and utility of multi-state distress prediction models has been widely appreciated, fairly limited efforts have been devoted to developing such models (Jones and Hensher, 2007). The second research objective is that in addition to conventional dichotomous distress prediction modelling, this study also aims to model Chinese financial distress in a multi-state setting. Unlike binary distress prediction models that are subject to oversimplification of the underlying economic reality of firms, multi-state models can better approximate the continuum of corporate financial health observable across Chinese listed companies. Moreover, companies are not simply distressed or healthy, but they possess certain degrees of financial distress that varies from time to time (Ward, 1994). In the Chinese setting, predicting the likelihood that a listed company would enter different distress states could help investors to manage their stock portfolio risk and assist creditors, suppliers, and customers to better evaluate a company's credit risk, as different severity levels of financial distress are associated with different levels of risks in China's stock market (Zhou, Tam, and Fujita, 2016). As such, in addition to the conventional binary distress prediction setting in which healthy firms are discriminated from distressed firms, this study also aims to model Chinese distressed firms from a three-state and five-state modelling perspective.

A large number of studies in the distress prediction literature focus solely on the predictive ability of accounting-based measures; this is especially the case with regards to Chinese distress prediction research. Recent research on turnaround probability of corporate financial distress in China has shown that accounting-based variables alone provide the highest prediction accuracy in comparison with a model that combines accounting-based, market-based, and other variables (Kim, Ma, and Zhou, 2016). This contradicts the U.S. evidence from Shumway (2001) and Hillegeist et al. (2004), where market-based variables are found to significantly contribute to the incremental predictive accuracy of financial distress prediction models. In addition, there has been limited research attention on the performance of a number of 'non-conventional' distress predictor variables as opposed to accounting-based and market-price predictors. Based on a large U.S. sample of 1,115 bankruptcy filings and 91 predictor variables, Jones (2017) concludes that ownership structure/concentration and CEO compensation contribute the most predictive power.

The third research objective of this thesis is to evaluate and compare how well these 'Western-style' bankruptcy predictor variables predict in the unique context of China's ST system. This study aims to examine the predictive and explanatory power of a wide range of financial and non-financial variables in the unique Chinese setting, including accounting-based variables, market-price indicators, shareholder ownership/concentration variables, corporate governance proxies, macroeconomic variables, executive compensation variables, corporate social responsibility (CSR) variables, industry background, and other variables.

Lastly, following the approach of Jones (2017), this study employs an advanced machine learning technique – the gradient boosting (GB) model to examine the predictive performance of a large number of conventional and non-conventional distress predictor variables. A commercial version of the GB model known as the TreeNet Gradient Boosting Machine (TreeNet®) is applied. TreeNet® is one of the most powerful commercial machine learning models available and is particularly helpful for empirical investigations that involve large numbers of input variables (Hastie, Tibshirani, and Friedman, 2009;

Jones, 2017).

1.5 Contributions of this research

This study extends the literature on corporate financial distress prediction in emerging markets. As the world's biggest developing country, the Chinese stock market has attracted considerable global attention. In comparison with developed economies, developing countries generally suffer from inadequate market transparency, insufficient market regulation, and a lack of sound and reliable distress prediction models to identify potential failures when compared to a more mature market such as the U.S. market. In terms of China, the Chinese market lacks an adequate level of corporate governance, such as independent outside directors, audit committee, and competition in the managerial labour market (Chen, Chen, and Su, 2001). As the economic landscape in China continues to transform to a free market economy, and investors and creditors face increasing exposure to rising corporate debt levels and escalating default rates, corporate distress prediction modelling is assuming far more relevance in the Chinese context. With China's rapid economic growth and globalisation, corporate distress prediction modelling in the Chinese context not only appeals to domestic and international investors and creditors for risk management purposes; it also has policy implications for regulators and practitioners.

This thesis extends the growing literature on corporate financial distress prediction by considering the case of China, where the institutional background is distinctly different from that of Western markets and there is historical, social, and cultural intolerance towards corporate failure[2]. There have been few bankruptcies and liquidations in China as

[2] See Chapter 2 for more detail.

the Socialist state government prioritises maintenance of social stability and employment. However, the CSRC introduced the ST system regarding the suspension and termination of Chinese listed loss making firms in 1998 to provide investors and creditors with an early warning system to identify distressed companies as well as providing a regulatory mechanism by which struggling companies can improve their performance over time. The class of financial distress prediction models developed in this thesis by considering the unique ST system adds a novel dimension to the current financial distress prediction literature.

Second, this thesis also contributes to the distress prediction literature by comparing and evaluating the predictive and explanatory power of a large number of 'Western-style' bankruptcy predictor variables in the unique context of China. The role of accounting-based ratios and market-price variables in bankruptcy prediction has been the subject of many empirical studies; however, few studies have examined the predictive power of other 'non-conventional' distress predictor variables which might also have plausible theoretical links to corporate financial distress. This study examines the predictive and explanatory performance of over 90 variables, which include accounting-based variables, market-price indicators, corporate governance proxies, ownership concentration/control variables, macroeconomic variables, executive compensation variables, corporate social responsibility variables, valuation multiples and other control variables. In particular, this study also includes a unique measure to the Chinese context – state ownership. Among the other control variables which typically include firm size and industry effects, this study also controls for earnings management using the measure developed by Kothari, Leone, and Wasley (2005) because previous empirical research has shown that Chinese listed companies tend to engage in earnings management practices when confronted with delisting risks.

Third, this thesis also contributes to the financial distress modelling literature from a multi-state perspective. As the TreeNet® model is not restricted to binary settings, this study also examines the predictive performance of TreeNet® in a multi-class setting where the financial health of listed Chinese companies is modelled as three-states and five-states respectively. In comparison with conventional dichotomous distress prediction studies, modelling financial health of companies in a multi-state setting can better approximate the continuum of corporate financial health observable across Chinese listed companies because companies are not simply distressed or healthy but possess certain degrees of financial distress that vary over time (Ward, 1994).

Rapid economic expansion and globalisation have transformed China into the world's second biggest economy with the fourth largest financial system in the world. The class of distress prediction models developed in this thesis could be of substantial interest to current and prospective investors in China for decision-making purposes. Financial distress prediction models able to identify potential distress entities and issue early warning signs to investors and creditors have attracted huge attention from analysts, practitioners, and corporate regulators in China. Sound distress prediction models based on China's unique ST system could also be used in measuring, monitoring, managing, and controlling financial and operational risks in the radically changing Chinese market (Ding, Song, and Zen, 2008). This thesis also provides further empirical evidence regarding the usefulness and effectiveness of the ST system on suspension and termination of financially struggling stocks in detecting distress from an early stage, in addition to providing early warning signals to investors and creditors.

1.6 Chapter conclusion

This chapter has introduced the topic of corporate financial distress prediction. Prior to the discussion of motivation, research objectives, and contributions of this thesis, preliminary background regarding the Chinese economy has been outlined, such as the corporate financial reporting system, the impact of state ownership and control, and the origin of the Special Treatment (ST) system. The ST system on suspension and termination of listed loss making firms is unique to the Chinese setting. There have been few bankruptcies and liquidations in China because the Chinese government is more concerned with maintaining social stability and employment. Given China's historical, social, and cultural intolerance towards corporate failure, the ST system provides a unique opportunity and distressed sample for Chinese distress prediction modelling.

This thesis aims to develop a class of accurate distress prediction models based on China's unique ST system. In addition to conventional binary distress prediction modelling, this thesis also models the financial health of Chinese listed companies from a multi-state setting, embracing a three-state distress prediction model and a five-state distress prediction model. It also examines the predictive and explanatory power of a wide range of financial and non-financial variables, including financial ratios, market returns, shareholder ownership/concentration, corporate governance proxies, macroeconomic variables, executive compensation variables, corporate social responsibility (CSR), industry background, and other variables. Following the approach of Jones (2017), this study employs an advanced machine learning method – TreeNet® to examine the predictive performance of over 90 input variables in a binary and multi-class setting respectively.

1.7 Organisation of this thesis

The remainder of this thesis is organised as follows. Chapter 2 discusses the legislative development of the Enterprise Bankruptcy Law (EBL) of China. It also explains the reasons why there are few bankruptcies and liquidations in the Chinese market. China's historical, social, and cultural intolerance towards corporate failure and other institutional information (introduced in Chapter 1) position this study to have distinctive contributions to the distress prediction literature. Chapter 3 of this thesis reviews prior literature by four themes – the developments in distress prediction modelling, alternative distress predictors, research on multi-state distress prediction, and the research on Chinese distress prediction. While the discussion of how distress prediction techniques have evolved over time shed light on TreeNet® as the appropriate empirical framework of this study which is further explored in Chapter 4, the discussion of alternative distress predictors provides motivations for variable selection of this study. The review of prior Chinese distress prediction studies reveals some limitations which this thesis overcome.

Data, variables, and methodology are described in Chapter 4 of this thesis, which includes sample and variable selections, variable definitions, data collection procedures and the formal Gradient Boosting (TreeNet®) model. The reasons why TreeNet® is selected as the appropriate empirical framework for this thesis are also explained in Chapter 4. The preliminary empirical findings of this thesis – descriptive statistics are presented in Chapter 5. Chapter 6 and Chapter 7 provide more empirical results of the predictive performance of the binary TreeNet® mode, five-state TreeNet® model, and three-state TreeNet® model. Chapter 8 provides concluding remarks in addition to a discussion of limitations of the current study and directions for future research.

Chapter 2

The Enterprise Bankruptcy Law of China

2.1 Chapter introduction

This chapter explores the development of the Enterprise Bankruptcy Law in China. Section 2.2 explores the history of bankruptcy regulation in China, while Section 2.3 examines the socialist ideology and bankruptcy system, explaining that 'bankruptcy' is not necessarily alien to 'socialist ideology'. On the contrary, China as a socialist country can actually benefit from having a bankruptcy system. This chapter then describes the evolution of the bankruptcy law development in China from a bifurcated bankruptcy regime to a unified bankruptcy system that applies to both SOEs and non-SOEs. The bifurcated bankruptcy regime in China includes the 1986 Chinese Bankruptcy Law (explored in Section 2.4) and Chapter XIX of The 1991 PRC Civil Procedure Law (explored in Section 2.5). Section 2.6 discusses complications inherent in the bifurcated bankruptcy system, highlighting the necessity of a unified bankruptcy system that applies more expansively to all enterprises. Section 2.7 explores the new Enterprise Bankruptcy Law in China. After the implementation of the new Enterprise Bankruptcy Law, Section 2.8 of this chapter explores a rather unique phenomenon in China wherein there is a comprehensive bankruptcy system, however there are few bankruptcies and liquidations. This is followed by some reasons for the inactiveness of bankruptcy practices explained in Section 2.9. Section 2.10 concludes the chapter.

2.2 The history of the bankruptcy system in China

In recent Chinese history when China was a purely centrally planned socialist economy, it was dominated by state-owned enterprises (SOEs) funded through government directed 'policy loans' by the state-owned commercial banks (SOCBs). In fact, a vast majority of the SOEs were actually poorly performing enterprises; according to a national survey conducted in 1997, out of the 14,923 large and medium sized SOEs at that time, 40.5% of them were operating at various degrees of losses (Booth, 2008). Despite the large proportion of 'non-performing loans' (NPLs) undertaken by SOEs, the Chinese government issued funding to SOEs with little or no concerns about their ultimate ability for loan repayment (Booth, 2008). Before the economic reform, as a communist state the Chinese government had been strongly influenced by the socialist ideology that commits to a fully employed and egalitarian society (Maskin, 1996). As a result, the issue of 'soft-budget constraint syndrome' (Kornai, 1980) is evident in the Chinese economy where the government continues to subsidise SOEs to prolong their lives even if their prospects are no longer economically viable.

The 1987 economic reform marked the start of the government's effort to make the transition from a centrally planned socialist economy to a market-oriented economy. As such, the theme of the economic reform was to 'reduce the role of state planning, strengthen the autonomy of enterprises, encourage competition among businesses and provide direct economic incentives for enhanced performance to enterprises and employees' (Zheng, 1986, p. 685). Due to the increased competition among enterprises in the Chinese market, some companies significantly improved their economic performance, while others were likely to fail due to sustained losses, as corporate bankruptcies are an implicit part of the new market economy towards which China is moving (Tomasic and Zhang, 2012). From the Chinese government's perspective, devising a suitable strategy to deal with companies that sustain losses became one of the priorities in the economic reform (Zheng, 1986).

It has been widely acknowledged that in the history of China, many historical, cultural, and social factors have shaped attitudes of Chinese people towards debt and bankruptcy (Tomasic, 2016). In fact, the concept of bankruptcy has never been formally recognised in the Chinese legal system until the first bankruptcy law enacted in 1906 during the late Qing Dynasty (Li, 2001). However, it was abolished two years later in 1908 by Emperor Guang Xu as a result of difficulties in implementation (Li, 2001). The initial attempt to introduce a set of bankruptcy regulations in the history of China was unsuccessful. A second attempt to implement bankruptcy law arose in 1935 during the era of the Republic of China. It has been said that the 1935 bankruptcy law by the Nationalist Government is still in use in Taiwan today (Li, 2001). After the establishment of the People's Republic of China in 1949, the Communist Party annulled all pre-existing laws by the Nationalist Government (Arsenault, 2008). The Communist Party of the People's Republic of China at that time believed that bankruptcy regulations were not necessary in a socialist country (Carr, 2008).

Thereafter, no bankruptcy law existed in China for more than 30 years and the issue of bankruptcy legislative development was largely disregarded (Wu, 2004; Arsenault, 2008).

In fact, under the planned economic system, because all profits and losses of state-owned enterprises were centrally managed, and the state government would offset any losses via subsidisation, bankruptcy was never an issue of concern (Li, 2001). Some 'central plan strategies' include writing off losses directly through the state budget, requiring banks to provide cheap policy loans, tax exemptions, reorganisations, changing business operations of enterprises, or more extremely merging loss-making companies with profitable ones (Miller, 1996). Without bankruptcy law which works as a proper market exit mechanism, at that time economic unviable companies exited from the market without going through any legal procedures (Li, 2001). It was not until the early 1980s that the deficiencies in the way the planned economic system dealt with insolvent companies were finally recognised by Chinese economists, legal scholars, and government officials (Arsenault, 2008). This point marked the start of a legislative process towards the very first nationwide bankruptcy law, the *Enterprise Bankruptcy Law of the People's Republic of China (trial Implementation)*.

2.3 Socialist ideology and the bankruptcy system

In socialist China, SOEs play a vital role in the economy, providing not only the majority of goods and services but also employment opportunities for millions of workers (Booth, 2008). It used to be a common belief that socialist enterprises would not go bankrupt, and therefore employees of SOEs had what was referred to as 'iron rice bowls' with lifetime jobs and a series of guaranteed benefits, including housing, education, and health care (Booth, 2008). The inherent belief that socialist enterprises would never go bankrupt was once regarded as a feature that made it superior to capitalist economies (Zheng, 1986). For many, even the idea of bankruptcy was unimaginable in what had been a communist state (Tomasic and Zhang, 2012), let alone to come up with a set of bankruptcy legislation.

It is a deep-rooted cultural tradition in China that a debt must be paid off and there used to be an old saying that the son is responsible for the debts incurred by the father (unpaid debts are carried forward from one generation to the next) (Arsenault, 2008). The Western notion of bankruptcy to discharge and forgive debt contradicts traditional values and how Chinese people perceive debt (Xu and Zhang, 2016). In addition, one of the most important issues that hindered the process of bankruptcy law reform in China was the fear of social disruption through the displacement of workers in bankrupt SOEs (Tomasic and Zhang, 2012). Indeed, the socialist ideology has been strongly influenced by the philosophy that commits to a fully employed and egalitarian society (Maskin, 1996).

Despite the seemingly contradictory nature of the notion of bankruptcy and socialist ideology, some theoretical development can help explain that bankruptcy is not necessarily alien to the socialist ideology. One of the potential theories that helps establish a potential linkage between socialist ideology and bankruptcy is developed based on competition. Since it is generally accepted that competition is encouraged in a socialist economy, it only remains at a superficial level in the absence of an exit mechanism that allows enterprises to fail (Zheng, 1986). In addition, rapid economic development and growth can be achieved in a more efficient manner once backward sectors and enterprises are abolished (Zheng, 1986). Having a bankruptcy system provides an opportunity to eliminate poorly performing enterprises while promoting the development of promising enterprises.

2.4 The 1986 Chinese Bankruptcy Law

As one of the most important goals of the economic reform was to restructure SOEs to prevent their widespread losses (Lee, 2001), it highlighted the need for a comprehensive insolvency system to deal with insolvent SOEs that struggle for survival and debt repayments (Booth, 2008). In addition, China's on-going transition to a market economy also requires a systematic legal system to encourage and protect investments, business enterprises and other relevant market participants (Lee and Ho, 2010). As has been suggested by Booth (2004), a set of effective bankruptcy laws could work as a fundamental part of the institutional framework necessary for a successful transition towards a market economy. China's very first nation wide Enterprise Bankruptcy Law, *The Enterprise Bankruptcy Law of the People's Republic of China (trial Implementation)*, was implemented in 1986 on a trial basis (the 1986 Chinese Bankruptcy Law). It was enacted on 2 December 1986, and came into operation on 1 October 1988. The enactment of the 1986 Chinese Bankruptcy Law also marked the end of the 'iron rice bowl' social policy era since it is no longer the case that SOEs are not subject to bankruptcy (Booth, 2008).

2.5 The 1991 PRC Civil Procedure Law

With the development of economic reform, the composition of the economy started to change, which not only included SOEs but also privately-owned enterprises (Ding, Song, and Zen, 2008). Due to the appearance of non-SOEs such as privately-owned enterprises, the 1986 Chinese Bankruptcy Law could no longer serve its intended purposes due to its very limited scope of application only to SOEs (Patel, 2009). With the growing proportion of non-SOEs in the economy, the Chinese government approved the *Civil Procedure Law of the People's Republic of China* (the 1991 PRC Civil Procedure Law) On April 9, 1991, in which Chapter XIX could be applied to the bankruptcy of non-SOEs with legal person status (Booth, 2008). Therefore, by 1991, China had a bifurcated insolvency system with separate sets of bankruptcy laws co-existing dependent on the nature of the enterprises (Lee and Ho, 2010).

2.6 Some problems of the bifurcated bankruptcy system

Arguably, one of the most controversial issues with regard to the bifurcated bankruptcy system was the different treatment in law between SOEs and non-SOEs. At that time, the 1986 Chinese Bankruptcy Law governed the bankruptcy procedures of SOEs, whilst bankruptcy applications of non-SOEs were subject to Chapter XIX of the 1991 PRC Civil Procedure Law. According to Lee and Ho (2010), having a bifurcated insolvency system contradicts the principle of equality. To make matters worse, despite having two sets of bankruptcy laws which seemed adequate and comprehensive, in fact both the 1986 Chinese Bankruptcy Law and Chapter XIX of the PRC Civil Procedure Law were fairly short in length, including only 43 articles and 8 articles, respectively (Lee and Ho, 2010). Therefore, the co-existence of different sets of bankruptcy laws not only made it difficult to apply and interpret various cases, but both sets of laws were deficient in detail, which left numerous gaps and omissions (Booth, 2008).

China's bankruptcy framework was further complicated by judicial interpretations of the Supreme Court, administrative regulations issued by the State Council, local regulations issued by different provinces, and liquidation procedures of foreign investment enterprises (Arsenault, 2008; Booth, 2008). According to Wu (2004), no unified bankruptcy system existed that applied to all types of business entities; instead there were several overlapping bankruptcy regimes that were applicable depending on the nature of debtors and their geographical locations. For example, on top of the 1986 Chinese Bankruptcy Law and the 1991 PRC Civil Procedure Law, there were also some regional bankruptcy regulations with limited provincial application, such as the Guangdong Province Company Bankruptcy Regulation (the Guangdong bankruptcy regulation) and the Shenzhen Special Economic Zone Enterprises Bankruptcy Regulations (the Shenzhen bankruptcy regulation) (Wu, 2004). Having several complicated bankruptcy regimes combined with a lack of clear guidance for law enforcement and a lack of transparency created inconsistency and complications (Arsenault, 2008), adding to inherent difficulties due to the brevity and superficial nature of the bankruptcy regulations (Wu, 2004).

During the transition period to a market economy, due to changes in ownership interests in SOEs, it was difficult to determine the proper scope of application between the 1986 Chinese Bankruptcy Law and the 1991 PRC Civil Procedure Law (Booth, 2004). In addition, there were several inconsistencies between the bankruptcy procedures applicable to SOEs and non-SOEs (Booth, 2008). After the enactment of the 1986 Chinese Bankruptcy Law and Chapter XIX of the PRC Civil Procedure Law, only a few bankruptcy cases were accepted and commenced. Chinese courts accepted a total number of 1,153 cases from 1989 to 1993, which is only representative of a very small fraction of the poorly performing enterprises in China at that time (Booth, 2008). There were over 8 million enterprises in the Chinese market by 1996, and it has been estimated that almost 50% of them were operating at a loss (Booth, 2008).

2.7 The new Enterprise Bankruptcy Law of China

As is evident from the above discussion, the 1986 Chinese Bankruptcy Law and the 1991 PRC Civil Procedure Law did not serve their intended purposes properly. Because the 1986 Chinese Bankruptcy Law was only promulgated on a trial basis with fairly general provisions and limited scope, the Chinese government decided to draft a new national bankruptcy law in February 1994 (Miller, 1996). A key objective of the bankruptcy law reform was to harmonise the overlapping bankruptcy regimes and to enact a unified bankruptcy law that is applicable to both SOEs and non-SOEs (Booth, 2008). As noted by Booth (2004), one of the biggest concerns that hindered the drafting process was the fear of social instability caused by a high level of unemployment if more SOEs were allowed to declare bankruptcy. The lengthy bankruptcy law reform in China, which started in 1994, finally came to an end in 2006 (Booth, 2008). Regarding the growing number of private entities in the Chinese market and their demand for bankruptcy, *The Enterprise Bankruptcy Law of the People's Republic of China* (2006 Chinese Bankruptcy Law or the new Enterprise Bankruptcy Law of China) was promulgated on August 27, 2006 which, which went into effect as of June 1, 2007 (Jiang, 2014).

The new Enterprise Bankruptcy Law of China has a much wider application than its predecessor legislation. The new Enterprise Bankruptcy Law of China applies more expansively to all enterprises with legal person status, including both SOEs and non-SOEs, private enterprises, foreign invested enterprises, and financial institutions, but does not yet extend to partnerships or individuals. Under the new bankruptcy law, there are different types of bankruptcy proceedings: reorganisation (Chapter VIII), settlement (Chapter IX), and liquidation (Chapter X). According to the new Enterprise Bankruptcy Law of China, while all three aforementioned bankruptcy proceedings are available for voluntary bankruptcy filed by debtors, only reorganisation and liquidation proceedings are available options for involuntary bankruptcy filed by creditors. The major objective of the new Enterprise Bankruptcy Law of China is to provide a holistic approach to insolvency and increase investor confidence for both domestic and foreign investors (Falke, 2007). By placing all enterprises – both SOEs and private entities on an equal footing, the enactment of the new bankruptcy law signifies a milestone change in China's bankruptcy law system (Lee and Ho, 2010).

According to the new Enterprise Bankruptcy Law of China, the new law aims to regulate bankruptcy procedures of enterprises, settle credits and debts in a fair way, protect legal rights of creditors and debtors and maintain the market order of the socialist economy. Despite the fact that it generally complies with international standards in the field of insolvency, the new bankruptcy law of China, although modelled after Western bankruptcy laws, appears to have some ‘Chinese characteristics’ (Falke, 2007; Arsenault, 2008; Tomasic, 2016). China’s cultural and political influence play significant roles in shaping perceptions and attitudes towards bankruptcy (Tomasic, 2016). As such, Tomasic (2016) suggests the new bankruptcy law of China should be understood with reference to the social context from which it emerged.

As one of the objectives of the new bankruptcy law is to maintain market order of the socialist economy, social disruption through the displacement of workers still remains the biggest concern that hinders bankruptcy development in the Chinese market (Tomasic and Zhang, 2012). According to Beraho (2011), the new bankruptcy law of China is a compromise between implementing international bankruptcy standards and concerns about social unrest. The new bankruptcy law is a legislative effort attempting to balance the rights of employees on the one hand with the claims of secured creditors on the other. The deep-rooted belief in collectivism has also influenced the application of the new bankruptcy law in the Chinese market. Some bankruptcy practices are negatively impacted by the cultural tradition of allocating more active roles to the court and the government (Jiang, 2014).

2.8 Inactive bankruptcy practices in China

Unlike the United States courts that publish bankruptcy related statistics on a regular basis, there are no official reports for the number of bankruptcy cases in China[1]. Lee (2011) has attributed the Chinese government’s decision not to publish official bankruptcy statistics to a means of concealing some implementation problems of the new bankruptcy law under

[1] Because official bankruptcy statistics in China are not available, this thesis relies on secondary sources on Chinese bankruptcy.

the current legal and political culture in the Chinese market. Despite recent bankruptcy reforms, the Chinese bankruptcy regime is considerably new and less developed than that of other Western economies such as the U.S. (Jiang, 2014). In fact, there have been comparatively few accepted bankruptcy cases in China. For example, in the year 2009, bankruptcy filings totalled 1,473,675 in the U.S. while the number of accepted bankruptcy applications in China reached only 2,434 (Jiang, 2014). According to some unofficial Chinese bankruptcy statistics from 1989 to 2007 as reported in Xu and Zhang (2016), there is a gradual increasing trend of Chinese bankruptcy filings after the implementation of the enterprise bankruptcy law until the year 2000 and then a decreasing trend thereafter. The number of bankruptcy filings in China surged from 38 cases in 1989 to 6233 cases in 1995, which then peaked at 8939 cases in 2000. After 2000, the number of bankruptcy filings in China gradually dropped from 6463 cases in 2001 to 2955 cases in 2007.

Despite the significant differences in terms of the number of bankruptcy filings in the U.S. and China, what is more shocking is the number of accepted bankruptcies in comparison with the number of companies that actually exited the market in China. The gap between the number of accepted bankruptcy cases in comparison with the number of companies that exited the market in China could be a good indication of whether the new bankruptcy law has been properly applied (Lee, 2011). Generally speaking, from 2005 to 2015, around 800,000 companies exited the market each year, while only 2,000 exited through bankruptcy liquidation (Lin, 2018). On average, only 3.3% companies exited the market by making use of the new enterprise bankruptcy law of China (Lin, 2018). For example, there were 3,139 enterprise bankruptcy cases in 2008; however, there were 780,000 companies that exited the market in the same year (Lee, 2011). Business closures that made use of the new enterprise bankruptcy law only accounted for 4.02% of the total number of enterprises exiting the market, which is an extremely small proportion in comparison with business closures through licence deregistration (48.71%) and licence cancellation (51.28%) (Lee, 2011).

2.9 Reasons for inactive bankruptcy practices in China

Several political, institutional, cultural, and economical reasons might help explain the inactive bankruptcy practices in the Chinese market. According to Jiang (2014), the fundamental reason that discourages the application of enterprise bankruptcy law is the excessively broad judicial discretion and government involvement in Chinese bankruptcy practices. China's authoritarian past and its deep-rooted belief in collectivism have shaped its dispute resolution system that leaves the majority of discretion and power to the court and the government (Jiang, 2014). Imbedded in China's collectivism beliefs are the Communist government's majoritarian preferences for social stability and a tendency to take collectivist approaches to favour the interests of the group over private or individual concerns in disputes (Peerenboom, 2017).

At the national level, the government in China (especially the provincial government) is strongly motivated by political and economic reasons to protect local companies from entering into bankruptcy liquidation even if they are no longer economically viable (Wei, 2017; Lin, 2018). The main rationale behind the efforts by local governments to keep economically unviable companies in the market is to maintain the employment rate and social stability as well as to stimulate local economic growth and development (Kim, Ma, and Zhou, 2016; Lin, 2018). As the priority of the Communist government is to maintain social stability, the provincial government typically bails out large companies through the reorganisation procedure within the framework of the bankruptcy law due to concerns of social repercussions caused by collective layoffs (Wei, 2017). In addition, local companies that go bankrupt would imply poor administrative ability of the provincial government and consequently bring great disgrace to the reputation of provincial government officials (Kim, Ma, and Zhou, 2016). As such, the provincial government also keep economically unviable companies in the market for political purposes as the number of local companies is a sign of administrative ability and political achievement (Chen, Lee, and Li, 2008). Economically unviable firms are often rescued by their provincial government by means of subsidies, granting taxation preferences or favouring listed firms in the project approval process (Chen, Lee, and Li, 2008).

2.10 Chapter conclusion

This chapter has discussed the development of the Enterprise Bankruptcy Law in China. Before the economic reform, as a communist state the Chinese government was strongly influenced by the socialist ideology which commits to a fully employed and egalitarian society (Maskin, 1996). No bankruptcy law existed after the funding of the People's Republic of China for more than 30 years and it used to be a common belief that bankruptcy regulation is not necessary in a socialist country. The most important issue that hindered the process of bankruptcy law development in China was governmental concern about social instability caused by a high level of unemployment if SOEs were allowed to declare bankruptcy. In terms of theoretical development, this chapter then explained that 'bankruptcy' and 'socialist ideology' are not necessarily two contradicting concepts; however, as a transitional economy China could actually benefit from having a set of bankruptcy regulations. Having a bankruptcy regime provides an opportunity to eliminate poorly performing enterprises while promoting the development of promising enterprises.

The development of the bankruptcy regulation in China started with the 1986 Chinese Bankruptcy Law, which applied only to bankruptcy applications of SOEs. With the economic reform and privatisation of small and medium sized SOEs, the 1986 Chinese Bankruptcy Law could no longer serve its intended purposes due to its limited scope of application. The 1991 PRC Civil Procedure Law then came into place in which Chapter XIX applies to the bankruptcy filings of non-SOEs with legal person status. Due to the implementation problems and other issues with regard to China's bifurcated bankruptcy system, bankruptcy law reform became necessary to harmonise the overlapping bankruptcy regimes and to enact a unified bankruptcy law.

The new Enterprise Bankruptcy Law of China which was finally promulgated in 2006, applies more expansively to all enterprises with legal person status, including both SOEs and non-SOEs. Despite having a comprehensive bankruptcy system that largely follows international bankruptcy standards, the Chinese bankruptcy regulation is considerably less developed than other major industrialised nations such as the U.S. In fact, there are very few bankruptcies and liquidations in China as the Communist government is more focused on maintaining social stability, taking collectivist approaches over private or individual concerns, and allocating more power to the courts and government in such disputes (Jiang, 2014). China as a socialist economy has historical, social, and cultural intolerance towards corporate failure.

Chapter 3

Literature Review

3.1 Chapter introduction

Chapter 3 reviews the literature on corporate financial distress prediction modelling. Section 3.2 provides a discussion of the definition of financial distress, while Section 3.3 presents the development of distress prediction by modelling techniques, which have evolved over time from simple statistical methods to more advanced machine learning techniques. Section 3.4 explores predictors of corporate failure, the discussion of which motivates the variable selection of this thesis. In addition to binary distress prediction, as this thesis also models Chinese financial distress in a multi-state setting, Section 3.5 reviews the literature on multi-state distress prediction modelling. Because the primary research objective of this study is to develop a class of accurate distress prediction models based on China's unique Special Treatment (ST) system, recent studies on Chinese financial distress prediction are reviewed in Section 3.6. This is followed in Section 3.7 by a discussion of some limitations of extant Chinese distress prediction studies that the current study overcomes. Section 3.8 concludes the chapter.

3.2 Definition of financial distress

In the financial distress prediction literature, there is a notable absence of unifying theory with which to define distress (Chen et al., 2006). As noted by Ohlson (1980, p. 111), 'there is no consensus on what constitutes "failure", with definitions varying significantly and arbitrarily across studies'. The definition of financial distress is not always obvious. Financial distress is a broad concept that describes situations in which companies face financial abnormalities or difficulties. The most commonly used terms to describe firms in financial difficulty are bankruptcy, failure, insolvency, and default (Doumpos and Zopounidis, 1999). Operationally, a company would be regarded as having failed when any of the following circumstances have occurred: bankruptcy, bond default, or an overdrawn bank account (Beaver, 1966).

To date, various terminologies have been adopted in the financial distress prediction literature to describe the 'death' or discontinuation of a company (Altman and Hotchkiss, 2010). While most of the studies in this field have use the term 'corporate bankruptcy' (see e.g., Altman (1968), Shumway (2001), and Jones and Johnstone (2012)), 'financial distress' (see e.g., Zmijewski (1984) and Hu (2011)) and 'corporate failure' (see e.g., Beaver (1966), Altman (1984), and Jones and Hensher (2007)) are also used. According to a general failure definition provided by Dimitras, Zanakis, and Zopounidis (1996, p. 487), 'failure is the situation that a firm cannot pay lenders, preferred stock shareholders, suppliers, etc., or a bill is overdrawn, or the firm is bankrupt according to law'. All aforementioned situations would result in a discontinuity of the firm's operations. In the United Kingdom and Australia, bankruptcy only applies to individuals, while corporate reorganisation and administration apply to companies. In the United States, bankruptcy applies more broadly as formal insolvency proceedings. Most of the U.S. based corporate bankruptcy prediction studies collect a bankrupt sample from firms that have filed either

Chapter 7 liquidation or Chapter 11 reorganisation under the United States Bankruptcy Code. A similar bankruptcy convention also applies to Canada, where bankruptcy equates insolvency.

According to Karels and Prakash (1987), the 'failure' definition in financial distress prediction studies is diverse. In fact, it can be defined in numerous ways depending on the specific interest or condition of the firm under examination (Dimitras, Zanakis, and Zopounidis, 1996). One of the important implications of inconsistent failure definitions across different corporate bankruptcy research is varying and incomparable results (Zavgren, 1983). While a large number of studies define failure as the actual filing for bankruptcy or liquidation, other studies define it as an inability to pay financial obligations as they mature (Beaver, 1966; Bellovary, Giacomino, and Akers, 2007). Some studies do not even provide an exact definition of failure.

Altman and Hotchkiss (2010) define failure as the situation where the realised rate of return on capital with allowances for risk consideration is significantly and continually lower than prevailing rates of similar investments. This definition of failure focuses more on the economic sense of companies and does not overly emphasis discontinuity of operations. To define failed firms as those that have filed for bankruptcy is also debatable because the legal concept of bankruptcy may not always reflect the underlying economic reality of firms (Jones and Hensher, 2007). In fact, a large number of financially distressed companies never file for bankruptcy as a result of acquisition or privatisation. Nevertheless, some healthy companies might abuse bankruptcy law and employ 'strategic bankruptcy' to avoid taxes, financial obligations to creditors, and expensive lawsuits (Delaney, 1992; Theodossiou et al., 1996).

In the context of China, the formal definition of 'bankruptcy' accounts for the legal process of corporate reorganisation (Chapter VIII of the Enterprise Bankruptcy Law), compromise (Chapter IX of the Enterprise Bankruptcy Law) and bankruptcy liquidation (Chapter X of the Enterprise Bankruptcy Law). In relation to this thesis, given China's historical, social, and cultural intolerance towards corporate failure, firms with specially treated stocks[1], including those stocks labelled with 'ST', '*ST' and 'delisting' are defined as firms in financial distress[2]. A more detailed definition of financial distress (the dependent variable of this thesis) in binary and multi-state settings is provided in Section 4.2.3 of Chapter 4.

3.3 The development of financial distress prediction

The prediction of corporate financial distress is a field of research that spans the past seven decades. Bankruptcy research extends back to at least the 1930s, when the Great Depression motivated the development of models for bankruptcy prediction. One of the most important features in the financial distress prediction literature is the use of financial ratios (such as current ratio) as bankruptcy predictors. Early researchers (see e.g., Ramser (1931) and Fitzpatrick (1932)) focused on financial ratio analysis. By comparing certain financial ratios in successful and failed companies, they concluded that in general failed companies exhibited weaker ratios. Merwin (1942) later showed that working capital to total assets ratio, net equity to debt ratio, and current ratio best forecast bankruptcy. Financial ratio analysis built the foundation for the development of more sophisticated bankruptcy prediction models, because if financial ratios exhibit significant differences across failed and non-failed firms, they contain predictive power and can be used as bankruptcy predictors. The literature on financial distress modelling has continued to evolve since these early attempts. One of the most important themes emerged

[1]A Special Treatment can be either a delisting risk warning (*ST) or other kind of Special Treatment (ST). Generally speaking, *ST stocks are in more severe financial distress states than ST stocks.

[2]See Section 1.3.3 for a a more detailed discussion of the ST system.

from such literature relates to the development of modelling techniques (i.e., refining and testing financial distress prediction models).

In the financial distress prediction literature, modelling techniques have evolved from more restrictive statistical methods such as univariate discriminant analysis (UDA), multivariate discriminant analysis (MDA), logistic regression model (logit), and probit regression model (probit) to fully nonlinear conventional machine learning techniques such as neutral network (NN) models and support vector machines (SVMs). Quite recently, some more advanced 'new age' machine learning techniques have been applied to financial distress prediction modelling, which include generalised boosting, AdaBoost, and random forests. As techniques for distress prediction modelling have evolved over time, Section 3.3 reviews these distress prediction techniques, including UDA (Section 3.3.1), MDA (Section 3.3.2), logit/probit (Section 3.3.3), the neural network (NN) model (Section 3.3.4), survival analysis models (Section 3.3.5), and the gradient boosting model, which is the conceptual foundation of the TreeNet® model used in this study (Section 3.3.6).

3.3.1 Univariate discriminant analysis (UDA)

The development of financial distress prediction models originated from financial ratio analysis, developed with the purpose of evaluating credit-worthiness (Beaver, 1966). By comparing the mean values of selected ratios, ratio analysis can outline the general relationship between failed and non-failed companies. Studies concerning potential business failure first emerged in the 1930s. Research was largely focused on univariate ratio analysis until the mid-1960s. A general conclusion from ratio analysis is that failing firms exhibit significantly different ratio measurements than healthy firms (see e.g., Merwin (1942)). Net working capital to total assets ratio and current ratio are recognised as the most useful ratios by early studies (Bellovary, Giacomino, and Akers, 2007). However, ratio analysis is not a predictive test as it can only demonstrate that a difference exists between failed and non-failed companies; It cannot provide evidence regarding how large the difference is and therefore no meaningful statement can be made with regard to the predictive ability of a ratio (Beaver, 1966). The most important implication of univariate studies is arguably that they laid the groundwork for the development of multivariate bankruptcy prediction models.

The evolution of bankruptcy prediction models began with the pioneering study of Beaver (1966), which predicted the failure status of firms by performing a dichotomous classification test, which is also called univariate discriminant analysis (UDA). The classification test makes a dichotomous prediction outcome that classifies a company either as failed or non-failed. The dichotomous classification test assumes a single variable (financial ratio) can be of predictive purposes, so financial ratios are tested individually and a cut-off point is estimated (by trial-and-error) for each ratio with the aim of minimising misclassification error rates.

Beaver (1966) collected a sample of 79 failed firms from 1954 to 1965. For each failed firm in the sample, a matched non-failed firm from the same database and which asset size is the closet to the failed firm is selected. Financial statement data of failed firms were collected from Moody's database up to five years prior to failure. The same procedure was performed on non-failed pairs for the same period. 30 financial ratios were collected and tested, which can be classified into six groups: cash flow ratios, net income ratios, debt to total asset ratios, liquid asset to total asset ratios, liquid asset to current debt ratios, and turnover ratios. Beaver (1966) identified that the differences in mean values contain predictive power in separating failed firms from non-failed firms for each ratio in all five years prior to failure. In general, failed firms tend to have lower cash flow and a smaller reservoir of liquid assets than non-failed firms. Failed firms also tend to incur more debt than their non-failed counterparts.

One of the most substantial findings from Beaver's (1966) study is that distressed firms are generally distinguishable from healthy firms along several financial dimensions. It also provides empirical evidence that financial ratio analysis can provide useful information in the prediction of corporate financial distress. Beaver (1966) also concluded that the cash flow to total debt ratio contained the strongest predictive ability in predicting bankruptcy followed by net income to total asset ratio and total debt to total asset ratio. One of the limitations of the UDA approach is that it treats the prediction outcome as dichotomous and it cannot reveal the impact of the magnitude of the ratio. The magnitude of the ratio can provide extra information regarding how confident the classification is. If one ratio is far away from the cut-off point, then more confidence can be placed into the prediction outcome than if it were close. Another arguably more severe limitation associated with this univariate analysis is that it is too simple; it is based on evaluation of the predictability of financial ratios one at a time. It is possible that a combination of different ratios better predicts financial distress.

Although subject to criticism for its over-simplicity and a lack of practicality, the original purpose of Beaver (1966) was not to find the best predictor of financial distress, but rather to evaluate the predictability of financial ratios using financial statement data. In general, financial ratios measuring profitability, liquidity, and solvency performed the best as bankruptcy predictors. However, no consensus was made as to which group of financial ratios performed better than other groups of ratios in detecting distress potentials. In his suggestions for future research section, Beaver (1966) indicated that higher predictive ability might be achieved if multiple ratios are considered simultaneously in contrast to single ratios considered sequentially. This sparked the the evolution of bankruptcy prediction models, with Beaver's UDA approach setting the stage for the development of more sophisticated and arguably more powerful prediction techniques.

3.3.2 Multivariate discriminant analysis (MDA)

As discussed in the above section, traditional ratio analysis involves analysing one financial ratio at a time. Due to its inherent univariate nature, emphasis can only be placed on individual signals. As Altman (1968) argues, the UDA approach is susceptible to faulty interpretation and ambiguity. For example, a company with poor profitability ratios might be considered as a potential bankrupt firm when analysing profitability ratios. However, the prospects of the same company might not be considered as severe if it has above average liquidity ratios and/or solvency ratios.

It has been suggested that the traditional ratio analysis lost its popularity in the academic environment due to its relatively unsophisticated manner. A meaningful extension of the traditional ratio analysis would be to select and combine several measures into a predictive model. In doing so, the UDA approach can be improved and extended. Financial ratios will take on greater statistical significance if analysed within a multivariate framework than sequential ratio comparisons. Altman (1968) was the first to expand the UDA to a multivariate discriminant analysis (MDA) in the context of bankruptcy prediction.

MDA is a statistical technique that has the ability to classify an observation into one of several established groups dependent upon the observation's characteristics. The primary use of MDA is to make classification when the dependent variable appears in a qualitative form, e.g., bankrupt or non-bankrupt. The MDA approach had been applied in biological and behavioural sciences, consumer credit evaluation, and investment classification. Unlike the UDA approach that can only take into account one ratio at a time, the classification ability of the MDA approach is achieved through the development of a multiple discriminant function. This makes it possible to combine multiple bankruptcy predictors in a linear form with the aim of minimising the probability of false judgment in sample classification. The fundamental advantage of MDA over UDA is the ability to evaluate the entire profile of characteristics as well as their interactions simultaneously rather than sequentially examining individual characteristics (Altman, 2000).

Altman (1968) is based on a matched-pair design with 33 bankrupt firms and 33 non-bankrupt firms. All bankrupt firms are from the manufacturing industry that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act during the period 1946–1965. Non-bankrupt firms are also restricted to the manufacturing industry and they are selected on a stratified random basis. All non-bankrupt firms are stratified by industry and by size and they have to be in existence in 1966. Financial statement data one reporting period prior to bankruptcy is used for the sample test and the data for non-bankrupt firms is collected from the same years as those that filed for bankruptcy.

Twenty two potentially useful predictor variables are used, which can be classified into five categories: liquidity, profitability, leverage, solvency, and activity. Among all candidate financial ratio variables, five ratios are selected as the combinations best able to predict corporate bankruptcy. The five selected ratios are: (1) working capital over total assets; (2) retained earnings over total assets; (3) earnings before interest and taxes over total assets; (4) market value of equity over book value of total liabilities; and (5) sales over total assets. The largest contributors to group separation of the discriminant function are EBIT to total assets, sales to total assets, and market value of equity to book value of total debt. The MDA approach is proven to be a powerful technique in bankruptcy prediction with a with-in sample classification accuracy of 95% one year prior to failure. Further, it is able to provide moderate prediction accuracy up to two years prior to failure with prediction accuracy diminishing rapidly as the lead time increases. The model's prediction accuracy is 79% when tested on a hold-out sample.

After the success of the MDA approach in bankruptcy prediction, Altman (1968) expanded it into a five-factor Z-score model for more general application. The Z score represents a discriminant score, and in general the lower the Z score, the greater a firm's bankruptcy potential. A cut-off point or optimum Z value was determined as 2.675 (the Z value that best discriminantes between the bankrupt and non-bankrupt firms). If a company's Z score is greater than 2.675, then the model will classify the company as non-bankrupt and vice versa. The five variables selected and tested by Altman (1968) remain popular in the financial distress prediction literature and they have been tested as input variables in a wide range of other bankruptcy prediction models (see e.g., Dimitras, Zanakis, and Zopounidis (1996)). The Z-score model has been extensively applied in the credit risk and ratings measurement context and remained as the primary failure prediction method until the 1980s (Ugurlu and Aksoy, 2006). The number and complexity of bankruptcy prediction models have increased dramatically since Altman's (1968) study.

Despite its popularity, the application of the Z-score model can be hampered by a series of restrictive assumptions and it also suffers from limited discriminatory power (Serrano-Cinca, 1997). There are certain statistical requirements regarding the distributional properties of the predictors for the proper application of the MDA approach. First, it requires normal multivariate distribution of independent variables. Second, it requires the same variance and covariance matrices of bankrupt and non-bankrupt groups. An important limitation associated with these statistical requirements is that the normally distributed restriction on predictor variables mitigates against the use of dummy independent variables such as qualitative independent variables (Halperin, Blackwelder, and Verter, 1971; Ohlson, 1980). In practice, it is difficult for predictor variables to satisfy such strict statistical assumptions (Truett, Cornfield, and Kannel, 1967). According to Greene (2008, p. 16) 'the assumption of multivariate normality is often held up as the most serious shortcoming of the MDA technique' (Press and Wilson, 1978). Another limitation associated with MDA is that the output of the MDA model is a score, which has little intuitive interpretation since it is basically an ordinal ranking, rather than a probabilistic outcome (Ohlson, 1980). In comparison, the output from a logistic regression model is a probability, which ranges from 0 to 1 and can be easily interpreted as the probability that an observation belongs a certain group (Serrano-Cinca, 1997).

Altman (1968) is also subject to choice based sample biases. Most estimation techniques require the use of an exogenous random sampling design, where an observation is randomly drawn and the dependent and independent variables are observed. In comparison, a choice based sample arises when the dependent variable (e.g. bankrupt or non-bankrupt) is first observed and then the sample is drawn based on this knowledge. The *Z*-score model was developed based on a matched-pair of 33 bankrupt and 33 non-bankrupt companies and it is subject to small sample and matched sample problems. In addition, the sample for the original study was drawn from manufacturing firms, demonstrating a narrow focus. The matched-pair design over-represents the incidence of bankruptcy relative to the population and therefore limits generalisability (Grice and Dugan, 2001). Studies using a 50% sample frequency rate over-sample bankrupt companies and will lead to asymptotically biased parameters and probability estimates (Zmijewski, 1984). The out-of-sample prediction will also be biased.

3.3.3 Logistic/Probit regression model (logit/probit)

Logistic/Probit (probability unit) regression models are probabilistic discriminant models, which require fewer assumptions in comparison with MDA models. Unlike MDA, the result from which is only valid under certain restrictive assumptions, including that independent variables are jointly multivariate normally distributed (Ohlson, 1980; Serrano-Cinca, 1997), logit models do not make assumptions on the distribution of independent variables. The multivariate normality of predictor variables is critical to the MDA estimation procedure because otherwise classification outcomes derived under non-normality will be suspect (Karels and Prakash, 1987). However, most studies using MDA fail to test for multivariate normality of predictor variables. Karels and Prakash (1987) selected and tested 50 financial ratio variables for normality and they concluded that only a very few ratios satisfy the conditions for univariate normality or log normality. They also found strong evidence of both multivariate skewness and kurtosis of the data, which suggest that the condition of multivariate normality is extremely hard to fulfil.

Like MDA, logit/probit also explains a categorical dependent variable (the class label, which usually takes the form of bankrupt and non-bankrupt) by the value of continuous independent variables (bankruptcy predictors). The purpose of logit/probit models is to predict the probability that an observation with certain characteristics will fall into one of the specified categories (bankrupt or non-bankrupt). Rather than a simple classification outcome (as provided by the MDA model), a logit/probit regression model can predict the probability that a firm will enter a bankrupt or non-bankrupt state. Such a probabilistic outcome can be estimated using a logistic link function for the logistic regression model and a probit link function for the probit regression model. Given any real value, a link function can transform this value into an interval between zero and one, which can then be interpreted as the probability of an observation belonging to one of the bankrupt or non-bankrupt groups. In practice, the results from logit regression models tend to be similar to those of probit regression models (Bishop, 2006). Both logit/probit and MDA lead to a linear classification rule. In MDA, the entire joint distribution $f(x,y) = f(x|y)f(y)$ is estimated; however, in logit/probit, since classification only requires specifying $f(y|x)$, it leaves the marginal distribution $f(x)$ unspecified (Wasserman, 2013). Because in logit/probit, only $f(y|x)$ is estimated, it is more flexible than MDA in terms of underlying statistical assumptions, which is considered as an advantage over MDA (Wasserman, 2013).

According to Jones, Johnstone, and Wilson (2017), the logit classifier only assumes the error structure to be independent and identically distributed (IID) but there is no statistical assumption on the distribution of the independent variables. By contrast, the probit and MDA classifiers both assume multivariate normality for independent variables and IID on the error structure (Jones, Johnstone, and Wilson, 2017). After comparing the empirical results between logit and MDA classifiers when the normality assumptions are violated, Press and Wilson (1978) concluded that logit outperformed MDA by a small margin and it is unlikely for the two methods to yield significantly different results (see also Greene (2008)). As has suggested by Halperin, Blackwelder, and Verter (1971, p. 152), 'the maximum likelihood method (logit) would be preferable over MDA, whenever practical, in situations where the normality assumptions are violated, especially when many of the independent variables are qualitative'.

Ohlson (1980) and Zmijewski (1984) were among the first to apply logit and probit regression models to bankruptcy prediction. In Ohlson (1980), the logit model is estimated for a sample of 105 bankrupt and 2,058 non-bankrupt industrial firms from 1970 to 1976. The data for bankrupt firms were collected from 10-K financial statements. Data three years prior to failure was collected. Nine predictor variables measuring firm size, leverage, liquidity, and performance were included in the model: (1) log (total assets/GNP price level index); (2) total liabilities/total assets; (3) working capital/total assets; (4) current liabilities/current assets; (5) one if total liabilities exceeds total assets, zero otherwise; (6) net income/total assets; (7) funds provided by operations/total liabilities; (8) one if net income was negative for the last two years, zero otherwise; and (9) $(NI_T - NI_{t-1})/(|NI_T| + |NI_{t-1}|)$, where NI_T is net income for the most recent period. Using a cut-off point of 0.038, 17.4% of the non-bankrupt and 12.4% of the bankrupt firms are misclassified one year prior to failure. In Zmijewski (1984), a probit model is developed based on a sample of 40 bankrupt and 800 non-bankrupt industrial companies from 1972 to 1978. Using a cut-off point of 0.5, the probit model correctly classifies 70.7% bankrupt firms and 99.5% non-bankrupt firms in out of sample prediction. Ohlson (1980) concluded that the predictive power of linear transforms of a vector of ratios seem to be robust across large sample estimation, and adding additional predictors might significantly improve the prediction. Ohlson (1980) also noted that the predictive power of the model can be enhanced by incorporating market transactions (price) data. The predictive power of market-price variables as distress predictors is now widely accepted and utilised in the literature[3].

Although logit models relax the assumption of normally distributed independent variables as required by MDA, they are still built based upon certain assumptions, such as independent and identically distributed (IID) errors and independence of irrelative alternatives (IIA) (Jones, Johnstone, and Wilson, 2015). Grice and Dugan (2001) evaluated Zmijewski's (1984) probit model and Ohlson's (1980) logit model using time periods, industries, and financial distress situations different from those used to develop the original

[3]See Section 3.4.1 for a detailed discussion of accounting-based versus market-price indicators in distress prediction.

models. They found that both the logit and the probit models were sensitive to time periods, indicating prediction accuracy declined when applied to time periods different from those in the original sample. The Y-score model was sensitive to industry classifications, while the X-score model was not. Both models were not sensitive to financial distress situations other than those defined in the original studies (Grice and Dugan, 2001).

After reviewing over 150 empirical studies in the credit risk and corporate bankruptcy prediction literature, Jones, Johnstone, and Wilson (2015) conclude that despite the evolution of modelling techniques towards more advanced machine learning techniques, much of the literature still relies on conventional classifiers such as logit/probit models and MDA, with the dominating classifier being the logit model. Hosmer and Lemeshow (2004) reach similar conclusions regarding the popularity of logit models, noting that the logit model has become the standard form of analysis in many fields over the last decade. As noted by Wilson and Sharda (1994), among the two mostly used statistical prediction techniques, which are MDA and logit, no technique clearly provides substantially better results.

3.3.4 Neural network (NN)

During the 1990s, despite the popularity of the logit model, artificial neural networks (NN) surged in the financial distress prediction literature (see e.g., Coats and Fant (1993) and Zhang et al. (1999)). In comparison with MDA and logit, the neural network model contain less restrictive data assumptions, priori model specifications, and distributional properties of the predictors (Etheridge and Sriram, 1997). The neural network model has non-linear, non-parametric adaptive learning properties in modelling and forecasting (Zhang et al., 1999). Odom and Sharda (1990) were one of the first to apply neural network models in the context of corporate bankruptcy prediction. They used the same five variables as Altman (1968) as inputs and their neural network model was estimated based on a total sample of 129 firms, of which 65 went bankrupt during 1975 to 1982 with 64 non-bankrupt firms matched based on industry and year. They found that in comparison with MDA, the neural network model provided higher prediction accuracy in both the training set and the holdout sample. They also concluded that not only did the neural network model outperform MDA in terms of prediction accuracy, it also appeared to be more robust and consistent (Odom and Sharda, 1990). Similar results has also been produced by Wilson and Sharda (1994), who concluded that the neural network model outperformed discriminant analysis in every instance, and it would perform as well or better with the inclusion of more bankruptcy predictors in the modelling process. Fletcher and Goss (1993) found that the neural network model offers forecasting capabilities superior to the logit model based on a matched-pair sample of 18 failed and 18 non-failed firms. Three predictor variables were included in the model, including current ratio, quick ratio, and income ratio.

Although a number of studies have demonstrated that the neural network model is capable of providing good predictive results and they are considered superior to other statistical prediction techniques (see e.g., Atiya (2001) and Pendharkar (2005)), other studies demonstrate a balanced degree of accuracy and other beneficial characteristics among MDA, logit, and the neural network model (Altman, Marco, and Varetto, 1994; Boritz and Kennedy, 1995). Despite a number of studies indicating that neural network models tend to outperform MDA (see e.g., Tam and Kiang (1992) and Zhang et al. (1999)), given the interpretability issues associated with the neural network model, some empirical studies find that simple classifiers such as MDA are actually preferable to the neural network model (Altman, Marco, and Varetto, 1994). Wang (2015) examined the performance of logit and the neural network model on private firms in the European Union, concluding that NN does not always improve prediction accuracy. As has suggested by Jones, Johnstone, and Wilson (2015, p. 84), 'simple model structures represent a viable alternative to more sophisticated approaches, particularly if statistical inference and interpretability is a major objective of the modelling exercise'.

The literature on the usefulness of the neural network model is quite divided. Like most of the machine learning techniques, the neural network model is also subject to important limitations, one of which is the 'black box' interpretability issue (Cybinski, 2001). Despite the strong nonlinear mapping ability that the neural network model offers, the 'black box' property causes a lack of interpretability, therefore making it difficult to understand the results (Sun, Jia, and Li, 2011). Because it is impossible to understand how the neural network model classifies each observation into different groups, it is possible that the neural network model may end up deriving an illogical network behaviour in response to different variations of the input values (Altman, Marco, and Varetto, 1994). Another potential issue associated with NN is the 'overfitting trap'. Because the layer structure of NN can be excessively complex, it may describe random error or noise instead of the underlying relationship (Lawrence, Giles, and Tsoi, 1997). As pointed out by Wu, Liang, and Yang (2008), previous studies that have generally reported the superiority of neural network models over MDA may have ignored an important aspect, namely that the neural network model suffers from the issue of overfitting if the dataset is too small. Other issues associated with the neural network model include: subjectively chosen learning rates, local minimum settlements, and sensitivity to the number of neutrons in hidden layers (Demuth et al., 2014). In addition, long processing time to accomplish the NN iterative process might be another concern (Altman, Marco, and Varetto, 1994; Zheng and Yanhui, 2007). According to Jones, Johnstone, and Wilson (2015), despite the fact that neural network models and SVMs are established in the literature, they are relatively 'older' machine learning techniques.

3.3.5 Survival analysis models

The empirical models reviewed so far are often referred to as static models or single-period models, in that they take into account one single firm-year observation for each firm. According to Shumway (2001), conventional static models estimate single-period classification models with multiple period bankruptcy data. In this way, conventional statistical models neglect the fact that the condition of firms changes with time, and therefore they may potentially provide biased or inconsistent bankruptcy probability estimates. On the other hand, a hazard model could provide consistent and unbiased prediction outputs (Shumway, 2001).

Survival analysis or hazard models are able to deal with this inconsistency problem by including time as a dependent variable (Hillegeist et al., 2004). The major difference between survival analysis and statistical models is that survival analysis does not assume a dichotomous dependent variable, which in the case of statistical models is usually bankrupt and non-bankrupt (Shumway, 2001). Survival analysis is based on a strict assumption that both bankrupt and non-bankrupt firms belong to the same population, where non-bankrupt firms represent cases in which failure has not yet occurred (Chava and Jarrow, 2004). The critical drawback of traditional statistical models that make dichotomous classification outcomes is that the input data is assumed to be composed of two distinct and seperate populations (Nam et al., 2008). In this way, the fate (bankrupt or non-bankrupt) of each companies is known in the estimation stage, which could lead to high prediction accuracy in the initial sample but a sharp decline in out-of-sample prediction accuracy (Nam et al., 2008).

Shumway (2001) developed a standard form hazard model that explicitly accounts for time. The dependent variable in a standard form hazard model is the time firms spend in the non-bankrupt group, which is also called the survival time. The Cox proportional hazard model allows for the inclusion of time dependent variables, which demonstrate the same value for all companies at the same time, such as macroeconomic variables (Miller Jr, 2011). In the hazard model, firms' bankruptcy risk changes with time and the financial health of each company is a function of its latest financial data and age (Shumway, 2001).

The initial two models estimated by Shumway (2001) incorporated accounting ratio variables previously tested by Altman (1968) and Zmijewski (1984), revealing that half of the predictor variables used to predict corporate bankruptcy are not statistically related to failure. Shumway (2001) subsequently developed a more accurate model that included a combination of accounting and market based variables to identify potential bankruptcy. The predictor variables included in the final model are: (1) market size; (2) past stock returns; (3) the idiosyncratic standard deviation of stock returns; (4) net income to total assets; and (5) total liabilities to total assets. In comparison with the models of Altman (1968) and Zmijewski (1984), the hazard model provided the most accurate out-of sample forecast. The superiority of the hazard model over MDA and logit models was later validated by Chava and Jarrow (2004) on an expanded U.S. dataset. Similar results are also found by Nam et al. (2008) using Korea Stock Exchange data and Bauer and Agarwal (2014) using London Stock Exchange data. Chava and Jarrow (2004) also provide further supporting evidence that traditional accounting-based variables add little explanatory powder when market-price variables are also included in the model.

Nonetheless, hazard models are also associated with several limitations. Luoma and Laitinen (1991) found that hazard models might provide sample specific results, as the proportion of bankrupt and non-bankrupt firms in the estimation sample affects hazard rates. Another problem is multicollinearity; that is, strong correlations between the selected independent variables which can affect the parameter estimates and must be rectified prior to model estimates (Lane, Looney, and Wansley, 1986). Both criticisms are similarly applicable to statistical models. Because this study collects up to five years of data prior to the year of distress (from time t which represents the year of distress to t-1, t-2 ... t-5), and hazard models are more suitable when the time horizon is much longer, they are not suitable for the current study (Jones, 2017).

3.3.6 The Gradient Boosting model (TreeNet®)

Corporate financial distress prediction has been a popular domain of research for decades, marked by the continual development of more robust prediction models and theoretically sound bankruptcy predictors. A remarkable feature in the financial distress prediction literature is the large number of empirical studies published. During the last 40 years, forecasting techniques have evolved with a trend of increasing sophistication after the introduction of machine learning in the financial distress prediction literature (Jones, 1987). While neural network models and SVMs are well recognised in the statistical learning literature, they have been superseded by more recent and arguably more powerful techniques, such as boosting and random forests (see, e.g. Cortés, Martínez, and Rubio (2007), Kim and Kang (2012), and Wang, Ma, and Yang (2014)).

To date in the corporate financial distress prediction literature, numerous statistical and machine learning techniques have been applied, but there is no agreement on a single all-rounder best performing prediction technique (Wang, Ma, and Yang, 2014). Relatively recently, the ensemble method that combines multiple predictors into an aggregated output has proven to outperform single classifiers in terms of prediction accuracy (Wang et al., 2011; Sun and Li, 2012). Boosting is one of the popular ensemble methods. According to Schapire and Freund (2012), the basic idea of boosting is to integrate the outputs of many weak classifiers to produce an overall powerful prediction outcome. As explained by Jones (2017), the boosting algorithm applies weak classification in a stage-wise process to repeatedly modified versions of the data by gradually increasing the likelihood of more difficult data points. The output of the boosting algorithm is a voting committee that contains a sequence of weak classifiers that predicts very accurately (Jones, 2017).

Following the approach of Jones (2017), this study employs a commercial version of the gradient boosting (GB) model known as TreeNet®[4] to examine the predictive and explanatory performance of over 90 input variables (Friedman, 2001). The GB model (which is the conceptual foundation of TreeNet®) is a flexible and powerful machine learning technique that is capable of generating very accurate predictive results. In the distress prediction modelling literature, to date much research has relied on parametric models such as MDA and logit, which are only capable of handling a small number of explanatory variables (see e.g., Altman (1968), Ohlson (1980)). One important limitation with regard to parametric models is that too many predictor variables usually leads to model over-fitting which would consequently reduce the model validity. As such, a majority of distress prediction studies are constrained to a very limited set of predictors, typically financial ratios, market-price variables, or both (Jones, 2017). A significant advantage of advanced machine learning techniques such as TreeNet® is that in comparison with conventional parametric models, TreeNet® models are particularly useful in high dimensional analysis where there are very large numbers of predictors. In addition, despite the complex model structure, unlike other machine learning methods that generally suffers from the 'black box' criticism as a result of a lack of interpretability, TreeNet® models are also capable of providing some sort of interpretability, such as through Relative Variable Importance (RVI) metrics which rank orders all input predictors based on their overall predictive power and partial dependency plots (or marginal effects), which reveals

[4]See Section 4.3 for reasons for the selection of the TreeNet® model as the appropriate empirical framework of this thesis.

the direction of the explanatory variables with respect to the distress outcome.(Friedman, 2001; Hastie, Tibshirani, and Friedman, 2009). The TreeNet® model, the conceptual foundation of which is the gradient boosting (GB) model is described in more detail in Chapter 4.

3.4 Predictors of corporate distress

The distress prediction modelling literature mainly focuses on the role of accounting-based or market-price indicators as explanatory variables. A great number of studies to date have modelled corporate financial distress using either accounting-based variables alone (see e.g., (Altman, 1968; Zmijewski, 1984) or a combination of accounting-based and market-price variables (see e.g., (Shumway, 2001; Beaver, McNichols, and Rhie, 2005). To an extent, Hillegeist et al. (2004) even suggest that future research on distress prediction should focus exclusively on market-price indicators. However, as has demonstrated in Jones, Johnstone, and Wilson (2015) and Jones (2017), many other non-conventional distress predictors can also potentially have strong predictive power in corporate failure prediction, such as shareholder concentration, analyst forecasts, credit ratings, macroeconomic factors, and other industry, and firm-specific factors.

As one of the research objectives of this thesis is to evaluate and compare the effectiveness of 'Western-style' bankruptcy predictor variables for Chinese distress prediction in the unique context of China's ST system[5], a large number of explanatory variables are used to predict distress of Chinese listed companies following the general approach of Jones (2017). In addition to the variables tested in Jones (2017), this study also includes

[5]See Section 1.3.3 for more details regarding China's ST system.

several non-conventional variables, such as valuation multiples and corporate social responsibility metrics. Furthermore, this study also incorporates a unique variable to the Chinese institutional setting – state ownership. Motivation for variable selection of more than 90 predictor variables is presented in this section. Section 3.4.1 explores the motivation for including accounting-based versus market-price variables. Section 3.4.2 provides motivation for selecting shareholder ownership/concentration variables in this thesis. Motivation for including macroeconomic indicators (Section 3.4.3), executive compensation variables (Section 3.4.4), corporate social responsibility (CSR) metrics (Section 3.4.5), valuation multiples (Section 3.4.6) and other control variables (Section 3.4.7) is also detailed.

3.4.1 Accounting-based versus market-price indicators

Accounting-based variables have a long history in the corporate financial distress prediction literature. Beaver (1966) was among the first to establish the predictive power of financial ratio variables for up to five years prior to bankruptcy. Beaver, McNichols, and Rhie (2005) further demonstrated that accounting-based variables are robust distress predictors over a 40-year period from 1962 to 2002. Despite the popularity of accounting-based measures in distress prediction modelling for over the past 50 years, market-price indicators have assumed much more importance recently (Shumway, 2001; Altman, 2002; Hillegeist et al., 2004; Beaver, McNichols, and Rhie, 2005). The research evidence is ultimately quite mixed when it comes to whether accounting-based or market-price variables contain more predictive power in distress prediction. As suggested by Hillegeist et al. (2004), it is ultimately an empirical question when it comes to the performance of accounting-based distress measures versus market-price distress measures.

Following Jones (2017) accounting-based variables[6] used in the study cover: (1) liquidity and solvency; (2) leverage; (3) profitability and cash flow; (4) asset efficiency; and (5) change/growth variables (such as three year and annual growth in operating cash flow, earnings, working capital, revenues and debt). Many of these variables have been tested in prior bankruptcy studies and have been shown to have strong relationships with corporate distress. Some unscaled measures are also included, such as total revenue and total assets, which proxy for firm size effects.

Despite the long history and widespread use of accounting-based variables in the distress prediction literature, arguably one of the most important issues associated with accounting-based variables as distress predictors is the lack of theoretical underpinning. There is limited underlying theory linking a firm's financial ratios to financial distress. As noted by Beaver, McNichols, and Rhie (2005), the exact combination of accounting-based variables is of minor importance to the overall prediction accuracy of the model because the predictor variables are correlated. Accounting-based distress prediction models extract the relevant information from corporate financial statements. In a way, they perform structured fundamental analysis using financial statement data to assess firms' risks of being financially distressed (Bauer and Agarwal, 2014).

There are several fundamental limitations associated with using financial statement information to assess the distress potentials of companies. First, by nature, financial statements are inherently backward looking and are designed to measure past performance rather than future prospects of companies; therefore they might not be informative about the future status of a company (Hillegeist et al., 2004; Vassalou and Xing, 2004). Second, financial statements are prepared under going concern and conservatism principles, which assume that the entity will remain in business for the foreseeable future. Therefore,

[6] See Appendix A for a full list of study variables and their definitions.

the predictive ability of financial statement data to assess distress potential of companies accurately and reliably is limited by design (Hillegeist et al., 2004). Third, financial statements are prepared based on a conservatism assumption and historical cost method, which casts doubt on their validity to assess distress risks as the reported figures might deviate from their real market values (Agarwal and Taffler, 2008). Fourth, financial statements are at least to some extent subject to managerial manipulation (Bauer and Agarwal, 2014). Accounting-based measurements from manipulated financial statements are less value relevant and therefore contain less information regarding the true underlying performance of companies.

As mentioned by Hillegeist et al. (2004), another important deficiency of accounting-based distress prediction models is that they fail to incorporate a measure of asset volatility, which can have predictive value in corporate distress prediction models. Beaver, McNichols, and Rhie (2005) explain that the market value of equity represents the 'equity cushion' and reflects the amount by which the value of assets can decline to a degree such that they become insufficient to cover the present value of the debt payments (Hillegeist et al., 2004). In accounting-based prediction models, it is implied that two firms with similar financial ratios will have similar likelihood of being financially distressed (Vassalou and Xing, 2004). However, two firms with identical leverage ratio can have significantly different probabilities of being financially distressed depending on their asset volatilities (Hillegeist et al., 2004).

Unlike accounting-based distress prediction models that lack underlying theory in directing the selection of input variables, market-based probability estimates of corporate financial distress have a strong theoretical grounding as they draw on the option pricing framework of Black and Scholes (1973) and Merton (1974). In option pricing models, equity is viewed as a call option on firms' assets, and the probability of being financially distressed is simply the probability that the call option is worth zero at maturity (i.e. market value of total assets is less than the face value of total liabilities) (Bauer and Agarwal, 2014). Hillegeist et al. (2004) suggest that the main advantage of using option pricing models in financial distress prediction is that they provide guidance about the theoretical determinants of financial distress risk. After evaluating whether the Z-Score model (Altman, 1968) and the O-Score model (Ohlson, 1980) effectively summarise all publicly available information about the probability of bankruptcy, Hillegeist et al. (2004) conclude that market-price indicators based on the Black-Scholes-Merton option-pricing model are superior to accounting-based measurements.

There are some appealing properties associated with market-price variables. First, the efficient market theory suggests that market prices reflect a rich and comprehensive mix of information, which includes financial statement information and other information not included in financial statements (Bauer and Agarwal, 2014; Jones, 2017). According to Beaver, McNichols, and Rhie (2005), market-price variables absorb much of the predictive power of accounting-based variables and provide additional explanatory power not reflected in the financial statements . Second, market-price variables are less likely to be impacted by accounting policies and they are also less likely to be influenced by managerial manipulation (Li and Du, 2011). Third, given the nature of corporate financial distress prediction studies, namely forward-looking, market-price variables reflect future expected cash flows and hence should be more appropriate for predictive purposes (Vassalou and Xing, 2004; Agarwal and Taffler, 2008).

While market-price variables have a theoretical basis in corporate financial distress prediction, they also suffer limitations that might explain some of the mixed evidence in the literature. For instance, market-price variables are derived from capital markets, which may not efficiently and accurately incorporate all publicly available information

(Hillegeist et al., 2004). In particular, Sloan (1996) finds that market prices do not accurately reflect all of the information from financial statements. According to Beaver, McNichols, and Rhie (2005), market-price variables should not be considered as substitutes for accounting-based variables, but rather a proxy for the total predictive power achievable by capturing the mix of information, including both financial statement and non-financial statement information.

In the Chinese context, the majority of Chinese distress prediction studies focus only on conventional financial variables as distress predictors. Few studies have examined non-financial variables in Chinese distress prediction, which include variables concerning corporate governance structure, ownership structure, macroeconomic conditions, and external market information (Deng and Wang, 2006; Li and Du, 2011; Xie, Luo, and Yu, 2011; Liu and Wang, 2016)[7]. In Xie, Luo, and Yu (2011), three variables concerning external market information are examined, namely liquidity of the stock, cumulative annual return, and qualified auditors' opinion. However, market variables do not prove to be significantly informative in predicting Chinese distress in the stepwise MDA method. Because models estimated using all variables outperformed models with only financial variables, Xie, Luo, and Yu (2011) confirmed the predictive power of non-financial variables in Chinese distress prediction. In the prediction of turnaround probability for distressed firms to remove the ST status conducted by Kim, Ma, and Zhou (2016), non-financial variables such as market-driven and ownership structure variables do not provide incremental predictive power in determining the turnaround probability of ST firms. Their findings are based a sample of 288 non-ST firms and 153 ST firms on either the Shenzhen or Shanghai Stock Exchanges from 1998 to 2011. Three groups of variables are examined, including: (1) accounting-driven variables, such as net income to total assets,

[7] See Section 3.6.4 for a detailed discussion of non-financial variables examined in Chinese distress prediction studies.

total liability to total assets, current assets to current liability and log of total assets; (2) market-driven variables, such as log of market capitalisation of firm over total market capitalisation, excess returns, tradable shares turnover and debt over market value of equity; and (3) ownership structure variables, such as largest shareholder's ownership, top 10 largest shareholders' ownership, state share, and a dummy variable of company restructure. The authors conclude that accounting-based variables are the most influential indicators in predicting the turnaround probability for a distressed firm to get their ST status revoked and return to normal listing status (Kim, Ma, and Zhou, 2016). Because the predictive power of market-price variables on Chinese distress prediction remains unclear in the literature, this thesis adds more empirical evidence on the performance of non-financial predictors regarding corporate financial distress prediction in the context of the Chinese market. The two market-price variables used in this study are: (1) equally value weighted market returns; and (2) market capitalisation.

3.4.2 Shareholder ownership/concentration variables

In the distress prediction literature, the relationships between governance style proxies such as shareholder ownership/concentration variables (including institutional ownership and insider ownership) and corporate failure have rarely been explored. However, as suggested by Jones (2017), there are good theoretical reasons for expecting an association between corporate governance proxies and corporate distress. Generally speaking, firms with appropriate corporate governance practices should be less likely to suffer from financial distress than those with weaker governance practices. Because financial distress can lead to corporate failure, which is typically very costly and ultimately destructive to stockholder value, based on the agency theory (Jensen and Meckling, 1976) insider ownership is expected to be negatively associated with the occurrence of financial distress.

There may be strong incentives for Chinese institutional shareholders (including insiders) to consider all available options to avoid a ST event and potentially direct management to improve financial performance.

Previous studies on ownership structure and financial distress regarding Chinese listed companies suggest that ownership concentration and state ownership are negatively associated with the possibility of firms entering into the distress state (Deng and Wang, 2006). As corporate failure is typically very costly and destroys shareholder value, insiders and large shareholders are motivated to prevent companies from falling into financial distress. They have resources and incentives to supervise the management to act on behalf of their interests to improve financial performance continuously (Deng and Wang, 2006).

In terms of firm operating performance and state ownership, research evidence is quite mixed in China (Yu, 2013). On the one hand, state ownership is found to be negatively related to operating performance and firm efficiency (Qi, Wu, and Zhang, 2000; Sun and Tong, 2003; Lin, Ma, and Su, 2009). Further, Wei (2007) identifies a non-linear relationship between state ownership and firm performance wherein there is no negative correlation when the proportion of state ownership is relatively small; however, there is a significant negative impact on firm performance when the proportion of state ownership exceeds 50%. Gunasekarage, Hess, and Hu (2007) identify a similar pattern where the negative influence of firm performance only becomes evident at high levels of state ownership. On the other hand, more complex and somewhat contradicting relationships have also been revealed in prior research that generally support the notion that state ownership can have a positive impact on firm performance. While Sun, Tong, and Tong (2002) find that the relationship between firm performance and state ownership is inverted U-shaped (concave), Tian and Estrin (2008), Ng, Yuce, and Chen (2009) and Yu (2013) find that the relationship between firm performance and state ownership is U-shaped (convex).

Sun, Tong, and Tong (2002) conclude that there is an optimal level of state ownership. Very high levels of state ownership may indicate the government has too much control and interference in the economic operations of firms, whereas companies with significantly low levels of state ownership may not get sufficient support from the government. Overall, this 'optimal' level of government political support through state ownership is valuable to promote firm performance, such as business connections, political connections, protection from industry threats, or subsidies. On the other hand, Tian and Estrin (2008) find a convex relationship between the level of state ownership and firm performance, wherein state ownership has a negative impact on firm performance but only up to a certain threshold, and can actually improve firm performance beyond that point. This is supported by Ng, Yuce, and Chen (2009), who further conclude that the convexity relationship appears to be non-symmetrical. The positive impact on firm performance is stronger at very high levels of state ownership in comparison with high levels of private ownership. Such contracting results between state ownership and firm performance may be attributable to different model specifications, firm performance measurements, sample selections, and time horizons.

In this study it is expected that state ownership is positively associated with the distress outcome. This is because higher state ownership may work as a disincentive for companies to improve financial performance expeditiously. As a socialist state, the Chinese government is typically more concerned with social stability and employment considerations rather than purely performance issues (Chen, Chen, and Huang, 2010). Therefore, managers of state-owned enterprises are not necessarily required to achieve certain performance targets but rather specific government policy objectives such as to assist local development and promote employment (Deng and Wang, 2006). In addition, the government also tends to financially support some failing companies in certain industries, which might serve as another disincentive for companies with a higher concentration of state ownership to improve their financial performance. Fan, Huang, and Zhu (2013) find that firms with higher levels of state ownership exhibit worse operating performance during periods of financial distress and are less likely recover from distress. In this thesis, five variables concerning shareholder ownership/concentration are examined, which include: (1) state ownership; (2) percentages of shares held by supervisors; (3) percentages of shares held by fund/institutions; (4) percentages of shares held by brokers; (5) total number of shareholders.

3.4.3 Macroeconomic variables

Previous literature has demonstrated that macroeconomic indicators can have an impact on credit ratings changes and corporate bankruptcy (Figlewski, Frydman, and Liang, 2012). In terms of the influence of macroeconomic indicators on Chinese distress prediction, it is expected that broader macroeconomic conditions and the state of the economy will have an impact on corporate distress in China. Xie, Luo, and Yu (2011) reveal that the correlation coefficient between net profit and fixed asset investment and the correlation coefficient between net profit and retail price index contain critical explanatory power regarding corporate financial distress in China. Their finding is based on a matched-pair sample of 130 listed ST manufacturing companies and 130 healthy companies randomly selected in the same industry between 2005 and 2007 using the MDA method. Similarly, Tsai, Lee, and Sun (2009) confirm the predictive value of macroeconomic variables in distress prediction based on a sample of 172 distressed and 1475 non-distressed companies listed on Taiwan Stock Exchanges from 1987 to 2006 using the hazard model. In particular, they find that an increase in consumer price index and Taiwan Stock Exchange price index change ratio reduces the probability of financial distress while an increase in interest rate increases the probability of financial distress.

Four broad macroeconomic indicators relating to overall economic health of the Chinese economy are selected and included in this study. These measures include: (1) GDP growth; (2) GDP per capita; (3) the CPI index; and (4) unemployment rates in urban areas. GDP growth is a key measure of the overall economic health and prosperity. Strong GDP growth generally signals a good macroeconomic environment that is expected to lead to a lower incidence of corporate distress. However, it is noted that the validity of the expected relationship between GDP growth and corporate distress ultimately depends on the credibility of the official GDP figures released by the Chinese government. There is a large body of literature that cast doubt on the accuracy of the published Chinese GDP data, indicating that the reported GDP growth figure considerably overstates the actual growth rate of the economy (see, e.g., Rawski (2001)). For instance, according to the measurement by Rawski (2001), the cumulative GDP growth during 1997 to 2001 is at least one-third less than the official statistics released by the Chinese government. The direct implication of unreliable Chinese GDP figures is that it affects the validity of the relationship between GDP growth and corporate distress. Although strong GDP growth is expected to lead to a lower incidence of corporate distress, if the reported GDP figure if unreliable, higher GDP growth may in the end result in higher probability of corporate distress in China.

Arguably concerns that Chinese GDP numbers are not reliable and potentially significantly overstated may largely be due to data quality and transparency issues in China (Rosen and Bao, 2015). As a socialist state economy, the decision whether or not to make China economic statistics accessible and transparent is still significantly influenced by political interests (Rosen and Bao, 2015). Another reason that might explain the reliability concerns of China's economic statistics may be due to the challenges in effectively capture GDP growth in transitioning China (Owyang and Shell, 2017). Furthermore, Owyang and Shell (2017) argue that deliberate falsification or misrepresentation of GDP numbers by Chinese officials is unlikely. The more likely reason is that economic growth in a transitioning China is just too challenging to capture as effectively as growth in developed countries.

The CPI index (inflation) is a widely cited economic indicator, and the general perception is that high inflation is unhealthy for the economy, although its economic impacts can be ambiguous (Jones, Johnstone, and Wilson, 2015). As higher inflation generally reflects a weaker economy, a positive association is therefore expected between the CPI index and the likelihood of financial distress in China. The unemployment rate in urban areas is another key measure of overall economic health. It is expected that higher unemployment rates in urban areas will be associated with weaker economic conditions and therefore an increased likelihood of corporate distress.

3.4.4 Executive compensation variables

Executive compensation variables are another set of factors that have not been properly investigated in prior bankruptcy research (Jones, 2017). The issue of firm performance and executive compensation is rarely explored in China. Before the economic reform in 1978, China as a purely communist economy with strong national preferences towards social equity dictated similar pay for all members of society (Adithipyangkul, Alon, and Zhang, 2011). Given the unique institutional setting of China, Banker, Bu, and Mehta (2016) tested two contradicting theories of pay gap and firm performance: sociological and economic theories. The sociological argument suggests that social inequity implied by larger pay gaps can diminish firm performance by adversely impacting on employee morale and productivity. On the other hand, economic theories of 'matching and managerial talent' imply that talented executives who generate better firm performance earn a pay premium. Empirical evidence from Banker, Bu, and Mehta (2016) supports the economic theory that pay premiums for executives in China are positively related to firm performance. Similarly, Kato and Long (2006) find evidence for a positive association between executive compensation and firm value in China, with a 10% (RMB 1,000) increase in shareholder value resulting in a 1.7% (RMB 0.045) increase in annual compensation for top executives. In addition, the authors find that the pay-performance link for executives is weaker in listed firms with a higher proportion of state ownership. This may indicate that state ownership is possibly making China's listed SOEs less effective in solving the agency problem by better aligning the rewards of executives with shareholders.

CEO compensation is used in this study as a proxy for the overall quality of top level management. Executive compensation variables tested in this study include: (1) total executive compensation of top three executives; and (2) total director compensation of top three directors. Total CEO compensation (which includes performance bonuses) is expected to be closely tied to firm financial performance. If top level managers are performing and meeting organisational objectives, their total compensation is expected to be higher. As previous empirical research in the Chinese context for executive compensation confirms the economic theory that pay premiums for executives in China are positively related to firm performance, a negative relationship is expected between executive compensation and firm financial distress in China.

3.4.5 Corporate social responsibility variables

Research on the linkage between corporate social responsibility and firm performance has become increasingly important in the literature. In comparison with other developing countries where CSR is a more popular field of research, CSR in China has attracted fairly limited research attention, which originated only in recent years. It seems that Chinese people perceive CSR differently when compared to people in Western countries. While

CSR is usually perceived as the responsibility of a good corporate citizen in Western economies, it is often viewed as a business strategy to maximise firm value in developing countries such as China (Cheng, Lin, and Wong, 2016). According to Qu (2009), CSR might be even more important to firm performance in China given the country's socialist legacy. Many studies have reported that better CSR performance is positively linked to corporate financial performance (Beck, Frost, and Jones, 2018).

According to Beck, Frost, and Jones (2018), the theoretical links between CSR and corporate financial performance stem from two different perspectives. One approach treats CSR as a means by which organisations can generate higher revenues to improve financial performance. Good corporate financial performance could be potentially achieved through more productive and loyal employees, the development of more cost efficient organisational processes, and more innovative products and services to meet social needs. Another argument suggested by Beck, Frost, and Jones (2018) is that CSR activities creates the appearance of doing 'good' even if there is no substance to the activity itself, which confers reputational value to organisations by raising positive perceptions among stakeholder groups.

With regard to the Chinese studies of the association between CSR and corporate financial performance, Chen and Wang (2011) confirm that CSR activities not only improve corporate financial performance in the current year but also in the next period. Chen and Wang (2011) find that the relationship between CSR and corporate financial performance is two fold. First, despite the inherent resource requirements, undertaking social responsibility activities satisfies the benefit requirements of every group of shareholders and thus ultimately improves corporate performance. Second, companies with good corporate financial performance are more likely to obtain scarce resources, which in turn provide more opportunities for them to undertake more social responsibility activities and improve their relationships with shareholders, thus generating better financial performance. Similarly, Cheng, Lin, and Wong (2016) find a positive relationship between current CSR disclosures and corporate financial performance in the subsequent year using Chinese listed firms sampled in 2008 and 2009. Further, they reveal that corporate donations are positively associated with improved firm performance in the following year.

For the purposes of this study, two key CSR measures from the China Stock Market and Accounting Research (CSMAR) database are included. These CSR measures are: (1) social donation; and (2) social contribution value per share. As good CSR practices are generally positively associated with improved corporate financial performance, it is expected that social donation and social contribution value per share will be negatively associated with the likelihood of corporate financial distress in China.

3.4.6 Valuation multiples

Conventional valuation theory implies that distressed companies will have lower valuation multiples such as price-earnings ratios and price-to-book ratios (Damodaran, 2016). Generally speaking, the price-earnings ratio is calculated as the share price divided by earnings per share. It indicates the dollar amount an investor is willing to pay per dollar of earnings received from the company. The price-earnings ratio if analysed using a dividend discount model is often defined as a function of the dividend payout ratio (dividends per share divided by earnings per share) divided by the discount rate minus the expected growth rate. Distressed companies are expected to attract higher discount rates to adjust for higher bankruptcy risk. In addition, distressed companies will also have diminished growth prospects, which will result in lower expected growth rate. In comparison with healthy companies, distressed companies are expected to have lower price-earnings ratios. Likewise, the price-to-book ratio analysed using the residual income valuation model (e.g. Ohlson and Johannesson (2016)) is defined as a function of expected return on equity (ROE) minus the discount rate divided by the discount rate minus the expected growth rate (Palepu, Healy, and Peek, 2013). As distressed firms are expected to have lower future ROE and/or attract higher discount rates, distressed companies are expected to have lower price-to-book ratios. For the purposes of this study, two variables concerning valuation multiples are included: (1) price-earnings ratio; and (2) price-to-book ratio.

3.4.7 Control variables

A number of other control variables, including firm size (proxied by measures such as market capitalisation, total assets, and employee numbers), industry background (based on the CSMAR industry definitions), and an earnings management proxy are included in the current research. Because the ST regime is partially defined by firms with more than two consecutive periods of negative profitability, and a company cannot be restated to normal listing status unless it returns to profitability, there may be strong incentives for earnings management practices among Chinese distressed firms (Green, Czernkowski, and Wang, 2009). Previous empirical research on the Special Treatment system in China's stock market has found that the Special Treatment system distorts management incentives and induces listed firms to engage in earnings manipulation when they are confronted with the risk of being delisted (Jiang and Wang, 2008; Chen, Chen, and Huang, 2010; Yang, Chi, and Young, 2012). In comparison with non-ST (healthy/active) companies, ST companies returning back to normal listing status are more likely to engage in practices indicating earnings manipulation (Green, Czernkowski, and Wang, 2009). For the purposes of this study, a standard earnings management proxy based on the Kothari, Leone, and Wasley (2005) measure is used.

3.5 Multi-class distress prediction studies

Despite the fact that the relevance and utility of multi-state distress prediction models have been extensively appreciated in the distress prediction modelling literature (Jones and Hensher, 2007), very few studies model corporate distress from a multi-state distress prediction perspective. To date the majority of distress prediction studies have modelled distress in terms of a simplistic dichotomous classification outcome. As argued by Jones and Hensher (2007), such binary classification design could be subject to oversimplification of the underlying economic reality of companies. Another major limitation of operationalising corporate distress as a dichotomous response measure (such as distress and non-distress) is that this ignores the important fact that firms are not simply distressed or active but possess different degrees of financial distress that vary with time (Ward, 1994). Although multi-state distress prediction models are believed to better approximate the continuum of corporate financial health observable across companies (Lau, 1987), there has been relatively little theoretical and empirical research devoted to developing such multi-state models.

Previous multi-state distress prediction studies have modelled different financial states of firms, ranging from a five-state to a three-state classification outcome. For example, Lau (1987), defines the financial health of firms in five states: 0 – financial stability (healthy/active firms); state 1– firms that are omitting or reducing dividend payments; state 2 – firms that are experiencing technical default and default on loan payments; state 3 – firms under Chapter X or XI of the Bankruptcy Act; and state 4 – bankruptcy and liquidation. In comparison, financial health of firms has also been defined in three-states and four states in previous studies (Ward, 1994; Jones and Hensher, 2004; Jones and Hensher, 2007). Jones and Hensher (2007) define financial health of firms in three states: state 0 – non-failed firms; state 1– insolvent firms, defined as: (i) loan default, (ii) failure to pay ASX annual listing fees as required by ASX Listing Rules, (iii) capital raising specifically to generate sufficient working capital to finance continuing operations, and (iv) a debt/equity restructure due to a diminished capacity to make loan repayments; and state 2 – financially distressed firms who were delisted from the ASX because they were subject to a merger or takeover arrangement. Ward (1994) models financial health in four states: state 0 – healthy; state 1– firms experienced a greater than forty percent reduction in dividends per share after a history of successive dividends per share; state 2 – firms that experienced a loan principal/interest default or debt accommodation; and state 3 – firms that filed or were forced to file for Chapter XI of the Bankruptcy Act.

In terms of the prediction methods used in multi-state prediction modelling, the majority of multi-state distress prediction studies have utilise multinomial logit models (see, e.g., Lau (1987), Johnsen and Melicher (1994), and Tsai (2013)). The mixed logit model was later introduced to accounting and finance, which not only substantially improved model-fit but also provided superior sample forecasting accuracy when compared with standard form multinomial logit models (Jones and Hensher, 2004). Based on the mixed logit model, Jones and Hensher (2007) then developed a multinomial nested logit model that has some distinct advantages over both standard multinomial logit and mixed logit models, particularly in terms of practical application in the modelling of corporate financial distress. With the development of statistical and artificial intelligence (AI) techniques, some machine learning approaches have also been applied in the field of multi-state distress prediction. For instance, the ordinal multi-class support vector machine model (OMSVM) has been applied to the domain of corporate credit rating prediction using a sample of Korean bond ratings (Kim and Kang, 2012). OMSVM is an extension of the traditional multi-class support vector machine (MSVM) using the ordinal pairwise partitioning (OPP) approach which takes into account the ordinal characteristics of classes (Kim and Kang, 2012). The authors further conclude that OMSVM is capable of handling multiple ordinal classes in an efficient and effective way and therefore improves predictive accuracy of the model when compared to the conventional MSVM.

In terms of multi-state Chinese distress prediction studies, Zhou, Tam, and Fujita (2016) are one of the first to model the listing status of Chinese listed companies from a multi-state classification perspective. Unlike existing Chinese distress prediction literature in which the listing status of companies is usually modelled as a binary classification problem by predicting whether an active company will be specially treated (enter into ST status)), their study utilises a four-state setting: (1) normal listing status ('A'); (2) abnormal status with other risk warning ('B'); (3) abnormal status with delisting risk warning ('D'); and (4) delisted status ('X'). Three aggregative models are applied, which include One-vs-All aggregative model with parallel ensemble strategy (OVAPES), One-vs-All aggregative model with hierarchical ensemble strategy (OVAHES) and One-vs-One aggregative model (OVOAM). The authors conclude that none of the three proposed aggregative models provide satisfactory classification results due to the difficulty of distinguishing between the characteristics of companies with other risk warning ('B') and companies with delisting risk warnings ('D').

In the distress prediction literature, generally speaking the predictive results of multi-state distress prediction models are usually not as impressive as the predictive results of binary distress prediction models at first glance. However, the predictive performance of multi-state prediction models is not directly comparable to that of binary prediction models. This is because multi-state models permit many more types of misclassification errors than are possible in the binary prediction models (Lau, 1987). For instance, while there are only two possible types of misclassification errors in a binary model, there are 20 possible types of misclassification errors in five-state models. This implies that a case could be far more easily misclassified in a five-state prediction model than in a binary prediction model. As such, the significant difference in possible misclassification errors should be accounted for when analysing the predictive results of a multi-state prediction model in comparison with a binary prediction model (Johnsen and Melicher, 1994).

3.6 Chinese distress prediction studies

Research on Chinese distress prediction modelling is still in its infancy and has attracted fairly limited research attention. Table 3.1 provides a summary of selected Chinese distress prediction studies. Several features of Chinese distress prediction studies are revealed in Table 3.1, including the late start of Chinese distress prediction studies (discussed in Section 3.6.1), the issues of small distressed firm sample and short sample period (Section 3.6.2), the prediction techniques employed (Section 3.6.3) and the predictive power of non-financial predictor variables in Chinese distress prediction (Section 3.6.4).

3.6.1 Late start of Chinese distress prediction studies

Chinese distress prediction studies began to emerge from the year 1999 (Zhang, Altman, and Yen, 2010), which indicates a very late start in comparison with similar studies conducted from the perspective of western economies' that dates back to the 1930s. Two potential reasons might explain this delay in distress prediction studies from the Chinese market perspective. First, the research on Chinese distress prediction modelling has been constrained by an insufficient distressed firm sample. The first nationwide Enterprise Bankruptcy Law of the People's Republic of China (Trial Implementation) was passed on 2 December 1989 and after that a number of companies, particularly non-listed companies, declared bankruptcy under the law. However, the bankruptcy process went through different levels of courts in China, including the country level, municipal level, and provincial level, making it difficult to retrieve financial records for these bankrupt companies (Altman, Zhang, and Yen, 2007). As for publicly listed companies, there has been no official record for any listed companies that have declared bankruptcy despite the poor financial status and unviability of some listed companies. The reason for the continuation of distressed companies is because the Chinese government wanted to strike a balance between a steady social security system to avoid large-scale social problems and the degree to which Chinese society can afford to let companies go bankrupt (Altman, Zhang, and Yen, 2007). As explained in Section 2.9, the priorities of the Communist government is more focused on maintaining social stability, taking collectivist approaches over private or individual concerns, and allocating more power to the courts and government in such disputes (Jiang, 2014).

The second reason for the late start in financial distress prediction studies in China may be due to a lack of exit mechanisms and the fact that bankruptcy law lagged behind its implementation and practice in the real world (Wang and Li, 2007). The Special Treatment system (ST) launched by the China Securities Regulatory Commission (CSRC) in 1998 finally provided a remedy for this situation. The ST system was introduced as a delisting mechanism for suspending and terminating listed loss-making firms. The introduction of the ST system provides a unique opportunity to investigate the financial performance of publicly listed companies in China (Wang and Li, 2007). Further, it also provides a sample of distressed listed companies that enables financial distress prediction studies in China to be implemented.

One of the first authors to examine financial distress prediction using a Chinese sample was Chen (1999) who constructed a MDA model using a matched-pair sample of 27 financially distressed and 27 healthy listed companies. However, the most important issue with this study is that the empirical results were not validated by an independent holdout sample and therefore the reliability of the reported 92.6% prediction accuracy is questionable. Without an appropriate holdout sample, the 92.6% prediction accuracy rate is the result from the training sample only. As suggested by Jones (1987), it is crucial for bankruptcy prediction studies to include a hold-out sample to test external validity. Clearly, Chen (1999) did not follow such a suggestion. One possible excuse for Chen's (1999) approach could be a lack of distressed firm data, as it was only one year after the implication of the ST system. Another issue with Chen (1999) was that it was published only in the Chinese language and thus lacked international influence. Since then, more research efforts have been devoted to the prediction of Chinese financially distress firms.

3.6.2 Issues of small distressed sample and short sample period

Another feature in the Chinese financial distress prediction literature is that distress prediction models developed from the Chinese market perspective are usually based on small samples and a short sample period. According to Zhou, Lai, and Yen (2012), the majority of distress prediction studies using a Chinese sample contain a distress sample of at most 100 distressed companies. For example, the logit model developed by Li and Du (2011) is based on a matched-pair sample of 50 financially distressed and 50 healthy listed manufacturing firms from 2005 to 2007. Similarly, Hua et al. (2007) developed an integrated binary discriminant rule through integration of a support vector machine (SVM) and logit model based on a matched-pair sample of 60 financially distressed and 60 healthy listed firms from 1999 to 2004. In addition, the SVM model estimated by Ding, Song, and Zen

(2008) is based on an unmatched sample of Chinese high technology manufacturing companies which contained 28 ST firms from 2001 to 2004 and 97 non-ST firms in the year 2004. The Z_{China}-score model by Zhang, Altman, and Yen (2010) was estimated based on a matched-pair sample of 30 financially distressed firms and 30 healthy firms from 1998 to 1999. Chen et al. (2006) utilised four models estimated based on different prediction techniques, including MDA, logit, decision trees (DT), and NN. Their models are estimated on an unmatched sample of 39 ST firms and 517 non-ST firms from 1999 to 2003. The model developed by Cao, Wan, and Wang (2011) which integrates Rough Set (RS) theory and SVM is based on a matched-pair sample of 53 ST firms and 53 non-ST firms from 2008 to 2009. One direct implication of distress prediction models developed based on small samples sizes and a short sample period is that it limits their generalisability (Grice and Dugan, 2001).

3.6.3 Machine learning versus statistical methods

In a more recent review study of corporate financial distress prediction, Sun et al. (2014) summarise the research process of financial distress prediction as techniques evolved over time from conventional statistical methods to machine learning techniques based on artificial intelligence. As a result of the late start, much of the Chinese distress prediction studies rely on machine learning techniques rather than conventional statistical methods. In particular, classifier ensembles are often used in Chinese distress prediction studies (see e.g., Sun and Li (2009), Sun, Jia, and Li (2011), and Zhou, Lai, and Yen (2012)). According to Sun et al. (2014), the application of a classifier ensemble to corporate financial distress prediction is a fairly new trend which only emerged after 2005. One of the advantages of combining different classifiers in corporate financial distress prediction is to overcome some limitations of single classifiers and therefore achieve better predictive results (Xiao et al., 2012). As explained by Sun et al. (2014), a classifier ensemble is capable of exploiting each base classifier's characteristic that contains unique information for classification, reducing the variance of estimated error than each of the single base classifiers alone (Sun et al., 2014).

One of the more recent studies on corporate financial distress prediction from the Chinese market's perspective is Sun, Jia, and Li (2011). They developed four prediction models that include AdaBoost ensemble with SAT (single attribute test, which is also known as univariate analysis), AdaBoost ensemble with DT (decision tree), single DT, and single SVM. This study by Sun, Jia, and Li (2011) is among the few Chinese financial distress prediction studies that has been estimated based on a relatively large sample and a large number of predictor variables. Their initial sample includes a total number of 692 listed companies from 2000 to 2008, in which the healthy firm sample was selected as companies that had never been specially treated during the same time period by matching industry and asset size. The initial sample was then subsequently divided into two subsets, of which 2/3 of the 692 companies were used as a training set and the remaining 1/3 were used as the test or validation set (Sun, Jia, and Li, 2011). 41 financial ratios covering profitability, activity, solvency, growth, risk level, per share ratios and cash flow ratios were selected and tested, which arguably reflect a comprehensive picture of the financial and operational state of companies (Sun, Jia, and Li, 2011). The authors conclude that the AdaBoost ensemble with SAT outperformed the other three models.

Similarly, Xiao et al. (2012) also find that a classifier ensemble has advantages of higher prediction accuracy in comparison with single classifiers. As argued by Sun and Li (2009), one important limitation associated with single classifiers is that the classification performance of single classifiers largely depends on the sample's pattern characteristics, and each single classifier has its own uncertainty. A classifier ensemble overcomes such limitations by combining a set of weak classifiers to obtain an ensemble model which predicts better than any of the weak classifiers alone (Zhou, Lai, and Yen, 2012). The classifier ensemble developed by Xiao et al. (2012) is based on rough set theory and Dempster-Shafer (D-S) evidence theory. The authors applied rough set theory to determine the weight of each single classifier and then used D-S evidence theory as the combination method. Their model was developed based on a sample of 92 financially distressed listed companies and 161 healthy companies between 2007 and 2009 using 39 financial variables.

After testing more than 20 distress prediction models based on various widely used techniques, such as MDA, quadratic discriminant analysis, linear regression, logit, probit, DT, k-nearest neighbour, Bayes classifiers, AdaBoost, NN, and SVM with 26 financial ratio variables, Zhou, Lai, and Yen (2012) conclude that the AdaBoost ensemble performed the best on both a sample of Chinese listed companies sample and U.S. sample. The U.S. sample contains a matched-pair of 417 distressed companies and the same number of randomly drawn healthy companies from 1992 to 2007. The Chinese sample includes a matched-pair of 290 financially distressed and the same number of healthy companies from 1999 to 2006. According to Zhou, Lai, and Yen (2012), because there exist significant differences between China and the U.S. in terms of economic and business environment as well as the definition of financial distress, for AdaBoost to predict accurately on both datasets demonstrates some appealing properties of the model.

In contrasts to Sun, Jia, and Li (2011), Xiao et al. (2012) and Zhou, Lai, and Yen (2012), Geng, Bose, and Chen (2015) provide evidence that a single classifier – neural networks outperforms other three classifiers in terms of prediction accuracy, including DT, SVM, and an ensemble of multiple classifiers combined using majority voting. Their conclusion is based on a matched-pair sample of 107 financially distressed and the same number of healthy listed Chinese firms from 2001 to 2008. All four models were estimated using 31 financial indicators as explanatory variables, of which net profit margin of total assets, return on total assets, earnings per share, and cash flow per share contributed the most predictive power to the overall prediction accuracy of the model (Geng, Bose, and Chen, 2015).

In the Chinese distress prediction literature, only a few studies have been undertaken using statistical methods. For example, based on the Z-score model (Altman, 1968), Zhang, Altman, and Yen (2010) developed a Z_{China}-score model to capture the distress risk of Chinese listed companies. Similar to the Z''-score model developed for non-manufacturing companies (Altman, 2000) and the emerging market scoring model (Altman, 2005), the Z_{China}-score model is also a linear discriminant analysis model (MDA model), which consists of four variables: (1) total liabilities / total assets; (2) net profit / average total assets; (3) working capital / total assets; and (4) retained earnings / total assets. This Z_{China}-score model was estimated based on an estimation a sample of 60 listed companies, of which 30 were financially distressed firms in 1998 and 1999, and 30 were healthy firms from the top 50 companies in 1998 securities ranking (Zhang, Altman, and Yen, 2010). Another study undertaken using conventional statistical method is by Li and Du (2011). They developed logit models to assess corporate financial distress in the Chinese market using a matched-pair of 50 financially distressed listed manufacturing companies and 50 healthy companies from 2005 to 2007.

More recently, conventional statistical methods have also been applied to assess distress probabilities of Chinese listed companies based on larger sample sizes. For example, Li, Crook, and Andreeva (2014) developed a logit model based on seventeen financial variables and three efficiency measures computed by Data Envelopment Analysis (DEA). Their logit model is estimated on a sample of 2104 listed Chinese companies between

1998 and 2010. They decomposed Technical Efficiency (TE) into Pure Technical Efficiency (PTE) and Scale Efficiency (SE) by assuming Variable Returns to Scale (VRS). However, they found that decomposition of TE did not improve model prediction accuracy in comparison with a simpler logit model estimated only on TE and other financial variables. In addition, Liu and Wang (2016) developed a logit model based on a sample of 3485 non-financial Chinese listed companies. Seven financial variables and five macroeconomic variables are included in their model. The financial variables include debt-to-asset, current ratios, quick ratios, accounts receivable turnover, inventory turnover, growth of net assets and cash to current liabilities. Macroeconomic variables include correlation coefficients between net profit and GDP, correlation coefficients between net profit and money supply, correlation coefficients between net profit and CPI, correlation coefficients between net profit and real interest rate and correlation coefficients between net profit and RMB and USD exchange rate.

3.6.4 The predictive power of non-financial predictors

Table 3.1 demonstrates that more recently at least some research attention has been paid to assessing the predictive power of non-financial variables as distress predictors, especially after 2011. These non-financial measures include variables concerning corporate governance (see Li and Du (2011) and Xie, Luo, and Yu (2011)), macroeconomic variables (see Xie, Luo, and Yu (2011) and Liu and Wang (2016)), ownership structure (see Wang and Li (2007) and Li and Du (2011)) and external market information (see Xie, Luo, and Yu (2011)). Despite the fact that the general economic conditions are the same for every company in the market, it is argued that healthy companies can adapt appropriate policies to respond to economic changes in a timely manner (Xie, Luo, and Yu, 2011). Li, Crook, and

Andreeva (2014) have also examined the predictive ability of corporate efficiency measures by decomposing Technical Efficiency (TE) into Pure Technical Efficiency (PTE) and Scale Efficiency (SE) in Chinese distress prediction. It is argued that theoretically non-financial variables could capture distress signs of a company earlier than financial variables (Li and Du, 2011). In addition, non-financial variables contain several desirable properties that could complement the use of financial variables in corporate financial distress prediction. First, in comparison with financial variables, non-financial variables are usually available in a timely manner. This is because financial information is only made available after the publication of financial reports, which contains past information about the performance and position of a company. Second, non-financial information is more difficult to manipulate (Li and Du, 2011), and might therefore comprise a more reliable measure of the state of a firm than financial measures. Finally, non-financial information is generally less sensitive than financial information as it is less likely to be associated with extreme values or outliers (Li and Du, 2011; Xie, Luo, and Yu, 2011).

Wang and Li (2007) were among the first to introduce non-financial predictors into financial distress prediction in the Chinese market setting. Their study included not only accounting ratio variables, but also variables concerning cash flow and corporate governance were included. In total 39 variables were collected comprising 34 financial variables (measurements for the ability to pay, profitability, asset utilisation, growth, and cash flow) and five non-financial variables reflecting corporate governance characteristics and ownership reformation. These five non-financial variables are ownership concentration coefficient, affiliated debt, affiliated exchange, pledge, and irregularity. The authors developed a model based on rough set theory (RS) to predict the distress risk of Chinese listed companies based on a matched-pair sample of 212 financially distressed firms and 212 healthy firms from 1998 to 2005. Tthey found that growth ratio of equity per share, net return on assets, earnings per share, interest coverage, ownership concentration, net profit margin, pledge, retained earnings ratio, and total assets turnover contained the highest prediction power in distress prediction of Chinese listed companies (Wang and Li, 2007). After re-estimating the same RS model without the five non-financial variables, they found that the model combining financial and non-financial ratios outperformed the one containing financial ratio variables only. Wang and Li (2007) further concluded that when constructing financial distress prediction models, it is necessary to consider every aspect of a company, not just limiting the analysis to financial characteristics. Because ownership structure and corporate governance of a company might influence its financial situation, the requirement of proper ownership structure by supervision authorities of China's stock exchange can be an effective measure to prevent firms from getting into financial distress (Wang and Li, 2007).

Li and Du (2011) also emphasise the necessity of including non-financial predictors into financial distress prediction in the Chinese market. In their study, several non-financial indicators concerning corporate governance structure and ownership structure were introduced, including board size, the ratio of independent directors, the ratio of director ownership, the sum of the top 5 shareholding ratio (CR-5 indicator), and Z indicator that measures the power of the largest shareholder relative to other smaller shareholders. Two logit models were developed and estimated, one of which included only financial indicators as independent variables and the other model employing a mixture of financial and non-financial indicators. The logit model with only financial predictors included: (1) cash to current liability ratio; (2) debt to equity ratio; (3) debt to asset ratio; (4) inventory turnover; and (5) total assets turnover. On top of the above-mentioned five financial variables, the second model with both financial and non-financial indicators also included: (1) board size; (2) independent director ratio; (3) director ownership ratio; (4) CR-5 indicator; and (5) Z indicator. After reviewing the predictability of both models, they concluded that adding non-financial variables into financial distress prediction models could improve prediction accuracy, as the model with both financial and non-financial variables performed better than the model with financial variables alone (Li and Du, 2011).

In addition to internal corporate governance and ownership structure variables introduced by Wang and Li (2007) and Li and Du (2011), Xie, Luo, and Yu (2011) introduced a number of macroeconomic variables and external market variables into corporate financial distress prediction in China. Their sample consists of a matched-pair of 130 listed ST manufacturing companies and 130 healthy companies randomly selected in the same industry between 2005 and 2007. Internal governance and external market variables include: (1) shares concentration; (2) the equity ratio of executives; (3) board size; (4) CEO duality; (5) liquidity of the stock; (6) cumulative annual return; and (7) qualified auditors' opinion. Several macroeconomic variables were also included, which are measures concerning: (1) economic environment, such as correlation coefficient between net profit and GDP; (2) money supply; (3) inflation rate, such as correlation coefficient between net profit and CPI; (4) interest rate, such as correlation coefficient between net profit and actual interest rate; and (5) exchange rate, such as correlation coefficient between net profit and CNY/USD exchange rate.

After model estimation with financial variables alone and a combination of financial and non-financial variables based on SVM and MDA, they concluded that non-financial variables are associated with the financial distress of Chinese listed companies from a theoretical and empirical point of view (Xie, Luo, and Yu, 2011). Their conclusion is evidenced by higher prediction accuracy when models are estimated using a combination of financial and non-financial variables, and lower prediction accuracy when models are estimated using financial variables alone. Their SVM model estimated using all variables provided an out-of-sample prediction accuracy of 83.08% whereas the prediction accuracy of the SVM model estimated based only on financial variables is 78.46%. In terms of the predictive results of the MDA models, the prediction accuracy of the full model is 83.08% in comparison with 76.15% when estimated with financial variables alone. Despite the comparable predictive performance of MDA and SVM, SVM models suffer from the 'black-box' criticism and fail to disclose information on critical variables with high discriminate power. From the MDA models, non-financial variables, especially macroeconomic variables such as the correlation coefficient between net profit and fixed asset investment and correlation coefficient between net profit and retail price index have critical explanatory power of corporate financial distress in China (Xie, Luo, and Yu, 2011).

3.7 Limitations of distress prediction studies in China

In this section, some limitations associated with existing literature on corporate financial distress in China are discussed followed by some proposed remedies. In the corporate financial distress prediction literature, a sample of financially distressed firms and a sample of healthy firms are required for model estimation. A number of studies have undertaken a matched-pair sample selection method. 'Matched-pair' sample selection refers to the process in which known bankrupt companies are matched with non-bankrupt companies from the same standard industry classification code and of similar asset size (Platt and Platt, 2002). A majority of extant Chinese financial distress prediction studies have adopted such a matched-pair sample selection design. Matched-pair sample selection design has been criticised for oversampling distressed firms and therefore resulting in choice-based sample biases (Zmijewski, 1984). In the ideal world, the healthy firm sample should be drawn randomly from the entire population. Therefore, matching healthy firms by industry and size with financially distressed firms will result in biased parameter and probability estimates as well as biased out-of-sample prediction accuracy rates (Zmijewski, 1984). The observed result of this bias is that the distressed firm sample is oversampled as it has a sample probability larger than the population probability. Therefore, the oversampled group (in this case the financially distressed sample) will have understated classification and prediction error rates (Zmijewski, 1984).

Platt and Platt (2002) empirically tested and confirmed the presence of choice-based sample bias introduced by Zmijewski (1984)), finding that such bias increases as the proportion of financially distressed to healthy firms within a sample increases. In order to describe and quantify the impact of choice-based sample bias, Platt and Platt (2002) estimated 50 random regressions designed with matched-pair samples, concluding that only less than 20% of the coefficient estimates were within the 95% confidence interval around the true population parameter. In addition, there is another issue associated with the matched-pair design. Because healthy firms are usually matched with financially distressed firms based on certain characteristics concerning industry and asset size, this makes it impossible to include industry and size characteristics of companies as explanatory variables in a distress prediction model (Jones, 1987). Due to the fact that sample selection can negatively affect the results of corporate financial distress prediction models that are not built using all the available data from the population (Platt and Platt, 2002), and to avoid over-sampling problems and choice-based sample bias associated with matched-pair design, this study includes all available active firms listed on the Shanghai and Shenzhen stock exchanges. No attempt has been made to match distressed and active firms by factors such as industry and size.

Another limitation of existing Chinese financial distress prediction research is the small number of financially distressed firms included in the estimation sample. The small sample size problem is largely due to the very recent enforcement of the ST system in the Chinese stock market and inconsistency of Enterprise bankruptcy Laws in China to govern bankruptcy cases (Chen et al., 2006). This has led to a lack of historical financially distressed firms in the Chinese economy. With the enforcement of the ST system by CSRC in 1998, a unique opportunity has only recently emerged to investigate the financial performance of publicly distressed firms in China and its determinants. In contrast, the bankruptcy and insolvency databases in Western economies (e.g., Moody's or Standard & Poor's databases) contain many thousands of bankruptcy cases spanning over 30 years (Zhang, Altman, and Yen, 2010). To best deal with the small sample size problem that might limit generalisability (Grice and Dugan, 2001), this research employs a sample of all listed firms on both the Shanghai stock exchange and Shenzhen stock exchange from the period 1998 to 2016. 1998 has been chosen as the beginning of the sample period since it is the first year that ST firms became observable across stock exchanges and 2016 accounts for the most recent year of evidence at the time of data collection.

The relative predictive performance of non-financial variables has attracted little research attention in the context of Chinese distress prediction modelling. In addition to conventional financial indicators, Jones (2017) finds that many non-conventional bankruptcy predictors, particularly some non-financial measures, such as market-price indicators, shareholder ownership/ concentration variables, executive compensation measures, macroeconomic variables, and other variables also have a high degree of predictive power based a large sample of U.S. bankruptcies. In the Chinese distress prediction literature, only four groups of non-financial variables have been previously examined, including corporate governance, ownership structure, macroeconomic, and external market information. In addition to conventional financial variables, the empirical framework employed for this thesis – TreeNet® is also capable of examining the predictive performance of a wide range of non-financial variables such as market-price indicators, shareholder ownership/concentration variables, corporate governance proxies, macroeconomic variables, executive compensation variables, corporate social responsibility (CSR) variables, valuation multiples, industry background and other control variables. The wide range of over

90 financial and non-financial variables examined in this thesis captures comprehensive aspects of corporate financial health in Chinese listed companies.

To date, almost all Chinese corporate financial distress prediction studies have modelled corporate financial distress in terms of a simplistic binary classification outcome. Much of the research effort so far has been devoted to distinguishing financially distressed firms from healthy firms. According to Jones and Hensher (2007), such a binary classification design could be subject to oversimplification of the underlying economic reality of firms. In addition, as argued by Ward (1994), operationalising firm distress as a dichotomous response measure (such as distress and non-distress) ignores the important fact that firms are not simply distressed or active but possess different degrees of financial distress that vary with time. On the other hand, multi-state distress prediction models could better approximate the continuum of corporate financial health observable across companies (Lau, 1987). However, there has been little theoretical and empirical research regarding development of multi-state prediction models. In addition to the conventional binary prediction model, this thesis also examines Chinese financial distress from a three-state and five-state perspective.

TABLE 3.1: Tabular representation of selected Chinese distress prediction studies

Author(s)	Sample size	Sample period	Number/type of variables	Model(s) applied
Chen, J., Marshall, B. R., Zhang, J., & Ganesh, S. (2006)	39 ST & 517 non-ST	1999 – 2003	34 financial	MDA, Logit, DT & NN
Wang, Z., & Li, H. (2007)	212 ST & 212 non-ST	1999 – 2005	34 financial & 5 non-financial	Rough set (RS)
Hua, Z., Wang, Y., Xu, X., Zhang, B., & Liang, L. (2007)	60 ST & 60 non-ST	1999 – 2004	7 financial	Integration of SVM & Logit
Ding, Y., Song, X., & Zen, Y. (2008)	56 ST & 194 non-ST high-tech	2001 – 2004	33 financial	SVM
Sun, J., & Li, H. (2008)	135 ST & 135 non-ST	2000 – 2005	7 financial	Weighted majority voting combination of multiple classifiers
Li, H., & Sun, J. (2008)	135 ST & 135 non-ST	2000 – 2005	23 financial	Ranking-order case-based reasoning
Sun, J., & Li, H. (2009)	135 ST & 135 non-ST	2000 – 2005	35 financial	Serial combination of multiple classifiers
Zhang, L., Altman, E. I., & Yen, J. (2010)	30 ST & 30 non-ST	1998 – 1999	4 financial	MDA
Cao, Y., Wan, G., & Wang, F. (2011)	53 ST & 53 non-ST	2008 – 2009	20 financial	Integration of RS and SVM
Sun, J., Jia, M. Y., & Li, H. (2011)	692 listed	2000 – 2008	41 financial	AdaBoost ensemble with SAT and DT
Li, J. M., & Du, W. W. (2011)	50 listed manufacturing	2005 – 2007	5 financial & 5 governance	Logit
Xiao, Z., Yang, X., Pang, Y., & Dang, X. (2012)	92 ST & 161 non-ST	2007 – 2009	39 financial	integration of RS and Dempster-Shafer (D-S) evidence theory
Xie, C., Luo, C., & Yu, X. (2011)	130 ST & 130 non-ST	2005 – 2007	28 financial, 4 governance, 3 market & 10 macroeconomic	SVM & MDA
Zhou, L., Lai, K. K., & Yen, J. (2012)	290 ST & 290 non-ST	1999 – 2006	26 financial	20 models based on 6 features ranking strategies
Li, Z., Crook, J., & Andreeva, G. (2014)	2104 listed	1998 – 2010	17 financial & 3 efficiency measures (by Data Envelopment Analysis (DEA))	Logit
Geng, R., Bose, I., & Chen, X. (2015)	107 listed	2008 – 2011	31 financial	Data mining
Liu, Z. J., & Wang, Y. S. (2016)	3485 non-financial	2003 – 2013 excluding 2008	7 financial & 5 macroeconomic	Logit

3.8 Chapter conclusion

In this chapter, a number of prominent works on corporate financial distress prediction have been reviewed and discussed. This chapter did not simply provide a survey of published works; it also highlighted the relevant strengths and weaknesses of existing studies. This literature review chapter began with a discussion of the definition of financial distress, next delving into the evolution of financial distress prediction techniques, which have developed from statistical methods (such as UDA, MDA, logit/probit), to machine learning techniques (such as NN and SVMs) and then to some more advanced 'new age' machine learning techniques (such as boosting and random forests). With the advancement of prediction techniques, some previous restrictive assumptions (such as normally distributed independent variables and independent and identically distributed errors) that could rarely be met in practice have been gradually relaxed. The discussion of how distress prediction techniques have evolved over time confirms the choice of the gradient boosting (GB) model (TreeNet®) as the appropriate empirical framework of this study.

As this study aims to evaluate and compare how well a large number of 'Western-style' distress predictor variables apply to the context of China's unique ST system, a discussion of predictors of corporate failure has been provided which motivates the variable selection of the current study. Predictors of corporate distress for this study include accounting-based variables, market-price indicators, shareholder ownership/concentration variables, macroeconomic variables, executive compensation variables, corporate social responsibility variables, valuation multiples and other control variables. This chapter has also reviewed some more recent studies on Chinese financial distress prediction. A tabular representation of selected Chinese distress prediction studies is summarised in table 3.1. Several features of Chinese distress prediction studies are revealed in Table 3.1, which include the late start of Chinese distress prediction studies, issues of small distressed firm sample and short sample period, the prediction techniques employed, and the predictive power of non-financial predictor variables in Chinese distress prediction.

This chapter also discussed several limitations associated with current Chinese distress prediction studies that the current study overcomes. In order to avoid over-sampling problems and choice-based sample bias associated with the matched-pair sample design, this study includes all available active firms listed on the Shanghai and Shenzhen stock exchanges. No attempt has been made to match distressed and active firms by industry or size. With regard to the issue regarding the small distressed firm sample on China's stock market, this study uses a much larger sample drawn over a longer time frame from 1998 to 2016. Over 90 financial and non-financial variables are evaluated in this thesis to determine their relative role and importance in predicting financial distress distress of Chinese listed companies. This overcomes one of the limitations in previous literature that research attention has mainly been focused on financial variables as distress predictors. To overcome limitations associated with binary classification design in distress prediction modelling, this thesis also examines Chinese distress from a multi-state perspective, which arguably better approximates the continuum of corporate financial health observable across companies (Lau, 1987).

Chapter 4

Data, Variable definitions, and Methodology

4.1 Chapter introduction

This chapter presents the data, variables and methodology of this thesis. Section 4.2 describes the data and variables used in this thesis. Section 4.3 explores TreeNet® as the empirical framework of this thesis, highlighting several reasons for the selection of the TreeNet® model as the appropriate empirical framework. Section 4.4 discusses the TreeNet® model and its conceptual foundation (the gradient boosting algorithm) in more detail. Section 4.5 concludes this chapter.

4.2 Data and variables

Section 4.2.1 introduces the database used for data collection, and Section 4.2.2 details data collection procedures. Section 4.2.3 defines dependent and independent variables used in this thesis.

4.2.1 Database used for data collection

All data for this study is collected from the China Stock Market and Accounting Research (CSMAR) database. The CSMAR database is developed by Shenzhen GTA Education Tech Ltd., a leading information provider of financial market data in China. The CSMAR database is a comprehensive database covering data on China stock market series, factor research series, China listed firms research series, figure characteristic series, China fund marker series, China bond market series, China derivatives market series, China economic research series, green economy series, China industry research series, bank research series, overseas market research series, and monographic study series. It provides data on all companies listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). The CSMAR database is the most widely used database for empirical studies using China stock markets data and financial statements data of China's listed companies. The CSMAR database can also be accessed via Wharton Research Data Services (WRDS). Because the empirical results of this thesis ultimately depend on the reliability of data collected from the CSMAR database, if there are deficiencies in the Chinese financial reporting data, this can clearly have implications for the empirical results of this thesis. However, to date there is limited empirical evidence that there are any deficiencies in the CSMAR database.

4.2.2 Data collection procedures

The collection of distressed firm data requires definition of financial distress as well as specification of the population from which firms are drawn (Ohlson, 1980). In this study, firms in financial distress are defined by the Special Treatment (ST) system[1] introduced by the China Securities Regulatory Commission (CSRC) in 1998. Up to five annual reporting periods[2] of data are collected on all ST firms prior to their first year of ST designation. The same procedure is applied to the control (healthy/active) group from the most recent year. The population from which firms are drawn is restricted by: (1) the sample period from 1998 to 2016 (the year 1998 is chosen as the start of the sample period as the ST system was launched in 1998); and (2) only publicly listed firms on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) are included in the estimation and validation samples. In order to examine the predictive performance of the TreeNet® model several years prior to financial distress, this study follows the accepted practice in the financial distress prediction literature and codes previous years of a distressed firm as distressed (Jones, 2017). For example, if a company entered into ST for the first time in 2015 and all five preceding years of financial and market data exists for that firm, then all years are coded as ST. A control group of healthy or non-ST firms is also collected. The sample of non-distressed firms represents all 'active' publicly listed companies included in the CSMAR database.

For the financially distressed firm sample, the following data collection procedures are applied: (1) in order to determine the financially distressed firms for this study, information on change in listing status of all Chinese publicly listed companies from 1998 to 2016 were collected from the Special Treatment and Particular Transfer section under China Stock Market Series in CSMAR database; (2) the collected information was manually sorted to identify the first year that these financially distressed firms entered ST status; (3) once the first year (as denoted by time t) that these firms entered ST status was determined,

[1] See Section 1.3.3 for more information about the ST system.

[2] According to China's Accounting Law (Chapter 2, Article 8), fiscal year shall start on January 1 and end on December 31 on the Gregorian calendar. A condition is set during the data collection process for the ending date of fiscal year (date of accounting statement) to be December 31.

up to five years (from t-1, t-2, t-3, t-4 up until t-5) of financial information of all financially distressed firms was collected from Financial Statements section under China Listed Firms Research Series in the CSMAR database; (4) all non-financial variables, including market returns, shareholder ownership/concentration, corporate governance proxies, macroeconomic variables, executive compensation, corporate social responsibility, industry background, valuation multiples, and other variables were also collected from China Stock Market Series, China Listed Firms Research Series and China Economic Research Series of the CSMAR database. Specific sections of the CSMAR database visited include Stock Trading, Institutional Investor, Corporate Governance, Macroeconomic, Corporate Social Responsibility, Shareholder, Analyst Forecasts, and Audit Opinion.

The same procedure was applied to the control group from the most recent year. Following the approach of Ohlson (1980) and Jones and Hensher (2004), no firm is removed from the sample because it is newly or recently listed, and some firms in the sample had only one or two years of financial and non-financial data. For the purpose of the multi-state TreeNet® models, the number of times that a firm gets in and out of the ST status is required to determine the different states that a ST firm is classified into[3]. Information on the number of times that a firm gets in and out of the ST status is manually collected from the Special Treatment and Particular Transfer section under China Stock Market Series in the CSMAR database.

The final sample of this thesis includes a total of 3024 Chinese listed firms. The majority of firms within sample have a full six years of observations (including t, t-1, t-2, t-3, t-4, and t-5). 2072 out of 3024 (68.75%) of firms have full six years of data. 306 of firms have five years of data (10.1%). 167 firms have four years of data (5.5%). 88 firms have three years of data (2.9%). 157 firms have two years of data (5.2%). 227 firms have

[3]See Section 4.2.3 for more details.

one year of data (7.5%).

4.2.3 Dependent and independent variables and definitions

In addition to the conventional binary distress prediction modelling design, this study also models corporate financial distress in China in a five-state and a three-state setting. For modelling purposes, the five-state dependent variable, three-state dependent variable as well as the binary dependent variable is defined as follows.

For the five-state TreeNet® model, the dependent variable is defined in five states including:
State 0: if a company is active or healthy (ST=0);
State 1: if a company has experienced only one ST event (ST=1);
State 2: if a company has experienced more than once but less than four times of ST events ($1 < \text{ST} < 4$);
State 3: if a company has experienced four times or more of ST events ($\text{ST} \geq 4$);
State 4: if a company has been delisted as a result of ST events.

Following the approach of Lau (1987), the five-state dependent variable is defined based on the severity of financial distress. State 0 to State 4 are 'states of increasing severity of financial distress' (Lau, 1987, p. 128). Companies in State 1 (coded '1'), which have only entered into ST status once, are considered less distressed than companies in State 2 to State 4. Companies in State 2 (coded '2') and State 3 (coded '3'), which have gone in and out of ST status several times show more severe distress problems than State 1 companies. This also indicates that State 2 and State 3 companies may have difficulty in managing distress. Companies in State 4 (coded '4') represents the worst-case outcome of continued distress. They have been delisted from the Stock Exchange as a result of prolonged ST status. All other firms are coded ‘0’ as active or healthy.

For the three-state TreeNet® model, the dependent variable is defined in three states including:
State 0: if a company is active or healthy (ST=0);
State 1: if a company has experienced only one ST event (ST=1);
State 2: if a company has experienced more than one ST events including companies that have been delisted as a result of ST events (ST $>$ 1).

Similar to the definition of the five-state dependent variable, the three-state dependent variable is also defined based on the severity of financial distress. Companies in State 1(coded ‘1’), which have experienced a ST event only once, are considered less distressed than companies in State 2 (coded ‘2’), which have experienced more than one ST event. All other firms are coded ‘0’ as active or healthy.

For the binary TreeNet® model, the dependent variable is defined in two states including:
State 0: if a company is active or healthy (ST=0);
State 1: if a company has experienced ST event (ST=1).

In the binary setting, corporate distress in China has been defined as a binary dependent variable and coded ‘1’ if a company has experienced at least one ST event (this includes any *ST and delisted companies). All other firms are coded ‘0’ as active or healthy.

In this study more than 90 independent explanatory variables[4] are collected and computed from the CSMAR database. These variables include: (1) accounting-based variables, such as retained earnings to total assets, net profit margin, total assets to total liabilities, ROA, and ROE; (2) market-price indicators, such as market capitalisation and annual market returns; (3) macroeconomic indicators, such as GDP growth and unemployment rate; (4) shareholder ownership/concentration variables, such as state ownership, insider ownership, and institutional shareholders ownership; (5) executive compensation measures, such as the total compensation of the top three directors and the total compensation for the top three executives; (6) corporate governance proxies, such as number of directors and if the Chairman and general manager is concurrent; (7) corporate social responsibility metrics, such as social contribution value per share and social donation; (8) valuation multiples, such as price-to-book ratio and price-earnings ratio; (9) audit quality factors, such as qualified audit opinion and if the auditor is from a 'Big Four' firm or not; and (10) other control variables, such as firm size (proxied by measures such as market capitalisation, total assets and employee numbers), industry background (based on the CSMAR industry definitions) and an earnings management proxy using the Kothari, Leone, and Wasley (2005) measure. A full definition of study variables is provided in Appendix A of this thesis.

4.3 The empirical framework

Following the approach of Jones (2017), this thesis employs a commercial version of the gradient boosting (GB) model known as the TreeNet Gradient Boosting Machine (TreeNet®) to examine the predictive and explanatory performance of over 90 input variables. Following conventions in the statistical learning literature, the gradient boosting

[4]See Section 3.4 for a discussion of motivations for variable selection of this thesis.

algorithm randomly partitions 80% of the total observations to the training sample and 20% of observations to the test sample (Hastie, Tibshirani, and Friedman, 2009). The TreeNet® model provides several outputs such as the confusion matrix, average log-likelihood, area under the ROC curve (AUC), relative variable importances (RVIs), and partial dependency plots.

The TreeNet® model has been selected as the empirical framework of this thesis because it has several properties that are particularly appealing for distress prediction studies. First, the TreeNet® model is one of the most powerful commercial machine learning models available and it is particularly useful for high dimensional and nonlinear empirical analysis that involve large numbers of predictor variables; as mentioned by Jones (2017), this better reflects corporate financial distress in its real world context (Hastie, Tibshirani, and Friedman, 2009; Jones, 2017). Rather than optimising parameters jointly, the predictive ability of TreeNet® is achieved through a stage-wise process by optimising parameters one at a time (Jones, 2017). In this way, TreeNet® provides very accurate prediction outcomes while remaining highly resilient to model over-fitting (Friedman, 2001; Schapire and Freund, 2012). This property of the TreeNet® model matches the research objectives of this thesis as it provides an effective method for examining the predictive and explanatory power of a wide range of financial and non-financial predictors in a single statistical framework.

To date, a significant number of financial distress prediction studies have relied on parametric models such as MDA and logit (see e.g.,Altman (1968) and Ohlson (1980)). There are at least two issues with conventional parametric models for financial distress prediction studies. First, parametric models are only capable of handling a small number of variables and increasing the number of variables usually results in model over-fitting, which reduces the overall validity of the model (Jones, 2017). This is because parametric models rely on maximum likelihood to optimise parameters jointly with an aim of minimising misclassification error rates. Given the capacity constraint of parametric models, most distress prediction studies only use a limited set of financial ratios and/or market price variables (Jones, 2017). Second, parametric models rely on the rules of statistical inference, such as p-values and significance tests, which has garnered growing criticism in recent literature (see e.g., Ohlson (2015), Dyckman (2016), and Harvey (2017)). There are some inherent problems of significance tests that rely on p-values. As argued by Dyckman (2016), significance testing does not necessarily provide an objective, useful, and unambiguous measure of evidence in hypothesis testing. In addition, parametric models are also at risk of various forms of abuse, such as 'p-hacking' or 'selective reporting' and over-reporting of false positives (Ohlson, 2015; Harvey, 2017). Unlike parametric models, the TreeNet® model does not rely on the rules of statistical inference but is a data analysis approach that uses predictive ability as the basis for the selection and ranking of input variables (Jones, 2017).

Third, in contrast to other sophisticated machine learning models that generally suffer from the 'black box' criticism as a result of a lack of interpretability, the TreeNet® model provides outputs which allow the researcher to see through the 'black box', particularly through relative variable importances (RVIs) and partial dependence plots or marginal effects (Friedman, 2001; Jones, 2017). The out-of-sample predictive performance of the TreeNet® model can be interpreted through several conventional classification statistics such as the confusion matrix, average log-likelihood, and area under the ROC curve (AUC). The contribution of different predictor variables to the overall predictive performance of the model can be examined through the RVIs measure, which is rank ordered based on each predictor's weighted classification accuracy averaged across all predictors used in the model (Friedman, 2001). The RVIs measure produces relative scores based on weighted improvements that are summed and then scaled relative to the top contributing predictor (Jones, 2017). The predictor with the largest sum of improvements (the best performing variable) is scored 100, and all other predictors are scored and ranked relative to the best performing variable. Variables with higher RVIs scores contribute more predictive power to the model and they are ranked higher than those with lower RVIs scores. The variables that contribute little or nothing to the model's overall predictive power will have lower RVIs scores descending towards zero. All predictor variables with non-zero RVIs scores will contribute to out-of-sample predictive performance of the model in some way, although the strength of their contribution varies from one predictor to the other. The ability to rank order predictors based on the RVI metrics is not only useful for evaluating the role of alternative distress predictors but it can also help identify non-conventional distress predictors that are not widely explored in prior literature (Jones, 2017). In addition to the RVI metrics, the TreeNet® model can also be interpreted through partial dependence analysis, which represents the direction of a predictor variable's influence on the distress outcome as well as the magnitude of the effect (Hastie, Tibshirani, and Friedman, 2009).

Finally, according to Jones (2017), in comparison with conventional parametric models (such as logit) and other machine learning methods (such as neural networks and conventional boosting), the TreeNet® model is largely immune to outliers, missing data, database errors, scaling, monotonic transformations, or the inclusion of irrelevant inputs that can be very challenging for all types of predictive models. Furthermore, the TreeNet® model is also immune to the issue of multicollinearity among independent variables, which can severely impact the performance of parametric models and therefore reduce the interpretability and stability of the parameter estimates (Jones, 2017). Multicollinearity is not an issue with regard to the TreeNet® model as the underlying gradient boosting algorithm recognises the issue of multicollinearity as redundant information which does not affect the predictive performance of the TreeNet® model (Jones, 2017). As the TreeNet® model is not restricted to binary settings, it can also be applied to model corporate financial distress of Chinese listed companies from a multi-state distress prediction perspective.

4.4 The formal TreeNet® model

This section describes the the formal TreeNet® model. Section 4.4.1 illustrates the gradient boosting algorithm as set out by Friedman (2001), Hastie, Tibshirani, and Friedman (2009) and Jones (2017). Section 4.4.2 and Section 4.4.3 introduces important outputs such as relative variable importances and partial dependency plots from the TreeNet® model that provide some level of interpretability.

4.4.1 The gradient boosting machine (TreeNet®)

A powerful tree-based machine learning method known as TreeNet® is employed to evaluate the predictive and explanatory power of over 90 financial and non-financial 'Western-style' bankruptcy predictors in the context of Chinese distress prediction. The TreeNet® model is a commercial implementation of the gradient boosting (GB) model (Friedman, 2001). TreeNet® aims to build an accurate model by constructing a large number of small decision-trees in a stage-wise error-correcting fashion.

A decision-tree can be used to define a classifier via a series of threshold-type decisions, where the parent nodes are input features and the terminal notes are class labels (or responses). Figure 4.1 is an example of a two-level decision-tree for features $\{x_1, x_2\}$, class labels $\{-1, 1\}$, and thresholds $\{t_1, t_2\}$. For example, if we observe that $x_1 < t_1$ and

$x_2 \geq t_2$, the tree in Figure 4.1 will classify the pair of observed features into the class with label '1'.

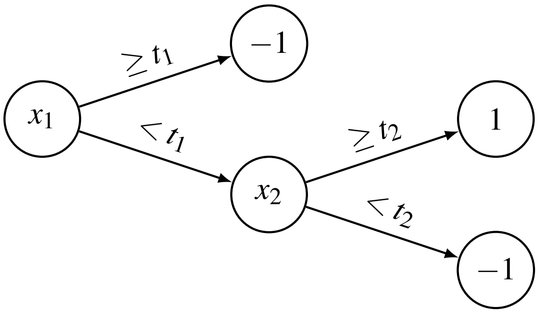

FIGURE 4.1: Example of a binary decision-tree with two levels.

As noted by Hastie, Tibshirani, and Friedman (2009) and Jones (2017), unlike classical parametric models such as logit, machine learning methods based on decision-trees such as TreeNet® have many desirable features, including the ability to deal with mixtures of numeric and categorical predictors, invariance under monotone transformations (e.g., scaling), robustness against outliers, ability to perform internal feature selection, and ability to handle irrelevant predictors. Furthermore, as illustrated by Friedman (2001), Hastie, Tibshirani, and Friedman (2009), and Jones (2017), unlike other machine learning methods such as those based on neural networks (e.g., deep-learning algorithms), the models generated by TreeNet® are interpretable via tools such as relative importance measures and partial dependency plots. The gradient boosting machine (Friedman, 2001) is the conceptual foundation of TreeNet®. As set out by Friedman (2001) and Hastie, Tibshirani, and Friedman (2009), the generic version of the gradient boosting machine is presented in Algorithm 1.

Algorithm 1 Gradient Boosting Machine

Input: $\{(\mathbf{x}_i, y_i)\}_{i=1}^N$ (training data), M (number of iterations).
Set $F_0 = \arg\min_\rho \sum_{i=1}^N L(y_i, \rho)$.
for $m \in \{1, \ldots, M\}$ **do**
    for $i \in \{1, \ldots, N\}$ **do**
        $r_i = -\left[\frac{\partial L(y_i, F(\mathbf{x}_i))}{\partial F(\mathbf{x}_i)}\right]_{F(\cdot)=F_{m-1}(\cdot)}$.
    end for
    $\mathbf{a}_m = \arg\min_{\mathbf{a},\beta} \sum_{i=1}^N [r_i - \beta h(\mathbf{x}_i; \mathbf{a})]^2$.
    $\rho_m = \arg\min_\rho \sum_{i=1}^N L(y_i, F_{m-1}(\mathbf{x}_i) + \rho h(\mathbf{x}_i; \mathbf{a}_m))$.
    $F_m(\cdot) = F_{m-1}(\cdot) + \rho_m h(\cdot; \mathbf{a}_m)$.
end for
Output: F_M.

In Algorithm 1, N is the number of training examples, M is the number of iterations, $\mathbf{x}_i$ denotes the vector of input features for the ith training example, y_i denotes the observed response (i.e., class label) associated with $\mathbf{x}_i$, L denotes a specified loss function that measures the discrepancy between the predicted and the observed responses, and $h(\mathbf{x}_i; \mathbf{a})$ is the predicted response for input $\mathbf{x}_i$ given by the decision-tree $h(\cdot; \mathbf{a})$, where $\mathbf{a}$ denotes the parameter vector characterising a decision-tree (e.g., splitting variables, split locations, and terminal node values).

As shown by Friedman (2001), Algorithm 1 can be considered as a procedure for loss minimisation in function space. More concretely, given training observations $\{(\mathbf{x}_i, y_i)\}_{i=1}^N$, the goal is to minimise the overall loss

$$\sum_{i=1}^N L(y_i, F(\mathbf{x}_i)) \tag{4.1}$$

with respect to F, where F is constrained to be a weighted sum of trees

$$F(\cdot) = \sum_{m=1}^S \rho_m h(\cdot; \mathbf{a}_m), \quad S \le M. \tag{4.2}$$

As noted by Friedman (2001), if the solution is constrained to take on the additive form in

Equation (4.2), it can be found by constructing a sequence of functions $\{F_m\}_{m=0}^{M}$ using a greedy stage-wise approach where a single tree is added at each stage. Specifically, on line 2 of Algorithm 1, the function sequence is initialised by F_0, which is the optimal constant model. The lines 4 to 9 are iterated M times, with each iteration (or stage) responsible for constructing F_m from F_{m-1}. Within each iteration, the set of generalised residuals $\{r_i\}_{i=1}^{N}$ is first obtained by repeating line 5 for each observed example, where each r_i corresponds to the ith component of the negative gradient of the objective function in Equation (4.1). On line 7, a decision-tree is then fitted to the generalised residuals by minimising the quadratic loss. The intuition is to approximate the direction in which the overall loss decreases most rapidly by a decision-tree (Hastie, Tibshirani, and Friedman, 2009). Next, on line 8, the optimal weight for each tree (also known as step-size or learning-rate) is determined by a line search step. Finally, at the end of each stage, the solution is updated according to line 9 (i.e., move from F_{m-1} to F_m). After M iterations, the resulting function F_M is outputted as the boosted tree model, that is, the strong classifier constructed by combining decision-trees.

4.4.2 Relative variable importances (RVIs)

Machine learning methods are generally able to model complex relationships and generate accurate predictive outcomes; however, they are often criticised for a lack of interpretability (Jones, Johnstone, and Wilson, 2015). While a TreeNet® model can be both high-dimensional and highly non-linear, there are now standard tools for interpreting the trained model, namely, relative variable importances (RVIs) and partial dependency plots (or marginal effects) (Jones, 2017). For high-dimensional models, only a few of these models include features that substantially influence the predicted response (i.e., the model is sparse). It is often useful to know the relative influence of each input feature on the variation of the predicted outcome. Breiman et al. (1984) proposed a measure of relative variable importance (RVI) for an individual tree with J terminal nodes. The squared RVI for input feature x_k is given by

$$\mathrm{RVI}_k^2(T) = \sum_{t=1}^{J-1} \hat{\iota}_t^2 I(v_t = k), \tag{4.3}$$

where v_t is the feature index associated with the tth internal node, and $\hat{\iota}_t^2$ denotes the squared improvement to the model as a result of splitting the tth internal node (Friedman, 2001). For a collection of trees $\{T_j\}_{j=1}^{M}$, the RVI can be generalised by averaging over all of the trees

$$\mathrm{RVI}_k^2 = \frac{1}{M} \sum_{j=1}^{M} \mathrm{RVI}_j^2(T_j). \tag{4.4}$$

As noted by Friedman (2001), the generalised measure in Equation (4.4) is more reliable (i.e., has lower variance) than the single-tree version in Equation (4.3) due to averaging.

4.4.3 Partial dependence analysis

The partial dependency plot shows the marginal effect a feature has on the predicted outcome of a classifier. It is a graphical representation of the value of F_M as a function of a chosen feature. It can indicate whether the relationship between the response and the feature is linear, monotonous or more complex. As defined in Hastie, Tibshirani, and Friedman (2009), the partial dependence function for feature x_k is given by

$$f(x_k) = \mathop{\mathbb{E}}_{\mathbf{x}_{\neg k}} \left[F_M(x_k, \mathbf{x}_{\neg k}) \right], \tag{4.5}$$

where $\mathbf{x}_{\neg k}$ denotes the vector containing all input features except x_k. The idea is to obtain the marginal function of x_k by 'averaging out' all the other features. As shown in

Hastie, Tibshirani, and Friedman (2009), given a finite number of observed examples, the expectation in Equation (4.5) can be approximated by

$$\hat{f}(x_k) = \frac{1}{N}\sum_{i=1}^{N} F_M(x_k, \mathbf{x}_{\neg ki}), \tag{4.6}$$

where $\mathbf{x}_{\neg ki}$ is the ith observed feature vector with the kth feature excluded. As noted by Friedman (2001), the partial dependence functions in Equations (4.5) and (4.6) reveal the relationship between x_k and the predicted response after accounting for the effects of all the other features, which is not the same as conditioning $\mathbf{x}_{\neg k}$ on some specified values. It is possible to generalise the partial dependence plot to higher dimensions, however visualising functions of more than two variables is a challenging task in itself (Hastie, Tibshirani, and Friedman, 2009).

4.5 Chapter conclusion

Data, variables, and methodological issues of this thesis are discussed in this chapter. All data for this thesis is collected from the CSMAR database. In the five-state TreeNet® model, the dependent variable is defined in five-states, including: (1) State 0: if a company is active or healthy (ST=0); (2) State 1: if a company has experienced only one ST event (ST=1); (3) State 2: if a company has experienced more than one but less than four ST events ($1 <$ ST < 4); (4) State 3: if a company has experienced four or more ST events (ST ≥ 4); and (5) State 4: if a company has been delisted as a result of ST events. In the three-state TreeNet® model, the dependent variable is defined in three-states, including: (1) State 0: if a company is active or healthy (ST=0); (2) State 1: if a company has experienced only one ST event (ST=1); and (3) State 2: if a company has experienced more than one ST events including companies that have been delisted as a result of ST events (ST > 1). In the binary TreeNet® model, the dependent variable is defined in two-state including: (1) State 0: if a company is active or healthy (ST=0) and (2) State 1: if a company has experienced ST event (ST=1).

In terms of the independent explanatory variables for this study, more than 90 independent variables are collected and computed from the CSMAR database, including: (1) accounting-based variables; (2) market-price indicators; (3) macroeconomic indicators; (4) shareholder ownership/concentration variables; (5) executive compensation measures; (6) corporate governance proxies; (7) corporate social responsibility metrics; (8) valuation multiples; (9) audit quality factors; and (10) other control variables. Up to five annual reporting periods of data are collected on all ST firms prior to their first year of ST designation. The same procedure procedure is applied to the control (healthy/active) group from the most recent year. Only publicly listed firms on both the SSE and SZSE are included in the sample. The sample period for this study spans over 18 years from 1998 to 2016 (the year 1998 is chosen as the start of the sample period because the ST system was only introduced by the CSRC in 1998).

TreeNet® has been chosen as the empirical framework for this thesis for several important reasons. First, the TreeNet® model is capable of accommodating large numbers of predictor variables, potentially many thousands, including nonlinear relationships and interaction effects (Jones, 2017). Second, unlike other sophisticated machine learning models that suffer from the 'black box' criticism as a result of a lack of interpretability, the TreeNet® model provides outputs that remedy this 'black box' situation, particularly through relative variable importances (RVIs) and partial dependency plots (marginal effects) (Friedman, 2001). Finally, the TreeNet® model is largely immune to outliers, missing data, database errors, scaling, monotonic transformations, the inclusion of irrelevant inputs and the issue of multicollinearity among independent variables (Jones, 2017).

Chapter 5

Descriptive Statistics

5.1 Chapter introduction

This chapter presents the descriptive statistics of the study sample. Section 5.2 describes the sample distress rates, with Tables 5.1 and 5.1 providing the distribution of active and distressed firm-year observations and firms within the sample. A breakdown of the distribution of distressed firm-year observations by distress states, industry, and year is provided is Table 5.3, Table 5.4, and Table 5.5, respectively. Section 5.3 presents descriptive statistics and independent sample t-tests for equality of means between active and distressed firm years (Table 5.6). Distress symptoms over a five-year period leading up to the distress event are discussed in Section 5.4. These distress symptoms are represented by multiple line graphs of the active group against that of the distressed group as shown in Figures 5.1 to 5.12. Section 5.5 concludes this chapter.

5.2 Distress rates

Tables 5.1 and 5.2 provide summary statistics for the distribution of active and distressed firm-year observations and firms within sample. As Table 5.1 indicates, there are 3,348 distressed firm-year observations during the sample period between 1998 and 2016, representing 21.6% of the total 15,504 available firm-year observations. There are 12,156 active firm-year observations included in the sample which represents 78.4% of the total firm-year observations. Similarly, as table 5.2 indicates, there are 646 distressed firms during the sample period between 1998 and 2016, representing 21.4% of the total 3,024 firms. There are 2,378 active firms included in the sample which represents 78.6% of the total firms.

In comparison with the U.S. sample used in Jones (2017), the bankruptcy rate of 12.3% is slightly lower than the distress rate of 21.6% in the current study. However, Jones (2017) modelled failed firms in terms of Chapter 11 bankruptcy, which is arguably a more severe outcome for investors than a ST event on the Chinese market. In comparison with the securities market in the U.S., the securities market in China is far from mature. Generally speaking, the most distinctive characteristic of the securities market in China is the existence of the Special Treatment system (Zhou, 2017). According to Arnopol (1992) only between 10% and 27% of Chapter 11 filings successfully reorganise. However, 65% of ST companies return to normal listing status (Kim, Ma, and Zhou, 2016). In addition, after comparing the number of listed companies designated with the ST status to the number of companies that have their ST status revoked from 1999 to 2016, Zhou (2017) concludes that on average 83.23% of ST companies eventually have their ST status removed and return to normal listing status. Green, Czernkowski, and Wang (2009) find that the majority of ST companies have their ST status removed by the third year after the initial ST designation.

TABLE 5.1: Distribution of active and distressed firm-year observations

Firm status	**No. of firm-years**	**Percentage**
Distressed	3,348	21.6%
Active	12,156	78.4%
Total	15,504	100%

TABLE 5.2: Distribution of active and distressed firms

Firm status	**No. of firms**	**Percentage**
Distressed	646	21.4%
Active	2,378	78.6%
Total	3,024	100%

Following the four distress states as defined in Section 4.2.3, Table 5.3 provides summary statistics for the distribution of distressed firm-year observations by four different distress states. From Table 5.3, it is evident that among the total 3,348 distressed firm-year observations, 222 firm years relate to companies that experienced a single ST event; 1620 firm years relate to companies that confronted between 1 and 4 ST events; 993 firm years relate to companies that experienced more than 4 ST events over the sample period; and 514 firm years relate to companies that were delisted as a result of ST designation. As Table 5.3 suggests, within the distressed sample, the majority of firm-year observations (48.4%) are associated with companies that experienced more than one but less than four ST events. This is followed by firm-year observations relating to companies that experienced more than 4 ST events (29.7%), firm-year observations relating to companies that were delisted as a result of ST designation (15.4%), and firm-year observations relating to companies that only experienced one ST event (6.6%).

From Table 5.3, the highest concentration (48.4%) of distressed firm-year observations stem from ST companies that have received the ST designation more than once but less than four times. In other words, the majority of the distressed sample in this study comprises ST companies that have remained under ST status for more than a year but less than four years. In principle, a ST firm cannot stay under ST status for more than four consecutive years. A listed firm would receive a ST designation after two consecutive years of losses and it would then be classified as a delisting risk warning (*ST) stock if it continues to make a third year of loss. It would then be suspended from listing as a result of three-year consecutive losses. Suspended stocks would further be delisted if they continue to report losses in the year of stock suspension. However, in practice it is fairly rare for listing to happen. In the distressed sample of the current study, only 15.4% firm-year observations are delisted.

There are at least two important reasons for the rare occurrence of delisting on the stock exchange in China. First, due to the stringent and highly competitive Initial Public Offering (IPO) quota system that restricts the number of qualified firms to go public in each region, listing through a 'shell' purchase has became an alternative option (Chen, Lee, and Li, 2008; Kim, Ma, and Zhou, 2016). Capital hungry private companies wishing to go public view the value of financially distressed firms not only based on their fundamental value but also their 'shell' value, which represents the precious stock listing right. They are willing to pay a premium to gain ownership control through the ST restructuring process and to use the ST firm as a 'shell' to raise capital from the stock exchange (Kim, Ma, and Zhou, 2016). Gradually, listing through a 'shell' purchase has effectively reduced the probability of financially distressed firms being delisted from the stock market.

Second, distressed firms are often rescued by their provincial government (Chen, Lee, and Li, 2008). According to Kim, Ma, and Zhou (2016), the significance of stock listing rights to each province is threefold. Stock listing rights not only provide a pathway to raise equity capital, they also help maintain employment and stimulate local economic growth and development (Kim, Ma, and Zhou, 2016). As such, higher number of listed firms is often viewed as a sign of superb performance and political achievement for provincial government (Chen, Lee, and Li, 2008). On the other hand, delisting would imply poor administrative ability of the provincial government and consequently bring great disgrace to the reputation of provincial government officials (Kim, Ma, and Zhou, 2016). Delisting does not only indicate that the province has lost some stock listing rights; it also affects the future IPO quota for the province (Kim, Ma, and Zhou, 2016). Therefore, financially distressed firms are often rescued by provincial government by means of subsidies, granting taxation preference or favouring listed firms in the project approval process (Chen, Lee, and Li, 2008).

Under the Special Treatment system, a distressed firm could either return to normal listing status after it turns to profit, or it could continue in the distressed state before delisting occurs. In practice, a ST firm could continue under ST status for several years, and a firm could also get in and out of the ST status a number of times. For example, a firm could receive its first ST designation in 2003, and then could be listed under *ST status in 2004 as a result of three consecutive years of being in the red. In 2005, if it improves its financial performance and turns to profit, it would be operating under ST status. In 2006, if it continues to make a profit, it could get its ST status revoked and return to normal listing. However, if in 2006 it failed to make a profit, it would then be classified as a *ST stock again. In the distressed sample of the current study, 29.7% firm-year observations have been classified as distressed firms more than four times.

TABLE 5.3: Distribution of distressed firm-year observations by distress states

Distress states	**No. of firm-years**	**Percentage**
ST=1	222	6.6%
$1<$ ST <4	1620	48.4%
ST ≥ 4	993	29.7%
Delisted	514	15.4%
Total	3,348	100%

Table 5.4 provides summary statistics for the distribution of distressed firm-year observations by industry sectors. From Table 5.4, it is evident that among the total sample of 3,348 distressed firm-year observations, the majority (2030 observations) relate to the Chinese industrials sector, representing 60.6% of the distressed sample. 432 observations are associated with the properties sector, representing 12.9% of the distressed sample. There are 382 firm-year observations from the Chinese public utilities sector, representing 11.4% of the distressed sample. 228 distressed firm-year observations are from the conglomerate sector, representing 6.8% of the distressed sample. 196 and 80 firm-year observations are from the commercial and finance sector, representing 5.9% and 2.4% of the distressed sample, respectively.

The industrials sector of China includes mining, manufacturing, construction, and power. The development of the industrial sector has been has been top priority since the founding of the People's Republic of China. Despite the prosperity of the industrial sector that continues to account for almost 40% of China's GDP, the Chinese economy is confronted with a turning point whereby it struggles to restructure from a primarily manufacturing-based to a more innovative services-oriented economy. As part of the supply-side reform, the Chinese government has in recent years announced large-scale closures and redundancies in heavy and primary industries, many of which have been functioning as deeply distressed 'zombie' enterprises (Wei, 2017). The policy of large-scale closures in the struggling industrial sector may explain the reason for the high concentration (60.6%) of the industrial sector in the distressed sample of the current study.

TABLE 5.4: Distribution of distressed firm-year observations by industry

Industry sector	No. of firm-years	Percentage
Finance	80	2.4%
Public utilities	382	11.4%
Properties	432	12.9%
Conglomerate	228	6.8%
Industrials	2,030	60.6%
Commercial	196	5.9%
Total	3,348	100%

Table 5.5 provides summary statistics for the distribution of distressed firm-year observations over the sample period between 1998 and 2016. Table 5.5 reveals that the number of distressed firm-year observations demonstrates considerable fluctuation over the sample period. The number of distressed firm-year observations began to drop significantly from 2008. Before 2008, the annual average distressed firm-year observations are around 246 from 1998 to 2007. The year with the maximum number of distressed firm years over the sample period occurred in 2002, representing 298 distressed firm-year observations. The annual average distressed firm-year observations decreased sharply to only 119 firm years from 2008 to 2015. At the time of data collection in 2016, the CSMAR database provided 2 distressed firm-year observations for 2016 which might not be representative of the total distressed firm-year observations for the year.

In comparison with the distribution of the corporate bankruptcy sample in Jones (2017), no concentration of financial distress is observable around the dot-com bubble crash (2000-2002) or the global financial crisis and its immediate aftermath (2007-2010) on the Chinese market. Two reasons might explain such a difference. First, both the dot-com bubble crash and global financial crisis originated from the U.S., which would ultimately hit the U.S. market severely. Second, financial distress as defined by ST is significantly different from bankruptcy. As discussed in section 5.2, because the turnaround probability of ST firms is considerably higher than successful reorganisation of bankruptcies, the distressed sample in the current study is not directly comparable with the bankruptcy sample used in Jones (2017). One reason that may explain the relatively higher frequencies of ST events before 2008 (average distressed firm-year observations = 246 from 1998 to 2007) and lower frequencies of ST events thereafter (average distressed firm-year observations = 119 from 2008 to 2015) is that the new Enterprise Bankruptcy Law of China was promulgated in August 27, 2006 (going into effect as of June 1, 2007). After the implementation of the new Enterprise Bankruptcy Law, which has a much wider scope of application than its predecessor legislation, some struggling distressed firms may have applied for bankruptcy instead.

TABLE 5.5: Distribution of distressed firm-year observations by year

Year of distress	**No. of firm-years**	**Percentage**
1998	223	6.7%
1999	237	7.1%
2000	241	7.2%
2001	267	8.0%
2002	298	8.9%
2003	278	8.3%
2004	237	7.1%
2005	229	6.8%
2006	205	6.1%
2007	175	5.2%
2008	135	4.0%
2009	136	4.1%
2010	168	5.0%
2011	138	4.1%
2012	129	3.9%
2013	105	3.1%
2014	88	2.6%
2015	57	1.7%
2016	2	0.1%
Total	3,348	100%

5.3 Descriptive statistics

Table 5.6 provides descriptive statistics and independent sample t-tests for equality of means between the active and distressed firm-year observations. This table provides summary statistics including the number of observations, minimum, maximum, mean, standard deviation, skewness, and kurtosis of a number of firm-specific continuous variables. For each variable, descriptive statistics are reported separately for the active and distressed group. An independent sample t-test is also conducted in order to test if there are significant differences in terms of mean values of the active and distressed group with equal variance not assumed. The t-test statistics reported in Table 5.6 suggests that 14 out of 16 pairs of firm-specific predictor variables have different mean values that are statistically significant between the distressed and active group. By comparing the mean values of the distressed group against that of the healthy group, variables with different mean values that are statistically significant can be identified.

Table 5.6 discloses significant differences between active and distressed firms in terms of several firm-specific characteristics. On average, distressed companies experience much lower profitability than active firms in terms of operating cash flow per share (mean difference=0.21). Relative to active firms, distressed firms have a lower amount of net income relative to total assets. While the mean value of return on assets (ROA) is 0.05 for the active group, it is -0.08 for the distressed group. Having a negative ROA indicates that the net income is negative for the distressed group. The active group might be more efficient in managing assets to generate earnings (mean difference=0.12). Retained earnings to total assets (RE/TA) measures a company's cumulative profitability over time proportionate to its total assets. This ratio measures the leverage of a firm. In the sample, the active group has significantly higher RE/TA than the distressed group (mean difference=21.99), indicating that distressed companies tend to rely on debt instead of retention of profits to finance their assets. Reliance on debt financing leads to increased risk of falling into financial distress if a company fails to meet debt obligations. Cash flow returns to total assets (or Cash ROA) measures a company's cash flow from operations in relation to total assets. This ratio shows the efficiency of the firm in generating cash flows from its asset investments. In comparison with active firms, the distressed group has lower cash flow returns to total assets (mean difference=0.02), which indicates that the distressed group is less efficient in managing asset investment to generate operating cash flows. The current ratio (CA/CL) is a liquidity ratio that measures a company's ability to pay off financial obligations. It expresses the amount of current assets a company holds in proportion to its current liabilities. In comparison with the active group, the current ratio for the distressed group is lower (mean difference=1.45), which indicates that the distressed group is less capable of paying off obligations and is at a higher risk of distress or default.

The debt to total assets (Debt/TA) is a leverage ratio that reveals the percentage of total assets that are financed by debt rather than equity. Relative to the active group, the distressed group in the sample has higher Debt/TA ratio (mean difference=-0.02), which suggests that the distressed group has higher risk of default on loans. Cash resources to total assets is a liquidity ratio that measures the portion of a company's assets held in cash and cash equivalents and marketable securities. A higher cash resources to total assets ratio indicates that the company is in a strong financial position and it has some form of financial flexibility. In comparison with the active group, the distressed group has a significantly lower cash resources to total assets ratio (mean difference=10.77), which suggests that the distressed group is in a weaker financial position and is less financially flexible than the active group. Sales to total assets (Sales/TA or asset turnover) is an efficiency ratio that measures the efficiency of a company's ability to generate sales from its assets. This ratio represents how much sales revenue could be generated from each dollar amount of assets. A higher asset turnover ratio would suggests better efficiency in managing assets in relation to the sales revenue generated. In comparison with the active group, the distressed group has a lower asset turnover ratio (mean difference=0.12) which suggest that the distressed group is less efficient in managing assets to generate sales revenue. In comparison with the active group (mean value of asset turnover = 0.64), for every dollar of assets, the distressed group (mean value of asset turnover = 0.51) could generate 0.12 dollars less sales revenue. Working capital to total assets (WC/TA or working capital ratio) is a liquidity ratio that measures a company's ability to cover its short term financial obligations by expressing the net current assets of a company as a proportion of its total assets. When compared to the active group, the distressed group has a significantly lower WC/TA ratio (mean difference=22.38), which suggests the distressed group has notably lower liquidity than their active counterparts. In comparison with the active group, the distressed group is more likely to face serious cash flow difficulties, such as inability to make payments to suppliers and creditors. The significant mean difference of WC/TA ratio also indicates a higher chance of financial distress for the distressed group.

In terms of shareholder ownership/concentration variables, there are also some significant differences between the active and distressed group in the sample. Distressed companies have significantly higher levels of state owned shares to total shares outstanding (mean difference=-15.53). Higher state ownership may work as a disincentive for companies to improve their financial performance expeditiously. As a socialist state, the Chinese government is typically more concerned with social stability and employment considerations rather than purely performance issues (Chen, Chen, and Huang, 2010). Therefore, managers of state-owned enterprises are not necessarily required to achieve certain performance targets but rather specific government policy objectives (Deng and

Wang, 2006). State-owned enterprises are usually obliged to undertake social responsibilities, such as assisting local development and promoting employment (Deng and Wang, 2006). Kam, Citron, and Muradoglu (2010) find that the combination of the inefficiency of the bankruptcy laws of China and the pressure for the state government to maintain social stability contribute toward keeping non-viable distressed firms alive. In addition, the government also tends to financially support some failing companies in certain industries, which may serve as another disincentive for companies with a higher concentration of state ownership to improve their financial performance. Fan, Huang, and Zhu (2013) find that firms with higher levels of state ownership exhibit worse operating performance during periods of financial distress and are less likely recover from distress. China, as a socialist state that is still in transition to a more free market based economy, faces the somewhat unavoidable issue of 'soft-budget constraint syndrome' (Kornai, 1980) where the government continues to subsidise SOEs to prolong their lives (Chen, Lee, and Li, 2008). Underlying the 'soft-budget constraint syndrome' (Kornai, 1980) is the so-called communist ideology, a philosophy that commits to a fully employed and egalitarian society (Maskin, 1996). The communist ideology motivates the government to provide financial support to some failing SOEs for the sake of employment and social stability concerns (Maskin, 1996).

Compared to the active group, the distressed group has a lower percentage of shares held by institutions/funds (mean difference=1.17), but a higher percentage of shares held by brokers (mean difference=-0.45). In terms of corporate social responsibility (CSR) variables, when compared to the active group, the distressed group has a significantly lower social contribution value per share (mean difference=0.18) and lower social donations (mean difference=482.63). Despite the mean differences not being statistically significant (mean difference=-0.02), in comparison with the active group the distressed group within sample has higher levels of earnings management as proxied by the Kothari, Leone, and Wasley (2005) measure. As explained in Section 5.2, stock listing rights not only provide a channel to raise capital, they can also help maintain employment and stimulate local economic growth and development (Kim, Ma, and Zhou, 2016). Given the significance of stock listing rights on the Chinese stock exchanges, the Special Treatment regime has been found to distort management incentives and induce listed firms to engage in rampant earnings manipulation when they are confronted with the risk of being delisted (Jiang and Wang, 2008; Chen, Chen, and Huang, 2010; Yang, Chi, and Young, 2012). In comparison with non-ST (healthy/active) companies, ST companies returning back to normal listing status are more likely to engage in practices indicating earnings manipulation (Green, Czernkowski, and Wang, 2009). Moreover, according to Chen, Lee, and Li (2008), there also exist a special case of earnings management (local government assisted earnings management) on the Chinese stock market where the local government colludes with listed firms within their jurisdiction to meet the central government's regulatory requirements. The local government has the discretion to determine the timing and amount of subsidies provided to locally listed SOEs and can therefore help them promptly boost earnings above the regulatory threshold (Chen, Lee, and Li, 2008). However, in addition to earnings management activities, Cheng, Aerts, and Jorissen (2010) argue that the compulsory earnings-based delisting regulation on the Chinese stock market has also induced extensive performance-enhancing asset restructuring activities such as distressed assets sales and asset exchanges. In addition, they they find evidence of a negative relationship between earnings management and asset restructuring for firms that turn losses into profits and successfully avoid the delisting risk. More importantly, performance-enhancing asset restructuring may be a significant substitute for earnings management as it is not always feasible to manage earnings for severe loss-making firms when operations have been substantially reduced (Cheng, Aerts, and Jorissen, 2010).

One variable that is surprising and somewhat counter intuitive at first glance is annual market returns. In comparison with the active group, the distressed group actually has higher annual market returns (mean difference=-0.08). In terms of the stronger market returns of the distressed group, it is possible that distressed firms are attractive investment targets because there is an expectation that their financial performance will recover in the near term and the worst case outcome – delisting is not likely to occur. In fact, distressed companies often return to profitability through support from their SOE backed parent companies or bailouts from state-owned banks. As corporate failure prevents SOEs from helping the government fulfil intended political and social goals such as maintaining employment and enhancing local development, distressed SOEs are often rescued by administrative interventions (Deng and Wang, 2006; Yang, Chi, and Young, 2012). In addition, as explained in section 5.2, the market perceives the value of financially distressed firms based not simply on their fundamental value, but also their 'shell' value. Listing through a 'shell' purchase has became a popular alternative option for private companies wishing to be publicly listed due to China's highly competitive and highly strict IPO scheme (Chen, Lee, and Li, 2008; Kim, Ma, and Zhou, 2016). Furthermore, the earnings-based Special Treatment system fails to provide investors with any new value-relevant information regarding listed firms because it is solely based on publicly available historical earnings (Jiang and Wang, 2008). Investors have already processed and responded to past earnings information before the stock exchange designates ST status to distressed firms. There are some legitimate reasons for the market not to penalise ST stocks, especially in the long run; for example, when the ST firm is at the start-up stage that requires heavy investment into the business but returns on investment have not yet been realised (Jiang and Wang, 2008).

TABLE 5.6: Descriptive statistics and independent sample t-tests for equality of means between active and distress firm years

Variable	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis	Mean Difference	Sig.(2-tailed)
CFO per share-Active	11296	-12.77	141.92	0.47	2	35.51	2264.81	0.21	0.00
CFO per share-Distressed	1084	-4.62	6.57	0.25	0.88	0.62	10.17	0.21	0.00
ROA-Active	12156	-0.66	0.48	0.05	0.05	-0.59	15.53	0.12	0.00
ROA-Distressed	3348	-20.55	1.31	-0.08	0.52	-23.17	781.64	0.12	0.00
RE/TA-Active	12156	-74.59	46.25	14.72	10.99	-0.47	6.29	21.99	0.00
RE/TA-Distressed	3345	-74.59	46.25	-7.27	22.94	-1.51	1.95	21.99	0.00
CFO/TA-Active	12156	-0.57	0.55	0.04	0.08	-0.25	3.91	0.02	0.00
CFO/TA-Distressed	3328	-1.37	0.71	0.02	0.10	-2.08	28.10	0.02	0.00
Current ratio-Active	12063	0.00	128.66	2.77	4.49	8.23	121.77	1.45	0.00
Current ratio-Distressed	3298	0.00	51.28	1.32	1.98	14.41	275.82	1.45	0.00
Debt/TA-Active	12078	0.00	0.68	0.04	0.08	2.81	9.57	-0.02	0.00
Debt/TA-Distressed	3305	-0.07	1.60	0.06	0.10	3.48	26.46	-0.02	0.00
Cash Resources/TA-Active	12156	0.00	93.09	21.95	16.66	1.33	1.50	10.77	0.00
Cash Resources/TA-Distressed	3348	0.02	72.38	11.18	10.00	1.69	3.97	10.77	0.00
Sales/TA-Active	12156	0.03	2.46	0.64	0.44	1.78	3.94	0.12	0.00
Sales/TA-Distressed	3342	0.03	2.46	0.51	0.42	1.88	4.53	0.12	0.00
WC/TA-Active	12099	-48.49	83.43	25.43	26.63	0.11	-0.54	22.38	0.00
WC/TA-Distressed	3336	-48.49	83.43	3.05	25.45	-0.03	-0.30	22.38	0.00
State owned/total shares-Active	11872	0.00	92.19	4.72	13.94	3.41	11.34	-15.53	0.00
State owned/total shares-Distressed	1987	0.00	91.48	20.25	24.85	0.85	-0.69	-15.53	0.00
Percentage of shares held by fund-Active	10431	0.00	29.27	2.66	3.58	1.99	4.58	1.17	0.00
Percentage of shares held by fund-Distressed	1181	0.00	16.63	1.49	2.74	2.58	7.10	1.17	0.00
Percentage of shares held by brokers-Active	10431	0.00	35.20	0.59	1.29	5.34	67.86	-0.45	0.00
Percentage of shares held by brokers-Distressed	1181	0.00	66.28	1.04	4.98	11.05	134.75	-0.45	0.00
Social contribution value per share-Active	3356	-0.25	21.57	0.42	1.27	5.13	41.89	0.18	0.05
Social contribution value per share-Distressed	165	-0.76	8.74	0.25	1.10	5.82	36.36	0.18	0.05
Social donation-Active	3356	0.00	584891.00	795.16	11133.26	44.38	2270.93	482.63	0.03
Social donation-Distressed	165	0.00	9100.00	312.54	1256.31	5.39	30.42	482.63	0.03
Earnings management proxy-Active	8227	-13.12	8.52	-0.00	0.98	-3.56	33.32	-0.02	0.60
Earnings management proxy-Distressed	749	-10.22	7.91	0.02	1.17	-2.68	22.95	-0.02	0.60
Annual market returns-Active	12156	-0.21	0.53	0.10	0.24	0.66	-0.60	-0.08	0.00
Annual market returns-Distressed	3345	-0.62	1.72	0.18	0.56	1.40	1.18	-0.08	0.00

5.4 Distress symptoms leading up to distress

Figures 5.1 to 5.12 below illustrates how the mean values of 12 predictor variables change over time between the active group and the distressed group. The time span on the X-axis covers up to five years prior to reaching a distressed state (from t-5 to t-0). There are some general trends as revealed by Figures 5.1 to 5.12. First, there exist significant differences in terms of the mean values of the predictor variables between the active and the distressed group. The significant differences between the mean values of the two groups can be visualised by the noticeable distances between the line graphs of the active group against that of the distressed group in each figure during the five-year period leading up to the distress event. Second, when compared with the distressed group, the mean values of the predictor variables of the active group are generally more stable with less fluctuation. Third, as distressed firms approach a distressed state, the mean values of the majority of the predictor variables deteriorate continuously during a five-year period leading up to the distress event.

Fourth, a closer look at Figures 5.1 to 5.12 reveal that the mean values of the majority of predictor variables move in tandem in both the active group and the distressed group. In other words, there seems to be a positive correlation between the movement in mean values of variables in the active group and that of the distressed group. This could be due to some factors other than firm-specific factors that are driving the co-movement in mean values of the two groups, such as market factors and macroeconomic factors. Fifth, in comparison with the active group, on average the distressed group is less profitable and less liquid. In addition, the distressed group tends to rely excessively on debt financing and they hold significantly less cash resources on hand. These trends are generally consistent with the current literature, which confirms that measures associated with working capital, cash flow, earnings, and leverage are key predictors of corporate financial distress (Altman, 2002; Beaver, McNichols, and Rhie, 2005; Jones and Hensher, 2008b). These trends also provide some preliminary indication of the predictive power of variables concerning profitability, liquidity, and leverage of companies on the Chinese market. As evidenced by Chen et al. (2006), corporate financial distress in China is usually associated with firms with low liquidity, low operating efficiency, and high financial leverage.

Figures 5.1 to 5.12 not only provide some preliminary evidence regarding the predictive power of some variables, they also provide some insightful information regarding the early symptoms as financially distressed firms approach the distress event over a five-year period. These symptoms may serve as early warning signals that could help the diagnosis of financial distress from an early stage. From Figure 5.1, the mean values of ROA for the active group are quite stable over a five-year period. On the other hand, there is a huge drop in mean values of ROA for the distressed group 3 years and 2 years prior to the distress event followed by a slight recovery 1 year prior to the distress event. The mean value of ROA for the distressed group becomes negative slightly after t-3 (three years prior to the distress state) as a result of negative net income. The slight recovery 1 year prior to reaching the distress event may be attributable to some asset restructuring activities such as distressed assets sales and asset exchanges (Cheng, Aerts, and Jorissen, 2010).

A similar pattern is visible in Figure 5.2 except there is no sign of slight recovery in mean values of RE/TA for the distressed group 1 year prior to reaching the distress event. There is a sharp decline in mean values of RE/TA for the distressed group 3 years leading up to the distress event (from t-3 to t-0). The mean values of RE/TA for the distressed group begin to turn negative at around t-2 (two years prior to the distress event). Figure 5.3 discloses a steady decreasing trend in mean values of the current ratio for the distressed group over a five-year period leading up to the distress event. It is also quite noticeable that the current ratio for the active group is significantly stronger than that of the distressed group. As Figure 5.4 illustrates, the distressed group is severely leveraged in comparison with the active group and there is a considerable decline in mean values of Debt/TA for the distressed group 1 year prior to the distress event. It is possible that as the distressed group approaches the distress event, they start to breach debt covenants and therefore are no longer able to secure as much debt financing.

The pattern in Figure 5.5 reveals a gradual decline in mean values of Cash resources/TA for the distressed group from 5 years prior to the distress event until 1 year prior to the distress event followed by a slight recovery in the last year leading up to the distress event. The slight recovery 1 year prior to the distress event may be the result of some asset restructuring activities (Cheng, Aerts, and Jorissen, 2010). For example, some distressed firms may undertake asset divestment and sell some non-profit generating assets, non-core assets, or even profitable assets in order to raise cash to alleviate financial distress and fund other restructuring activities (Sudarsanam and Lai, 2001). Figure 5.6 uncovers a similar pattern to Figure 5.5 except there is a significant decrease in mean values of Sales/TA for the distressed group three and two years prior to the distress event. The slight recovery 1 year prior to the distress event may also be due to some asset restructuring activities (Cheng, Aerts, and Jorissen, 2010). Figure 5.7 reveals a declining trend in mean values of WC/TA in the distressed group over a five-year period leading up to the distress event. A more rapid decrease in mean values of WC/TA in the distressed group occurs in the last three years prior to the distress event. The WC/TA ratio for the distressed group begins to turn negative at around 1.5 years prior to the the distress event, indicating severe cash flow difficulties to cover short-term financial obligations.

Figure 5.8 shows that in comparison with the active group, the mean values of state owned shares to total shareholding in the distressed group is consistently higher over the five-year period leading up to the distress event. There is a steady decline in mean values of state owned shares to total shareholding as the distressed group approaches the distress event. However, the magnitude of such decline is only marginal. The pattern in mean values of percentage of shares held by fund/institutional shareholders is revealed by Figure 5.9, demonstrating a decreasing trend in both groups across the five years prior to the distress event. For the distressed group, the mean values decline until 2 years prior to the distress event, after which there exists a slight increase in mean values of percentage of shares held by fund/institutional shareholders. However, the magnitude of such increase is extremely marginal. From Figure 5.10, the mean values of percentage of shares held by brokers show considerable fluctuation in both groups over the five-year period leading up to the distress event. Despite the fact that the percentage of shares held by brokers in the distressed group is noticeably higher than that of the active group, the pattern for this predictor variable largely moves in tandem in both the active group and the distressed group. The mean values of percentage of shares held by brokers for the distressed group declines from t-5 to t-4 (from 5 years prior to the distress event to 4 years prior to the distress event) and then increased from t-4 to t-3 (from 4 years prior to the distress event to 3 years prior to the distress event) before decreasing again from t-3 to t-1 (from 3 years prior to the distress event to 1 year prior to the distress event). There is a trend of slight recovery of the mean values of percentage of shares held by brokers for the distressed group in the last year leading up to the distress event. It is noted that the pattern in the mean values of percentage of shares held by brokers in the distressed group over a five-year period mainly records fluctuations with rather minor changes in the actual magnitude of this variable.

Figure 5.11 displays the mean values of social contribution value per share for the active group against that of the distressed group over the five-year period leading up to the distress event. From Figure 5.11, the social contribution value per share for the active group is significantly higher than that of the distressed group, indicating that on average the active group contributes more to the society. As for the distressed group, despite some fluctuations, there is a declining trend of mean values of social contribution value per share starting from three years prior to the distress event. As the distressed group approaches the distress event, they make a reduced contribution to society. The mean values of annual market returns experience significant fluctuations over the five-year period in both groups as shown in Figure 5.12. Despite the fluctuations, there is an increasing trend of the mean values of annual market returns in the distressed group. The mean values of annual market returns of the distressed group increase sharply in the last two years leading up to the distress event. As explained in Section 5.3, there may be several reasons for the high market returns of the distressed stocks on the Chinese stock exchange. In addition, annual market returns seem to be the only predictor variable in which the active group fluctuates more than the distressed group.

After a more detailed analysis of the early symptoms as financially distressed firms approach the distress event over a five-year period (Figures 5.1 to 5.12), some insightful information can be gathered. First, on average, the distress symptoms become more prominent from 3 years prior to the distress event onwards (from t-3 to t-0). Second, some early warning signals of potential financial distress include a sharp decrease in return on assets, the ratio of retained earnings to total assets and the ratio of working capital to total assets. In addition, over a five-year period leading up to the distress event, the early symptoms of financial distress also include a gradual decline in the current ratio, the ratio of cash resources to total assets, and the ratio of sales to total assets. In terms of shareholder ownership/concentration variables, some early symptoms of financial distress include a continuous decrease in the ratio of state owned shares to total shareholding, a steady decline in the percentage of shares held by fund/institutional shareholders, and some fluctuations but generally an increasing trend of percentage of shares held by brokers.

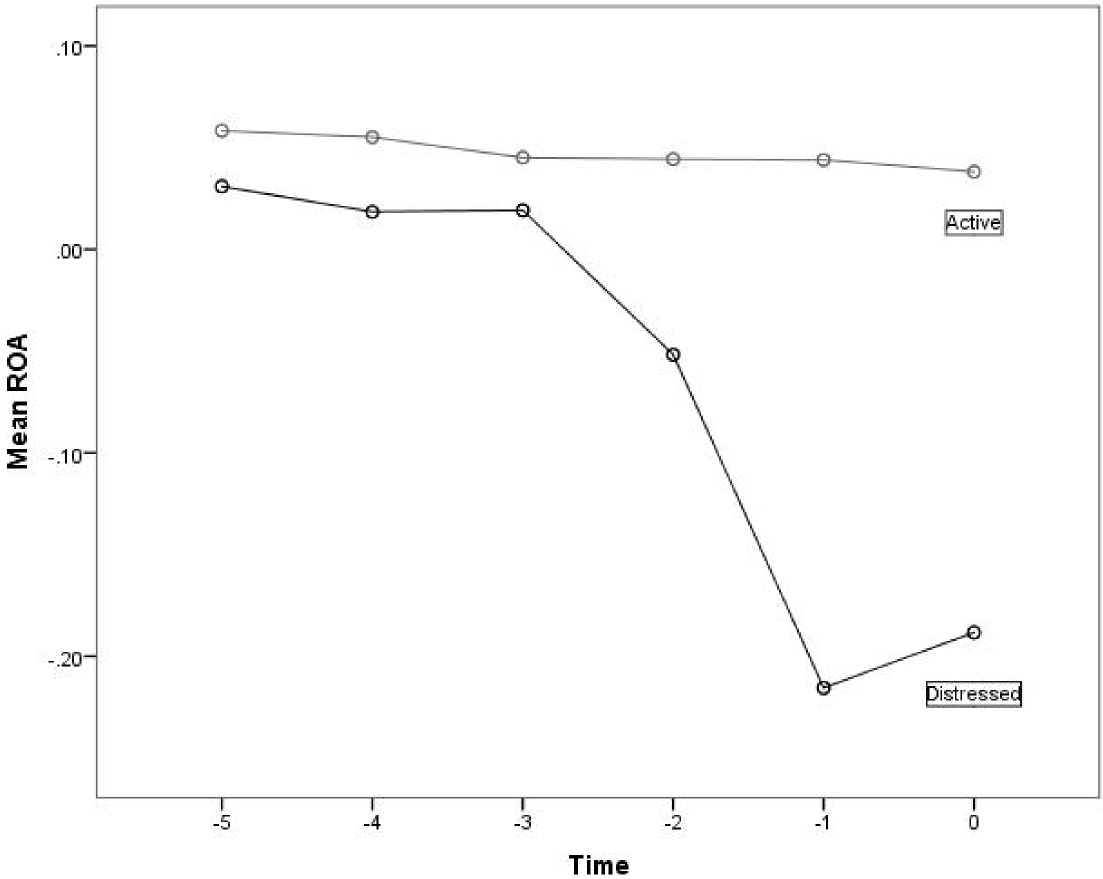

FIGURE 5.1: ROA 5 years leading up to distress (all data)

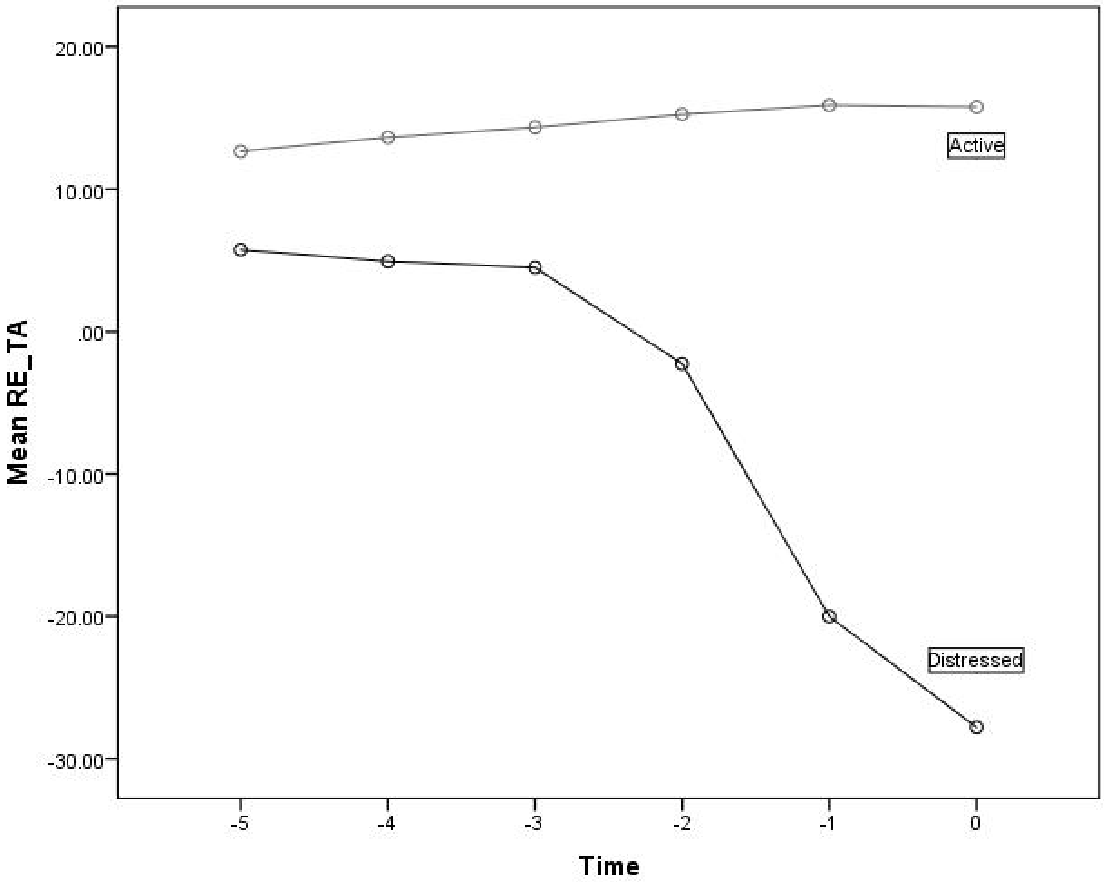

FIGURE 5.2: RE/TA 5 years leading up to distress (all data)

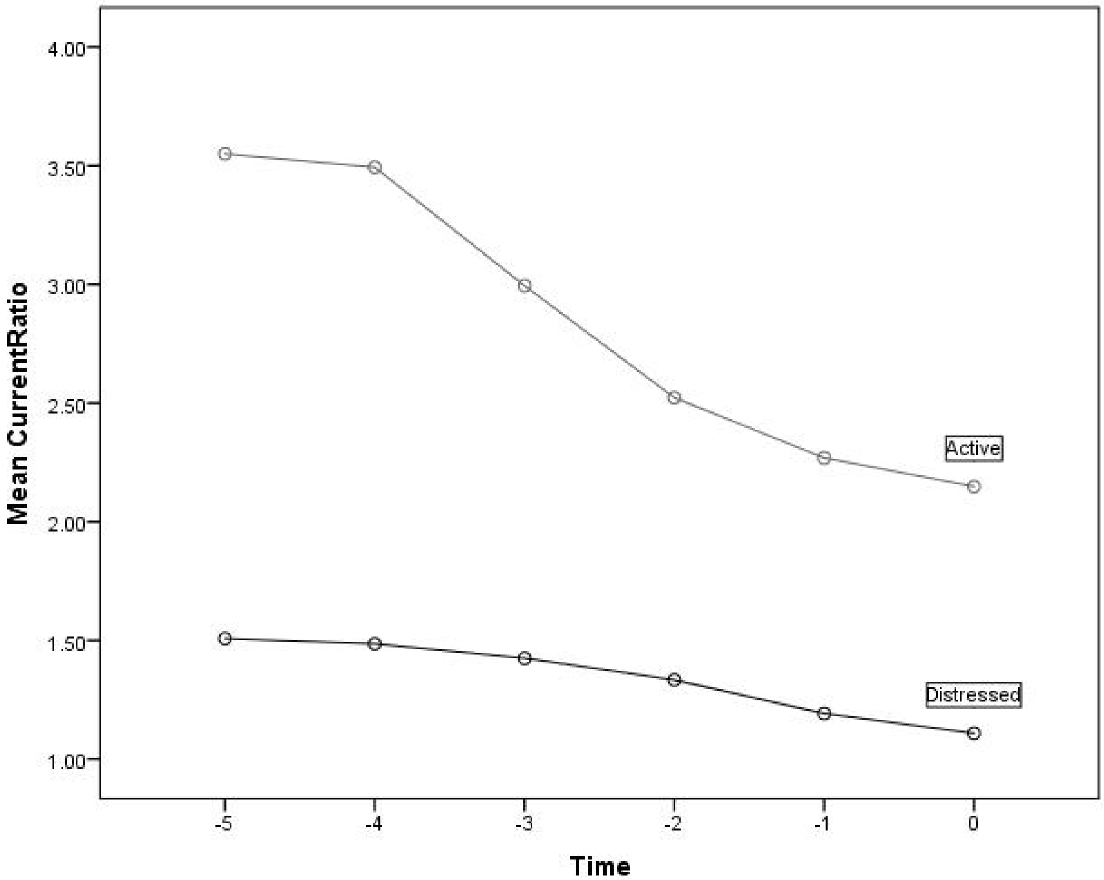

FIGURE 5.3: Current ratio 5 years leading up to distress (all data)

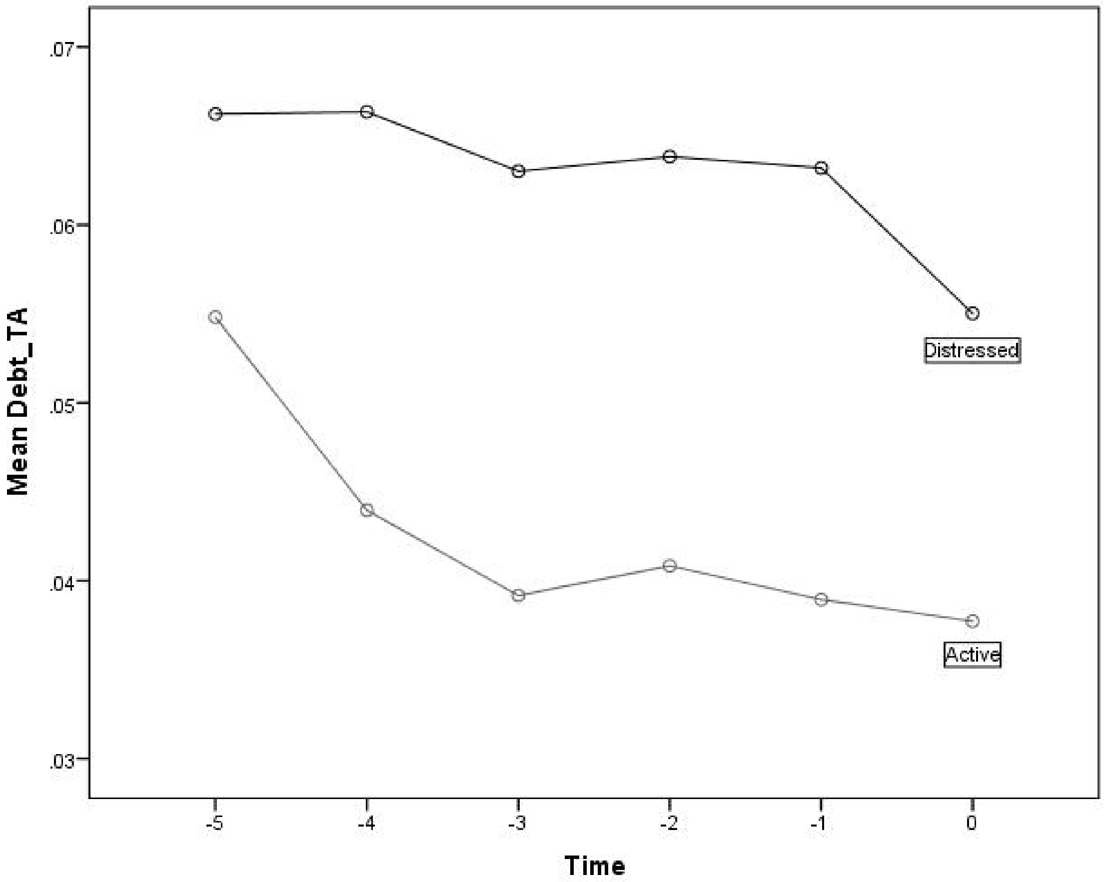

FIGURE 5.4: Debt/TA 5 years leading up to distress (all data)

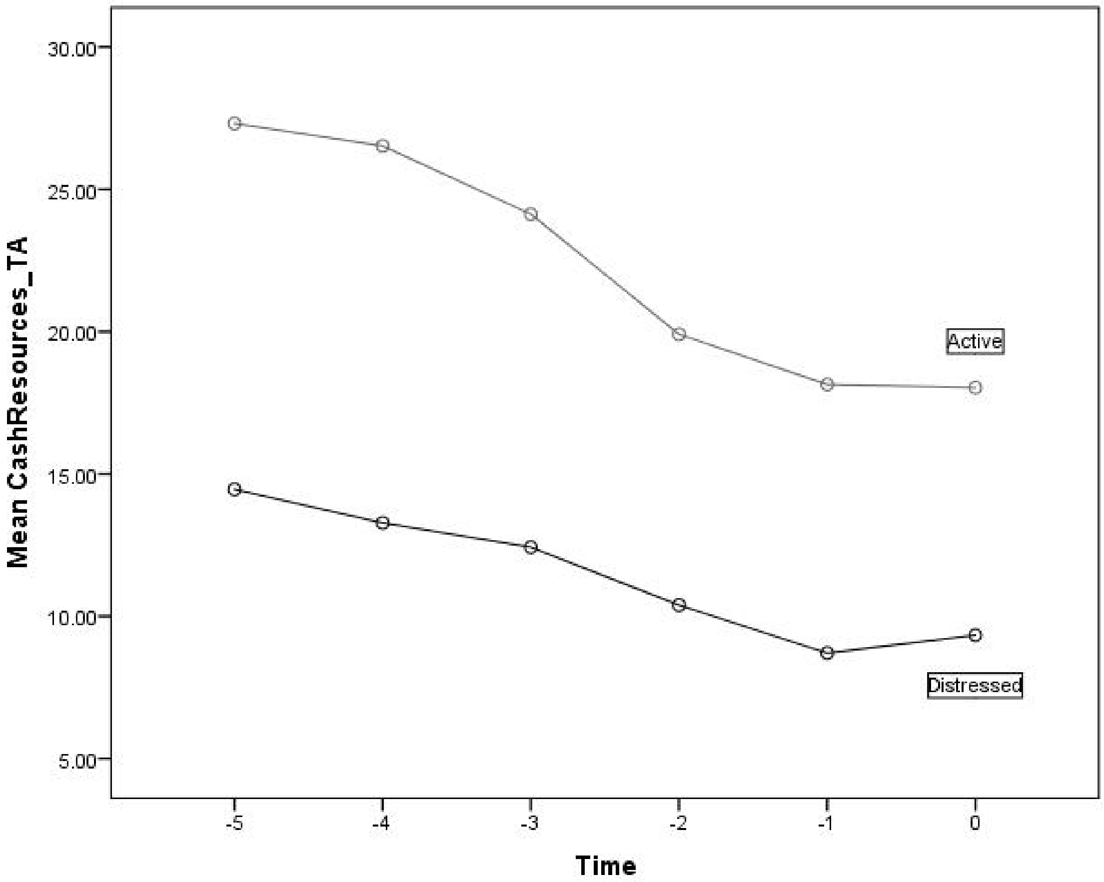

FIGURE 5.5: Cash resources/TA 5 years leading up to distress (all data)

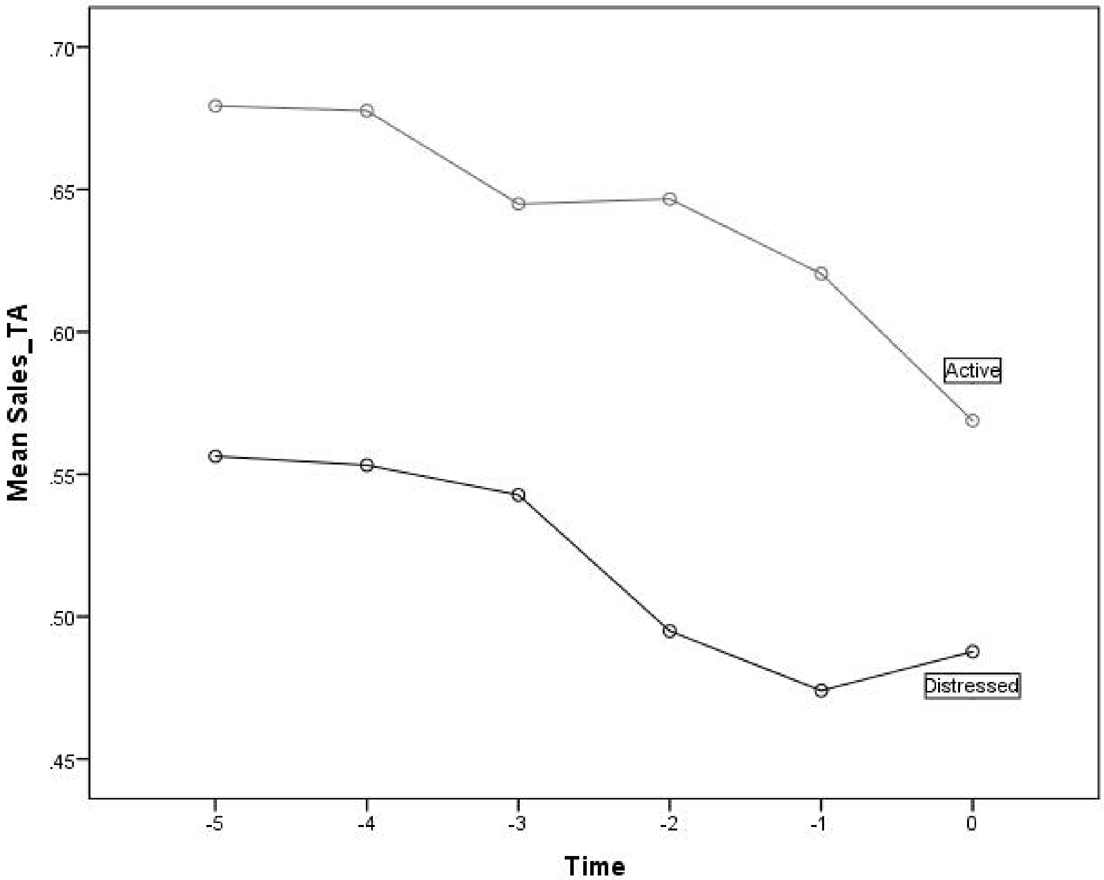

FIGURE 5.6: Sales/TA 5 years leading up to distress (all data)

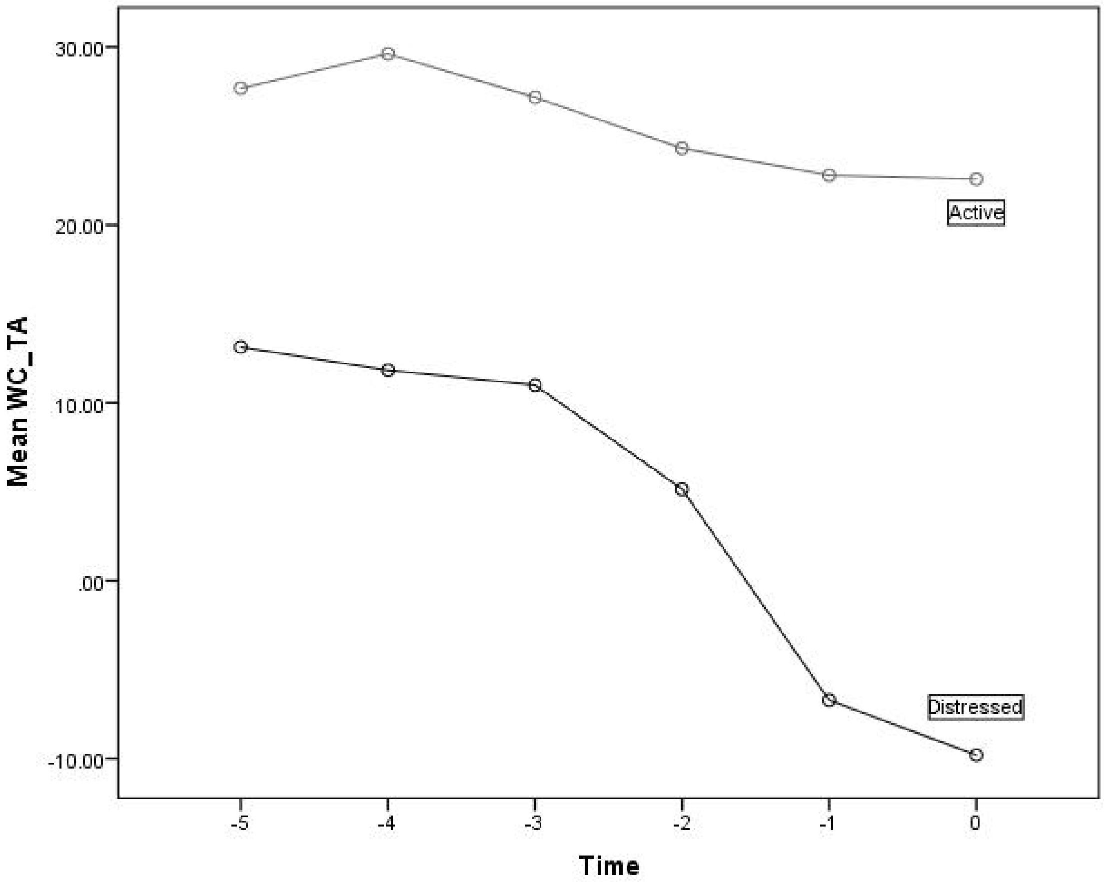

FIGURE 5.7: WC/TA 5 years leading up to distress (all data)

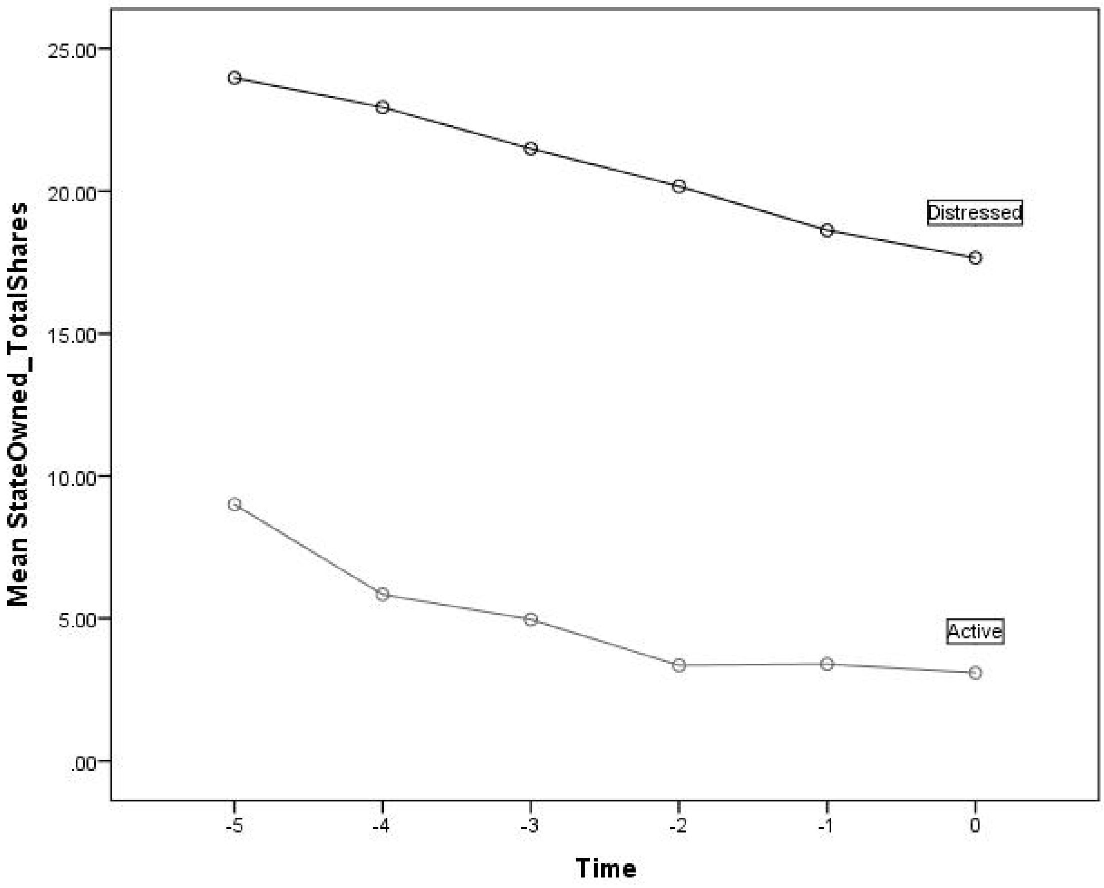

FIGURE 5.8: State owned/total shares 5 years leading up to distress (all data)

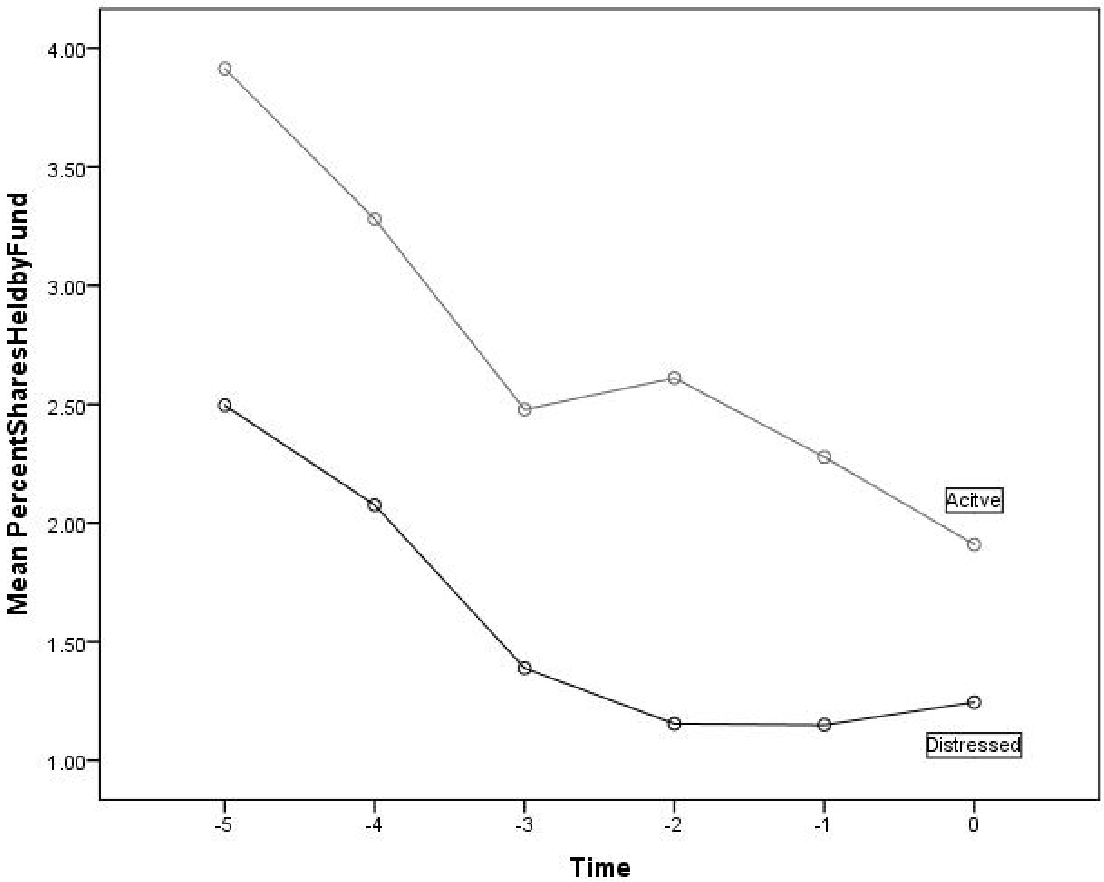

FIGURE 5.9: Percentage of shares held by fund 5 years leading up to distress (all data)

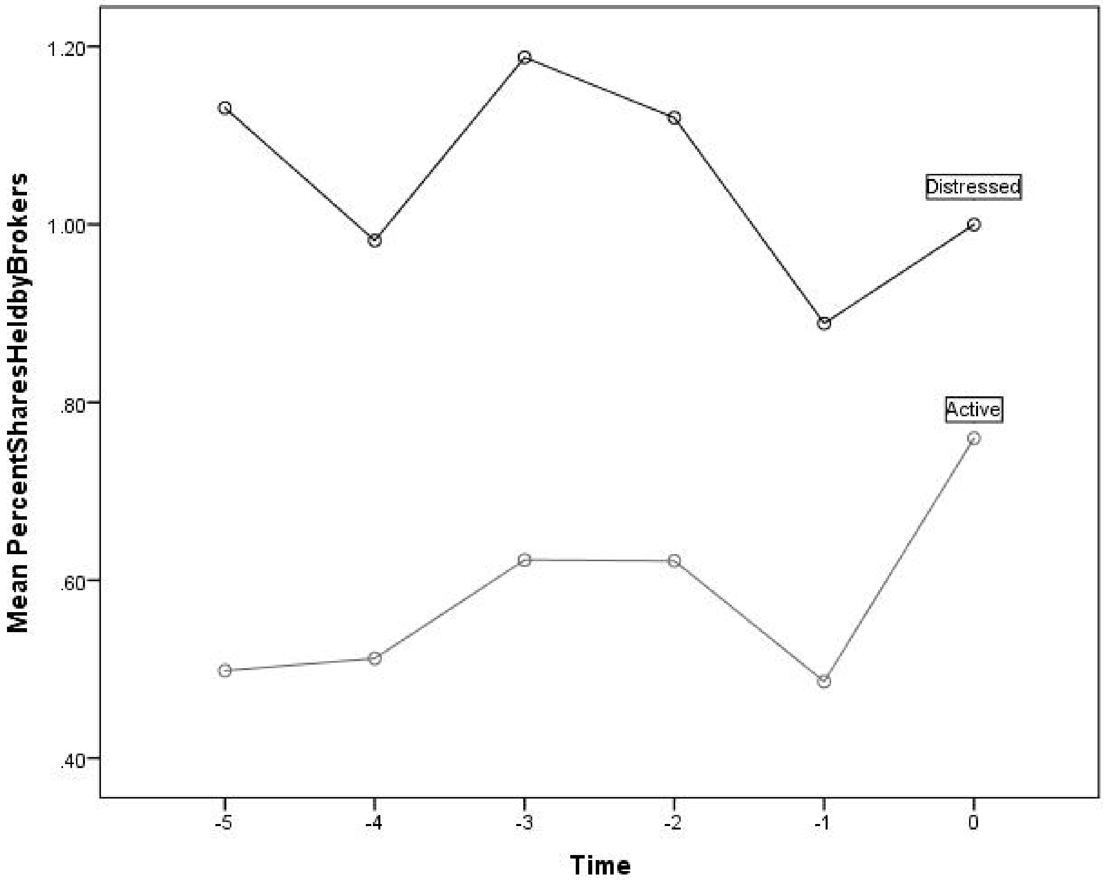

FIGURE 5.10: Percentage of shares held by brokers 5 years leading up to distress (all data)

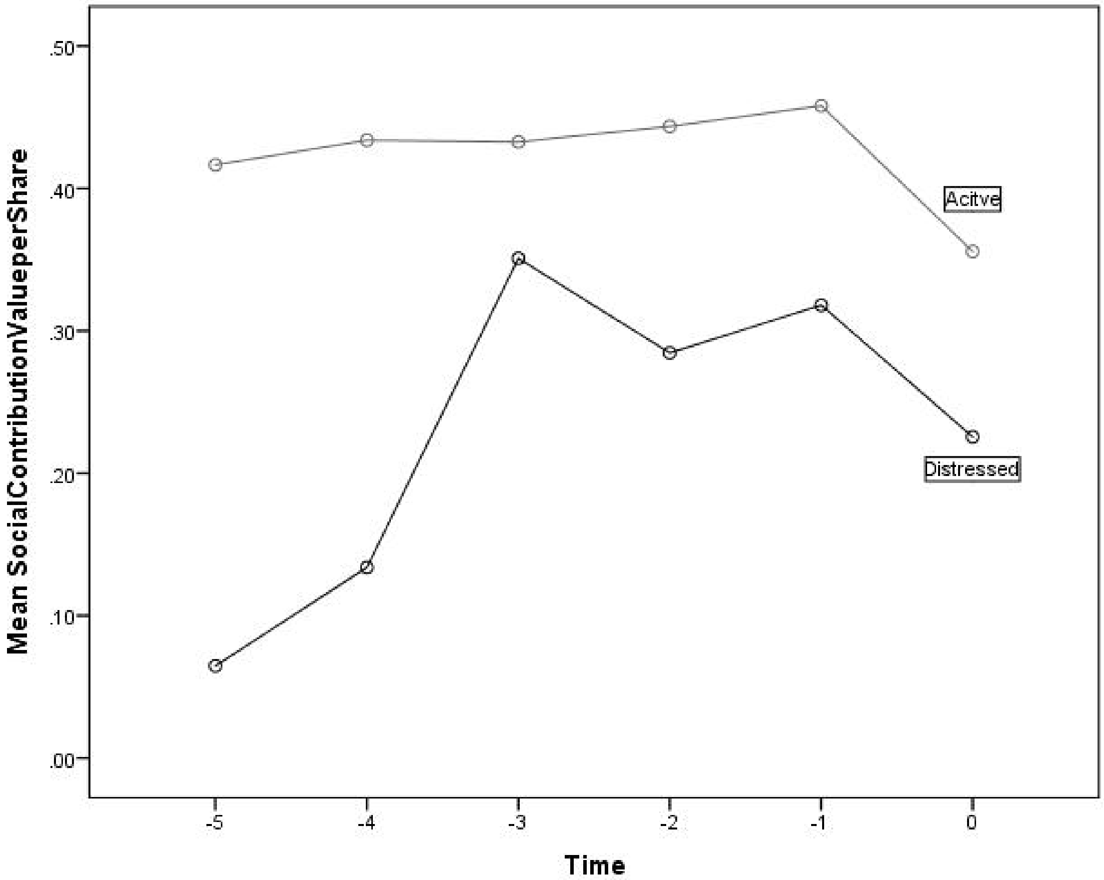

FIGURE 5.11: Social contribution value per share 5 years leading up to distress (all data)

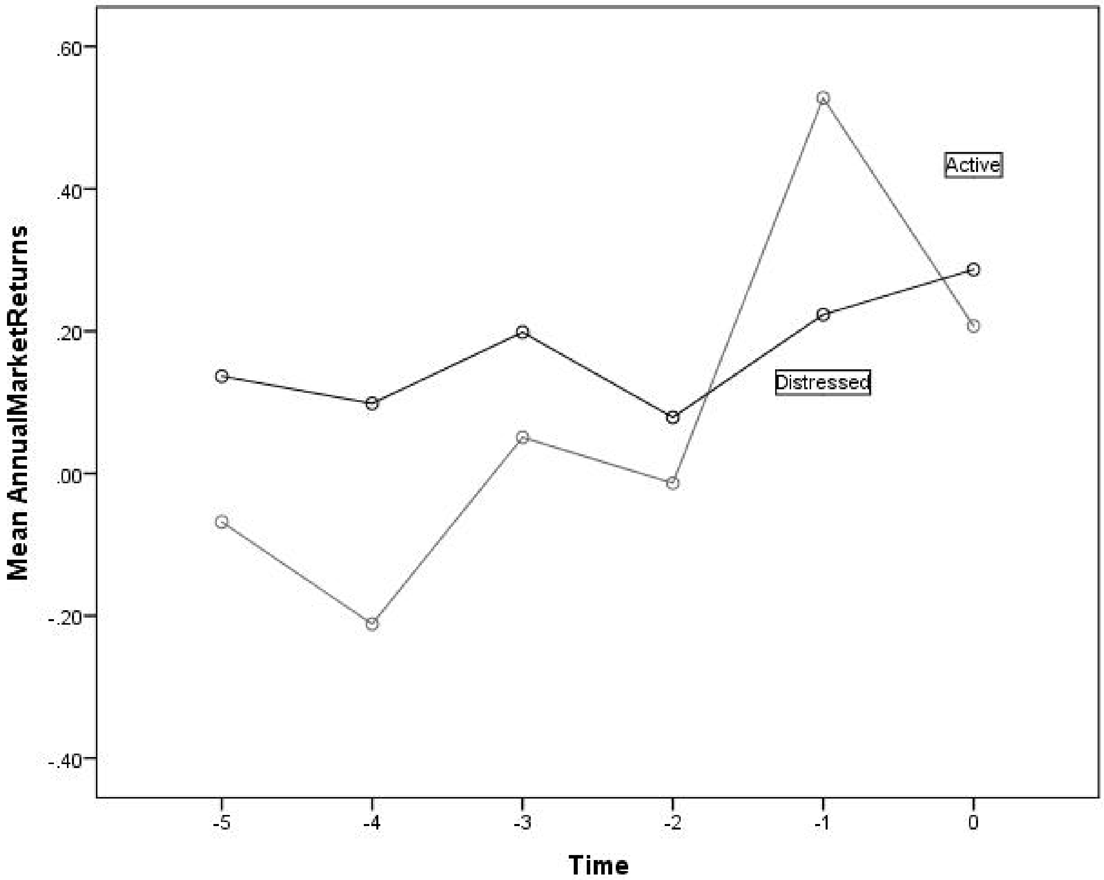

FIGURE 5.12: Annual market returns 5 years leading up to distress (all data)

5.5 Chapter conclusion

This chapter primarily focused on providing summary statistics on the distressed and active sample. The primary purpose of this chapter is to describe the basic features of the data used in the current study. Presenting the data in a more meaningful way allows for ease of interpretation and a better understanding of the sample. More importantly, it forms the basis of analysis of the empirical results in Chapter 6 and Chapter 7 of this thesis.

In order to obtain a clear understanding of the sample used in this study, this chapter began with an introduction of the distribution of active and distressed firm-year observations. In this study, there are a total of 15,504 available firm-year observations during the sample period of 1998 to 2016. Out of the total number of firm-year observations, there are 3,348 (21.6%) distressed firm-year observations and 12,156 (78.4%) active firm-year observations. To achieve a better understanding of the distressed sample used in this study, the distribution of distressed firm-year observations by distress states, industry, and year are summarised. Within the distressed sample, 222 firm years (6.6%) relate to companies that experienced a single ST event; 1620 firm years (48.4%) relate to companies that confronted between 1 and 4 ST events; 993 firm years (29.7%) relate to companies that experienced more than 4 ST events over the sample period; and 514 firm years (15.4%) relate to companies that were delisted as a result of ST designation.

Regarding the distribution of distressed firm-year observations by industry, 2030 firm-year observations (60.6%) relate to the Chinese industrials sector; 432 observations (12.9%) are associated with the properties sector; 382 firm-year observations (11.4%) are from the Chinese public utilities sector; 228 firm-year observations (6.8%) are from the conglomerate sector; 196 firm-year observations (5.9%) are from the commercial sector; and 80 firm-year observations (2.4%) relate to the finance sector. In terms of the distribution of distressed firm-year observations over the sample period, several features are revealed. First, the number of distressed firm-year observations demonstrates considerable fluctuation over the sample period. Second, the number of distressed firm-year observations began to drop significantly since 2008. Third, the single year with the maximum number of distressed observations over the sample period occurred in 2002, representing 298 distressed firm-year observations. Finally, the annual average number of distressed firm-year observations is around 246 from 1998 to 2007, after which it decreased sharply to only 119 firm years from 2008 to 2015.

Next, descriptive statistics and independent sample t-tests for equality of means between the active and distressed group was explored. 14 out of 16 pairs of firm-specific predictor variables have different mean values that are statistically significant between the distressed and active group. On average, the distressed group has lower operating cash flow per share (mean difference=0.21), lower ROA (mean difference=0.12), significantly lower RE/TA (mean difference=21.99), lower cash flow returns to total assets (mean difference=0.02), lower current ratio (mean difference=1.45), higher Debt/TA ratio (mean difference=-0.02), significantly lower cash resources to total assets ratio (mean difference=10.77), lower asset turnover ratio (mean difference=0.12), and significantly lower WC/TA ratio (mean difference=22.38). In comparison with the active group, the distressed group also has significantly higher levels of state owned shares to total shares outstanding (mean difference=-15.53), lower percentage of shares held by institutions/funds (mean difference=1.17), higher percentage of shares held by brokers (mean difference=-0.45), lower social contribution value per share (mean difference=0.18), lower social donations (mean difference=482.63), higher levels of earnings management (mean difference=-0.02), and higher annual market returns (mean difference=-0.08).

This chapter also discussed distress symptoms over the five-year period leading up to the distress event. The significance of analysing distress symptoms leading up to the distress event is that they may serve as early warning signals that assist the diagnosis of financial distress from an early stage. In general, when compared to the active group, the distressed group is less profitable and less liquid. In addition, the distressed group tends to rely excessively on debt financing and they hold significantly less cash resources on hand. Moreover, the mean values of the predictor variables of the active group are generally more stable and display less fluctuation than that of the distressed group. Lastly, as distressed firms approach the distress event, the mean values of the majority of the predictor variables deteriorate continuously during the five-year period leading up to the distress event.

Chapter 6

Empirical results – binary analysis

6.1 Chapter introduction

This chapter presents the empirical results of the binary TreeNet® model. As defined in Section 4.2.3, in the binary TreeNet® model, the dependent variable is specified as: (1) State 0: ST=0 (if a company is active or healthy); and (2) State 1: ST=1 (if a company has experienced ST event). The binary TreeNet® model is interpreted through several outputs, such as relative variable importances (RVIs), the confusion matrix, average log-likelihood, area under the ROC curve (AUC), prediction accuracy based on the baseline threshold, and partial dependency plots (marginal effects). Section 6.2 explorers the relative variable importances of the binary TreeNet® model as shown in Table 6.1. Section 6.3 presents the confusion matrix and summary of predictive performance of the binary TreeNet® model in Tables 6.2 and 6.3, respectively. Predictive results based on pooling all sampled observations are provided together with results on the predictive performance of the binary TreeNet® model 1 year, 3 years, and 5 years prior to the distress event. In addition to RVIs, the confusion matrix, and summary of predictive performance, Section 6.4 presents partial dependence analysis of the binary TreeNet® model shown in Figures

6.1 to 6.11. Section 6.5 concludes this chapter.

6.2 RVIs of the binary TreeNet® model

In the first step, a full binary TreeNet® model[1] is estimated based on pooling all sampled observations. Table 6.1 displays the binary TreeNet® model estimated on all explanatory variables defined in Appendix A using all sampled observations. As pointed out by Jones (2017), high dimensional models will typically involve many more variables, therefore increasing the number of variables with nonzero importance. Some of the very small RVI values can result from random noise. Hence, it is advisable to re-estimate the binary TreeNet® model excluding all variables with very small RVIs (close to zero). The binary TreeNet® model is then re-estimated on all variables with RVIs of at least 3 to eliminate potential noise effects. The ranking of RVIs does not substantially change following this treatment.

It can be seen from Table 6.1 that 87 out of the 94 predictor variables have nonzero RVI scores. This means that all 87 input variables contribute to the out-of-sample predictive performance in some way, although the predictive strength of different predictors varies. The RVIs in Table 6.1 are ranked according to each predictor variable's contribution to the overall predictive success of the TreeNet® model. The RVI scores reported in Table 6.1 are transformed by TreeNet® to a scale between 0 and 100, where the strongest predictor variable receives a score of 100 and all other input variables are rescaled to reflect their importance relative to the best performing predictor. Because TreeNet® uses decision trees as the base learning algorithm, the RVI scores are calculated based on the number of times a variable is selected for splitting, weighted by the squared improvement to the

[1]The TreeNet® algorithm randomly partitions 80% of the total observations to the training sample and 20% of observations to the test sample.

model as a result of each split, and then averaged over all trees (Friedman and Meulman, 2003; Hastie, Tibshirani, and Friedman, 2009; Jones, 2017).

Table 6.1 reveals that a diverse range of predictor variables dominate the TreeNet® model, reflecting several different dimensions of corporate financial distress underlying China's stock market. The different dimensions of financial distress are reflected in the dispersed RVI scores across a number of dimensions, such as financial variables, market-price variables, macroeconomic variables, executive compensation measures, shareholder ownership/concentration variables, valuation multiples and other variables. The predictor variables that feature most strongly in the binary analysis (RVIs $>$ 10) include: (1) market-price variables including market capitalisation and annual market returns; (2) a range of accounting-based variables and financial ratios including retained earnings to total assets, net profit margin, three year growth in equity, return on assets, one year growth in earnings per share, return on equity, and total assets to total liabilities; (3) executive compensation measures including total executive compensation (top 3 executives) and total director compensation (top 3 directors); and (4) macroeconomic variables such as registered unemployment rate in urban areas and GDP growth per capita.

As Table 6.1 displays, the strongest predictor variable overall is market capitalisation with an RVI score of 100. This is followed by equally weighted annual market returns (RVI = 40.66), retained earnings to total assets (RVI = 34.74), GDP growth (RVI = 22.63), and net profit margin (RVI = 22.47). The top ten contributing variables of the binary TreeNet® model also include the registered unemployment rate in urban areas (RVI = 20.16), three year growth in equity (RVI = 19.81), return on assets (RVI = 16.34), one year growth in earnings per share (RVI = 14.14), and total executive compensation (top 3 executives) (RVI = 12.70). Other high impacting variables of the binary model also include: total director compensation (top 3 directors) (RVI = 12.64), GDP growth per capita (RVI = 12.54), return on equity (RVI = 11.96), total assets to total liabilities (RVI = 10.13), market capitalisation to total debt (RVI = 9.91), total number of shareholders (RVI = 9.78), three year growth in operating revenue (RVI = 9.60), total operating revenue (RVI = 9.34), cash to current liabilities (RVI = 9.21), and three year growth in earnings per share (RVI = 9.17).

After analysing the variables with highest impact in the binary TreeNet® model, in order to get a better sense of which category of predictor variables is actually driving the predictive results, average RVIs across the different predictor categories are then calculated. In this binary TreeNet® model, the strongest predictor category overall is market-price variables with an average RVI of 50.19. The second and third best performing predictor categories are executive compensation variables (average RVI = 12.67) and macroeconomic variables (average RVI = 12.31). Despite the fact that financial variables featured strongly among the top predictors and within the whole model, their average RVI is around 8.21. Valuation multiple variables also show comparable predictive strength in the model with an average RVI of 7.50 followed by shareholder ownership/control variables with an average RVI of 7.34. The earnings management proxy variable also has reasonable predictive impact with an RVI of 7.49. Variables with the lowest impact in the binary TreeNet® model include audit variables (average RVI = 3.02), the corporate social responsibility variable (average RIV = 3.30), and industry variables (average RVI = 2.19).

The relative variable importances (RVIs) of the binary TreeNet® model as reported in Table 6.1 have a number of similarities and dissimilarities with with the findings of Jones (2017), which are based on a large sample of U.S. Chapter 11 filings. Broadly speaking, a wide range of financial and non-financial predictor variables are found to be predictive in both the Chinese and the U.S. context. It is quite surprising how well a number of 'Western-style' bankruptcy predictors perform in the context of Chinese distress prediction. While market-price variables ranked as the single most contributing predictor category in the binary TreeNet® model, they rank in third place in Jones's (2017) study. While market returns are a particularly strong predictor, ranking second in the binary TreeNet® model, market return variables ranked lower, in 13th and 15th place, in Jones's (2017) model. Furthermore, while macroeconomic factors have relatively weak predictive impact in Jones's (2017) study, they ranked in third place in the binary TreeNet® model. Executive compensation variables and financial variables appear to have quite reasonable predictive power, which is broadly consistent with some of the Jones's (2017) findings. However, shareholder ownership/concentration variables, which feature less significantly in the binary TreeNet® model, are the top contributing variables in Jones's (2017) study.

TABLE 6.1: RVIs of the binary TreeNet® Model – All Data

Variable	**Dimension**	**RVI Score**
Market capitalisation	Market/Size proxy	100.00
Annual market returns (equal weighted)	Market	40.66
Retained earnings to total assets	Financial	34.74
GDP Growth	Macroeconomic	22.63
Net profit margin	Financial	22.47
Registered unemployment rate (urban areas)	Macroeconomic	20.16
Growth in equity (3yrs)	Financial	19.81
Return on assets	Financial	16.34
Growth earnings per share (1yr)	Financial	14.14
Total executive compensation (top 3 executives)	Executive compensation	12.70
Total director compensation (top 3 directors)	Executive compensation	12.64
GDP growth per capita	Macroeconomic	12.54
Return on equity	Financial	11.96
Total assets to total liabilities	Financial	10.13
Market capitalisation to total debt	Market/Financial	9.91

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Table 6.1 – *Continued from previous page*

Variable	**Dimension**	**RVI Score**
Total number of shareholders	Shareholder ownership/control	9.78
Growth operating revenue (3yrs)	Financial	9.60
Total operating revenue	Financial	9.34
Cash to current liabilities	Financial	9.21
Growth earnings per share (3yrs)	Financial	9.17
Number of employees	Size proxy	8.87
Inventory turnover	Financial	8.85
Earnings per share	Financial	8.82
Growth net profit (1yr)	Financial	8.54
Working capital to total liabilities	Financial	8.52
Price earnings ratio	Valuation multiple	8.45
Intangible assets to total assets	Financial	8.33
Total assets	Financial	8.15
Operating cash flow per share	Financial	7.88
Accounts payables to total liabilities	Financial	7.84
Debt to tangible assets	Financial	7.49
Earnings management proxy	Earnings Management Proxy	7.49
Percentage of state owned shares	Shareholder ownership/control	7.39
Operating cash flow to total assets	Financial	7.39
EBIT to operating cash flow	Financial	7.34
Working capital to total assets	Financial	7.29
Cash resources to total assets	Financial	7.18
Long term liabilities to total equity	Financial	7.17
Growth in cash (1yr)	Financial	7.07
Percentage of shares held by supervisors	Shareholder ownership/control	7.07
Percentage of shares held by brokers	Shareholder ownership/control	7.04
Growth operating cash flow (3yrs)	Financial	6.99
Growth total liabilities (3yrs)	Financial	6.84
Book value per share	Financial	6.70

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Table 6.1 – *Continued from previous page*

Variable	Dimension	RVI Score
Growth total liabilities (1yr)	Financial	6.70
Growth in EBIT (1yr)	Financial	6.68
Operating cash flow to total revenue	Financial	6.68
Growth total assets (3yrs)	Financial	6.64
Total profit margin	Financial	6.63
Price to book ratio	Valuation multiple	6.54
Growth in equity (1yr)	Financial	6.50
Sales to total assets	Financial	6.40
Growth working capital (1yr)	Financial	6.36
Total liabilities to total equity	Financial	6.28
Growth total assets (1yr)	Financial	6.24
Total audit fees	Audit	6.14
Growth operating cash flow (1yr)	Financial	6.13
Operating cash flow to equity	Financial	5.97
Working capital to sales	Financial	5.96
Current assets to total liabilities	Financial	5.89
EBIT to total assets	Financial	5.54
Percentage of shares held by funds/institutions	Shareholder ownership/control	5.43
Cash flow to debt	Financial	5.41
Growth net profit (3yrs)	Financial	4.94
Number of directors	Other – governance	4.76
EBIT margin	Financial	4.57
Debt to equity	Financial	4.43
General consumer price index	Macroeconomic	4.23
Current ratio	Financial	4.23
Growth in income (1yr)	Financial	4.18
Research report concern degree	Other – Research coverage	4.03
Growth operating revenue (1yr)	Financial	4.01
Social contribution value per share	CSR	3.40

Continued on next page

Table 6.1 – *Continued from previous page*

Variable	**Dimension**	**RVI Score**
Social donation	CSR	3.20
Industrial industry	Industry	3.16
Growth in income (3yrs)	Financial	2.85
Growth in working capital (3yrs)	Financial	2.65
Growth in long term debt (1yr)	Financial	2.44
Commercial industry	Industry	2.36
Growth in EBIT (3yrs)	Financial	2.30
Growth in cash (3yrs)	Financial	1.76
Chairman and general manager concurrent	Other – governance	1.70
Conglomerates industry	Industry	1.68
Public utility industry	Industry	1.56
Qualified audit opinion	Audit	1.53
Audit from Big4 firm	Audit	1.39

6.3 Confusion matrix and summary of predictive performance of the binary TreeNet® model

Table 6.2 reports the confusion matrix for the test sample of the binary TreeNet® model. A confusion matrix is a tabular representation of the predictive performance of a model. The overall prediction accuracy of the binary TreeNet® model is 94.57 percent using the baseline threshold as the cut-off score. The binary TreeNet® model is 93.74 percent accurate in predicting distress (a Type I error rate of 6.26 percent) and 94.81 percent accurate in predicting active/healthy companies (a Type II error rate of 5.19 percent).

Table 6.3 summarises predictive performance of the binary TreeNet® model. Panel A of Table 6.3 reports model performance based on all sampled data (five years of pooled observations). Panels B, C, and D of Table 6.3 summarise predictive performance of the binary TreeNet® model 1 year, 3 years, and 5 years prior to the distress event. Table 6.3 includes the average log-likelihood (negative), area under the ROC curve (AUC) and classification accuracy (baseline threshold).

The ROC curve is the most ubiquitous evaluation metrics used to measure classification performance of predictive models (Jones, 2017). It is a graphical plot that plots the true positive rate (sensitivity) relative to the false positive rate (1-specificity) with respect to various discrimination threshold settings. In other words, the ROC curve represents the class separation capability of a model in distinguishing between classes. The ROC measure reports the ability of the TreeNet® model to correctly rank records from most likely to least likely to be a class 1 (distress) or class 0 (active or healthy). Generally speaking, the steeper the ROC curve and the larger the AUC (Area Under Curve), the better the predictive performance of a model. Classifiers are expected to have an AUC score greater than 0.5 (ie., they should perform better than random guessing), whereas an AUC score of 1 represents perfect classification accuracy with zero Type I or Type II errors. It is a convention in the literature that AUC scores greater than 0.9 indicate a very strong classifier, whereas AUC scores between 0.8 and 0.9 indicate a strong classifier (Jones, 2017).

Panel A of Table 6.3 reports model predictive performance of TreeNet® based on pooling all five years of sampled observations. From Panel A of Table 6.3, the binary TreeNet® model misclassifies only 5.049 percent of observations for the test sample based on the baseline threshold (with overall classification accuracy of 94.951 percent). The ROC (Area Under Curve) for the binary TreeNet® model for the test sample based on all observations is 97.369 percent, which indicates that TreeNet® is a very strong classifier.

Despite the strong model predictive performance based on pooling all sampled observations, the TreeNet® model remains quite predictive even several years prior to the distress event. As can be seen from Panels B, C, and D of Table 6.3, classification accuracy for the test sample based on the baseline threshold is 98.053 percent one year prior to distress; 94.951 percent three years prior to distress; and 94.366 percent five years prior to distress. In comparison with the overall classification accuracy of 94.951 percent, the predictive performance of the binary TreeNet® model does not change significantly even when estimated on t-5 data (five years prior to the distress event).

From Panels B, C, and D of Table 6.3, the ROC (Area Under Curve) for the binary TreeNet® model also remains very robust over all time frames. There is little evidence of deterioration in ROC performance one year, three years, and five years prior to the distress event. The TreeNet® model scores a near perfect out-of-sample AUC of 0.99913 when estimated on t-1 data (1 year prior to the distress event), and the test sample AUC is still 0.94890 five years from the distress event. This result corroborates the findings of other studies including Jones (2017) that the gradient boosting model and TreeNet® in particular is a highly accurate classifier.

TABLE 6.2: Confusion matrix – test sample (binary model)

Actual class	**Total class**	**Percent correct**	**Predicted class**	
			0	1
			N=2309	N=783
0	2389	94.81%	2265	124
1	703	93.74%	44	659
Total	3092			
Average		94.28%		
Overall % correct		94.57%		

TABLE 6.3: Summary of predictive performance of the binary TreeNet® model

	Training sample	**Test sample**
Panel A (All Data)		
Average LogLikelihood (Negative)	0.09448	0.18782
ROC (Area Under Curve)	0.99888	0.97359
Classification accuracy (Baseline threshold)	0.97059	0.94951
Panel B (One year prior to distress (t-1))		
Average LogLikelihood (Negative)	0.02083	0.07921
ROC (Area Under Curve)	1.00000	0.99913
Classification accuracy (Baseline threshold)	0.98837	0.98053
Panel C (Three years prior to distress (t-3))		
Average LogLikelihood (Negative)	0.07846	0.19742
ROC (Area Under Curve)	0.99952	0.96688
Classification accuracy (Baseline threshold)	0.96912	0.94951
Panel D (Five years prior to distress (t-5))		
Average LogLikelihood (Negative)	0.10787	0.24404
ROC (Area Under Curve)	0.99922	0.94890
Classification accuracy (Baseline threshold)	0.98252	0.94366

6.4 Partial dependence analysis of the binary TreeNet® model

Having established that the binary TreeNet® model has very strong out-of-sample predictive accuracy, it is also important to assess whether the explanatory variables make sense in terms of their influence on the distress outcome. The RVIs reported in Table 6.1 are scalars that measure the overall predictive ability of a variable relative to all other variables in the model. Despite the fact that RVIs measure the predictive strength of a particular explanatory variable on the overall model classification success, they provide no indication of the direction of the explanatory variable regarding the distress outcome. For example, whether the retained earnings to total assets ratio increases or reduces the probability of distress remains unknown by referring only to the RVIs results. Partial dependency plots (or marginal effects) reveal the direction of the explanatory variables with respect to the distress outcome.

Unlike conventional distress prediction models such as MDA and logit in which parameter estimates are always linear in relation to the distress outcome, partial dependency plots from TreeNet® models are capable of capturing all nonlinear impacts, which are arguably more informative and descriptive of the behaviour of distress predictors in their real world context (Jones, 2017). In fact, analysis of the partial dependency plots indicates that many of the Table 6.1 predictor variables have nonlinear relationships with the distress outcome. In the majority of cases, the broad directions of the partial dependency plots are both logical and interpretable in the current study. This can be demonstrated by examining several illustrative examples from the variables described in Table 6.1, which are displayed in Figures 6.1 to 6.11. To make it easier to interpret the partial dependency plots, a first-order single knot spline has been included for each explanatory variable, which smooths out the underlying relationship and provides a clearer direction of the marginal effect with respect to the distress outcome (Jones, 2017). This inclusion of a first-order single knot spline is a valuable feature of the TreeNet® model that facilitates the partial dependence analysis.

As discussed earlier in this chapter, market capitalisation is the strongest predictor variable overall. Therefore, the influence of market capitalisation on the distress outcome is analysed first. Figure 6.1 displays the partial dependency plot for market capitalisation as an explanatory variable. The marginal effect of market capitalisation is highly nonlinear to the distress outcome. Generally speaking, market capitalisation increases the likelihood of non-distress, which means companies with more market capitalisation are less likely to enter the distressed state than companies with less market capitalisation. In addition, this relationship is stronger at increasingly lower levels of market capitalisation. This suggests that, holding the rest of the model constant, firms with the lowest levels of market capitalisation are more vulnerable to distress.

The partial dependency plot for annual market returns is reported in Figure 6.2. The marginal effect of annual market returns is somewhat counter intuitive as it shows that annual market returns increase the likelihood of distress but flatten out at very high levels of annual market returns. Figure 6.2 indicates that firms with higher annual market returns are more likely to enter the distressed state than firms with lower annual market returns. This is in contrast to Jones (2017) in which lower excess returns sharply increase the probability of bankruptcy. Two potential reasons might explain the contrasting results obtained for the marginal effects of market returns modelled by the Chinese ST system and U.S. Chapter 11.

In Jones (2017), failure is modelled using U.S. Chapter 11 filings. Chapter 11 is arguably a more severe outcome for investors and creditors than a ST event, which the current study models. Following Chapter 11 filings, successful reorganisation only occurs in a minority of cases and consequently losses to investors and creditors are usually very substantial when reorganisation fails. On the other hand, previous research has shown that the majority of ST companies resume normal trading within 2 to 3 years (Kim, Ma, and Zhou, 2016). In fact, distressed companies often return to profitability through support from their SOE backed parent companies or bailouts from state-owned banks. As corporate failure prevents SOEs from helping the government fulfil intended political and social goals such as maintaining employment and enhancing local development, distressed SOEs are often rescued by administrative interventions (Deng and Wang, 2006; Yang, Chi, and Young, 2012). It is possible that ST firms are attractive investment targets because there is an expectation that financial performance will recover in the near term and the worst case outcome – delisting rarely occurs.

Second, the market perceives the value of financially distressed firms not simply based on their fundamental value, but also on their 'shell' value. Listing through a 'shell' purchase has become a popular alternative option for private companies wishing to be publicly listed due to China's highly competitive and highly strict IPO scheme (Chen, Lee, and Li, 2008; Kim, Ma, and Zhou, 2016). This might also help explain why annual market returns increase distress in China's stock market. As not only the management of ST companies but also external parties (such as the government and other private companies wishing to go public) are all strongly motivated to bail out financially distressed ST companies, ST firms are usually perceived as profitable investment targets by investors and valuable 'shell' opportunities by other non-listed companies.

With respect to accounting-based variables, many of the partial dependency plots appear to make sense in terms of the direction of the marginal effect. For instance, Figure 6.3 displays the partial dependency plot for retained earnings on total assets. Like many other variables, the relationship of retained earnings to total assets ratio to the distress outcome is also highly nonlinear. From Figure 6.3, retained earnings to total assets ratio increases the likelihood of non-distress, which means that companies with a higher retained earnings to total assets ratio are less likely to enter into the distressed state than companies with a lower retained earnings to total assets ratio. It is also noted that the impact on the probability of distress is much stronger when the retained earnings to total assets ratio turns negative. This suggests, that holding the rest of the model constant, companies with a negative retained earnings to total assets ratio are more vulnerable to distress. Similar marginal effects are also identified for other key financial ratios, including ROA, ROE, EPS, and operating cash flow.

Figure 6.4 reveals the partial dependency of market capitalisation of equity to total debt. The marginal effect of the relationship between market capitalisation to total debt and the distress outcome is highly linear. Higher levels of debt financing increase the probability of distress. Greater reliance on debt increases a firm's risk of falling into financial distress if it fails to meet debt obligations. The marginal effect of capitalisation to total debt clearly decreases in the direction of higher distress. A similar relationship is also identified for the debt to equity ratio.

The partial dependency plot for valuation multiple variables such as price-to-book ratio is displayed in Figure 6.5. From Figure 6.5, the marginal effect of price-to-book ratio increases the likelihood of distress. This indicates that despite the fact that the magnitude of the influence of price-to-book ratio on the distress outcome is not strong, firms with higher price-to-book ratios are more likely to enter the distressed state than firms with lower price-to-book ratios. This relationship is also some somewhat counter intuitive as distressed companies are often expected to have lower valuation multiples. The explanation for the marginal effect of price-to-book ratio on the distress outcome is similar to that of annual market returns; namely that the ST event is not as severe as Chapter 11. In fact, there are very few bankruptcies and liquidations in China. Investors in China do not discount ST companies for bankruptcy risks as heavily as Chapter 11 filings in the U.S. The majority of ST companies get their ST status revoked and return to normal listing. A similar relationship is also found for another valuation multiple variable used in the current study – the price earnings ratio.

The partial dependency plot for executive compensation of the top three executives is illustrated in Figure 6.6. Despite the highly non-linear relationship of the influence of executive compensation on the distress outcome, higher executive compensation is associated with lower distress probabilities. Previous research has revealed a positive relationship between executive compensation and performance using a Chinese sample, indicating that more talented executives (who generate better firm performance) earn a pay premium (Banker, Bu, and Mehta, 2016). The marginal effect of executive compensation under the current Chinese setting is broadly in line with the U.S. evidence found in Jones (2017). From Figure 6.6, the impact of lower levels of executive compensation on the distress outcome is much more pronounced as executive compensation approaches zero.

In terms of share ownership and concentration variables, Figure 6.7 displays the partial dependency plot for percentage of shares held by supervisors (insiders). From Figure 6.7, percentage of shares held by supervisors increases the likelihood of distress, which indicates that firms with higher levels of insider ownership are more likely to be distressed than firms with lower levels of insider ownership. Despite the fact that the marginal effect of insider ownership on the distress outcome is non-linear, this relationship is much stronger at very high levels of insider ownership. A very similar result is found regarding the percentage of shares held by executives.

Figure 6.8 displays the partial dependency plot for percentage of shares held by funds/ institutions. From Figure 6.8, percentage of shares held by funds/institutions decreases the likelihood of distress, which means that companies with higher levels of institutional ownership are less likely to be distressed than companies with lower levels of institutional ownership. Such marginal effect is particularly noticeable when institutional ownership is below the 5 percent level. However, it is also noted that the magnitude of the marginal effect between institutional ownership and the distress outcome is not particularly strong.

The partial dependency plot for the percentage of shares owned by the state is displayed in Figure 6.9. From Figure 6.9, state ownership increases distress, which means that higher levels of state ownership increases the probability of distress while lower levels of state ownership decreases the probability of distress. However, the marginal effect of state ownership on the distress outcome is more significant at relatively high levels of state ownership, especially with more than 25% state ownership. As stated previously in Chapter 5, higher levels of state ownership might work as a disincentive for companies to improve their financial performance expeditiously. This may reflect the focus of the Chinese government on social stability and employment priorities over purely financial performance concerns. In addition, the government also tends to bail out some failing companies in certain industries, which may serve as yet another disincentive for companies to improve their financial performance.

Figure 6.10 displays the partial dependency plot for GDP growth. From Figure 6.10, the marginal effect of GDP growth increases the likelihood of distress, which means that higher GDP growth increases the probability of distress while lower GDP growth decreases the probability of distress. It is also noted that such relationship flattens out at very high levels of GDP growth. This finding is again somewhat counter intuitive as strong GDP growth is generally expected to lead to a lower incidence of corporate distress. There are two possible explanations for this somewhat counter intuitive relationship. First, the validity of such relationship between GDP growth and distress ultimately depends on the credibility of the official GDP figures released by the Chinese government; there have been many suggestions that Chinese GDP numbers are significantly overstated. According to Owyang and Shell (2017), China's economic statistics remain unreliable and are possibly severely overstated due to the challenges in effectively capturing GDP growth in transitioning China. As such, the marginal effect displayed in Figure 6.10 is at least partially spurious and may not truly reflect the underlying influence.

Second, a very fast growing economy can 'contribute' to distress in a variety of ways. For instance, rapid economic growth while the Chinese economy is also transitioning to a services based economy, may draw domestic and international capital away from manufacturing and infrastructure companies putting more economic stress on these sectors. As the Chinese economy transitions to a services economy, the emergence of new classes of companies and industries, such as technology, IT, E-commerce, healthcare, and clean technologies can also contribute to corporate distress. Most of these companies are growing strongly based on the prospect of future earnings growth, but weaker short term fundamentals are likely in the early stages of growth. Economic buoyancy can also create its own risks by exacerbating competition and encouraging excessive risk taking, such as over leveraging.

The marginal effects of other macroeconomic variables tend to follow a more predictable pattern. For instance, higher levels of unemployment rate are found to increase the probability of corporate distress. Unlike the relationship of unemployment rate and distress, no clear relationship is found for the CPI index. Figure 6.11 displays the partial dependency plot for the earning management proxy, revealing that the relation- ship between the earning management proxy and the distress outcome is highly non-linear. With the assistance of the spline plot, it is possible to discern that there is a generally weak positive relationship between the management proxy and distress. This suggests that companies that engage in higher levels of earnings management activities are less likely to be distressed than companies that engage in lower levels of earnings management activities. Overall, no convincing evidence of earnings management practices among Chinese ST firms is identified in the current study. This is in contrast to Green, Czernkowski, and Wang (2009), who find that in comparison with non-ST companies, ST companies are more likely to engage in earnings manipulation.

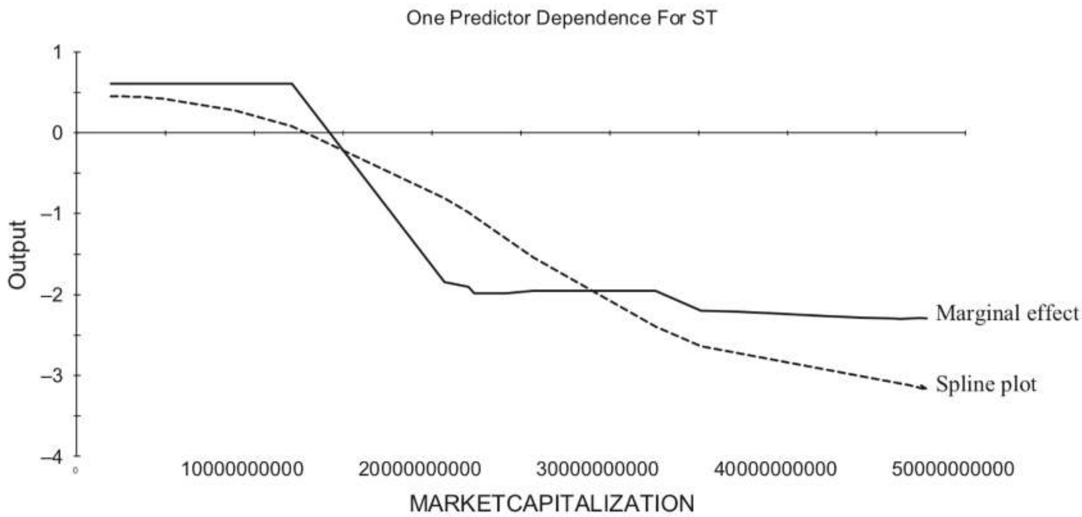

FIGURE 6.1: Partial dependency plot for market capitalisation

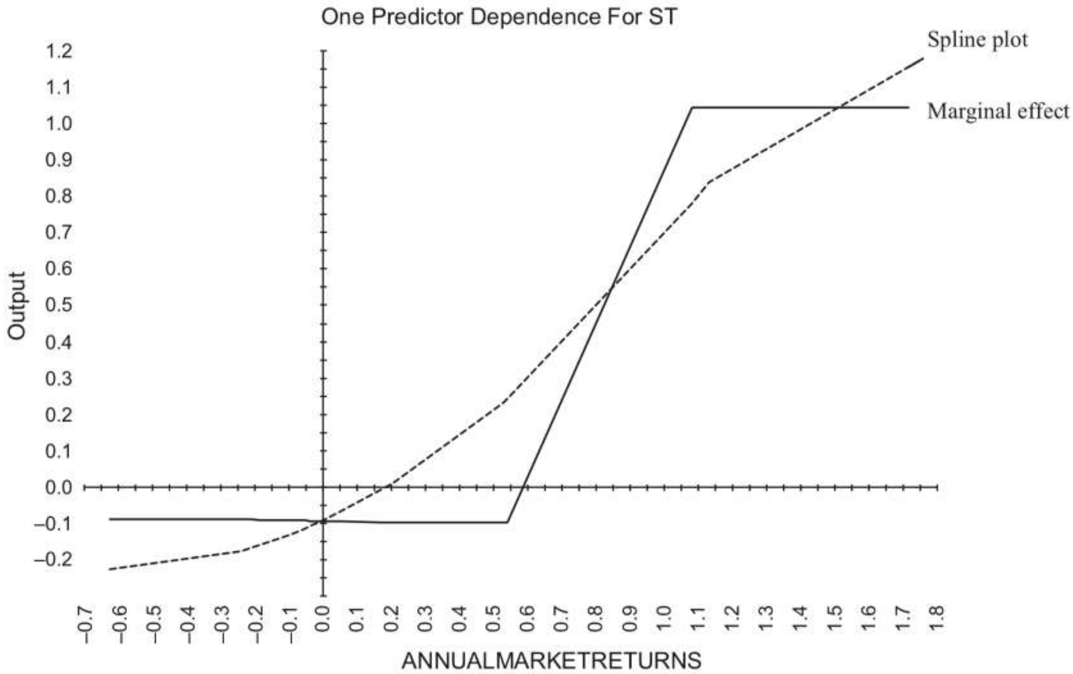

FIGURE 6.2: Partial dependency plot for annual market returns

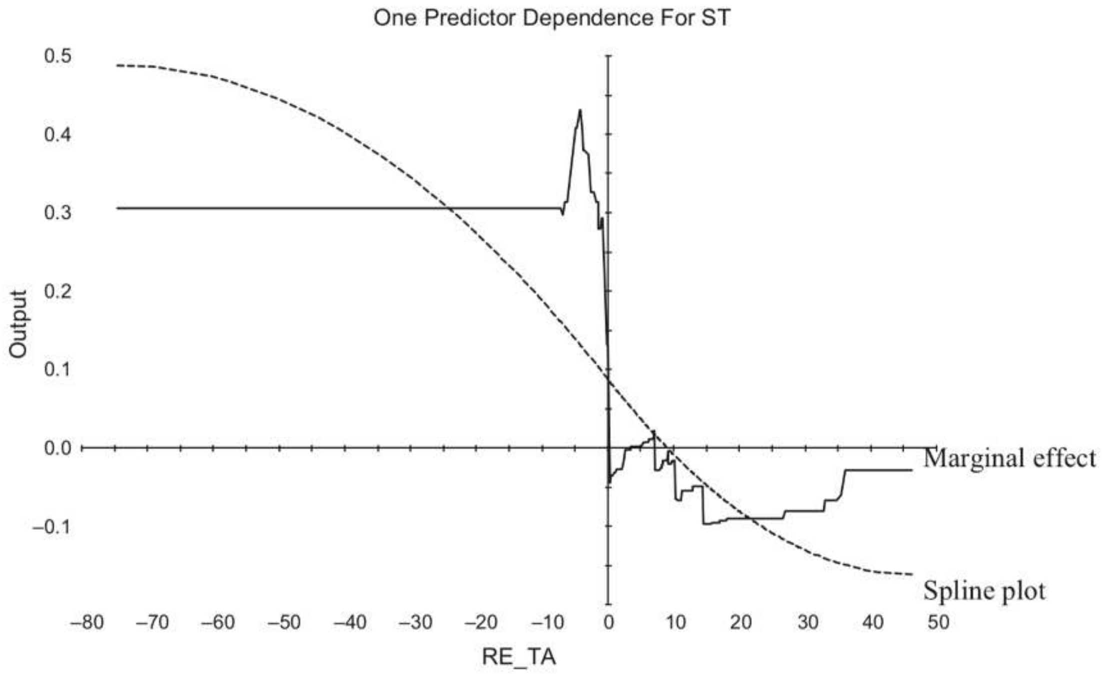

FIGURE 6.3: Partial dependency plot for retained earnings to total assets

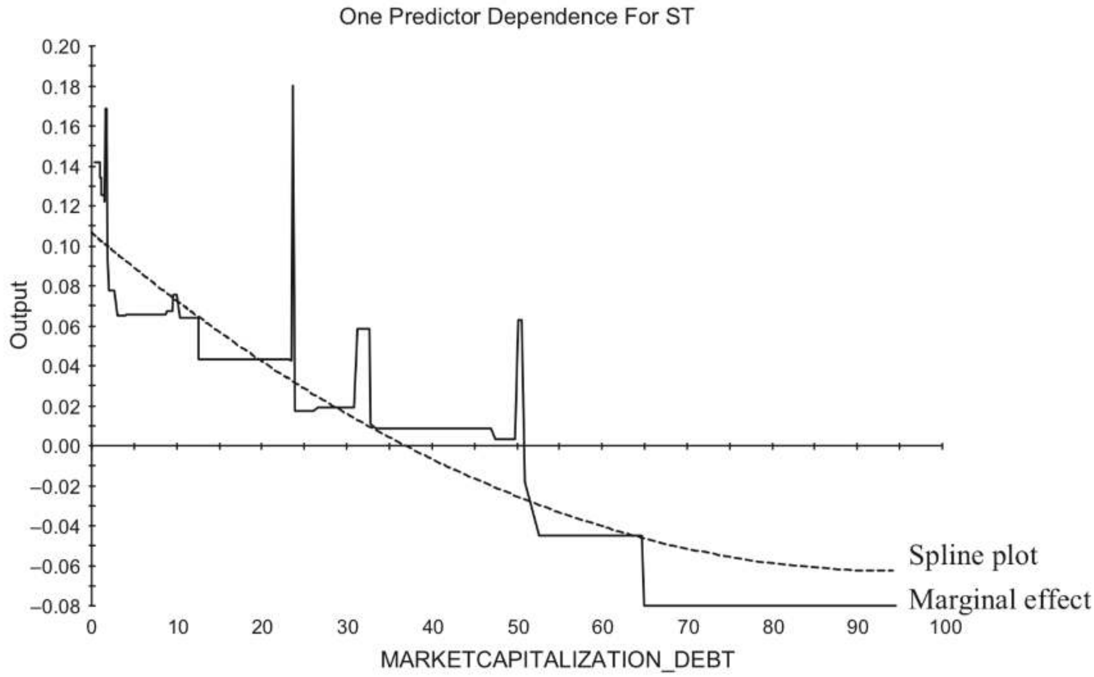

FIGURE 6.4: Partial dependency plot for market capitalisation to total debt

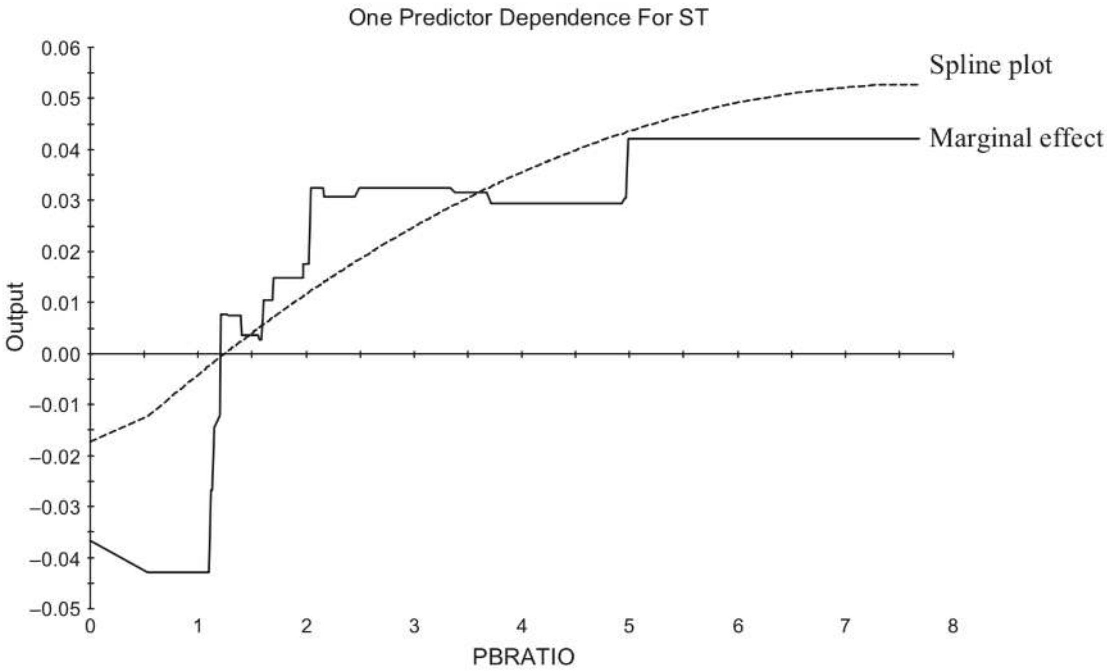

FIGURE 6.5: Partial dependency plot for price to book ratio

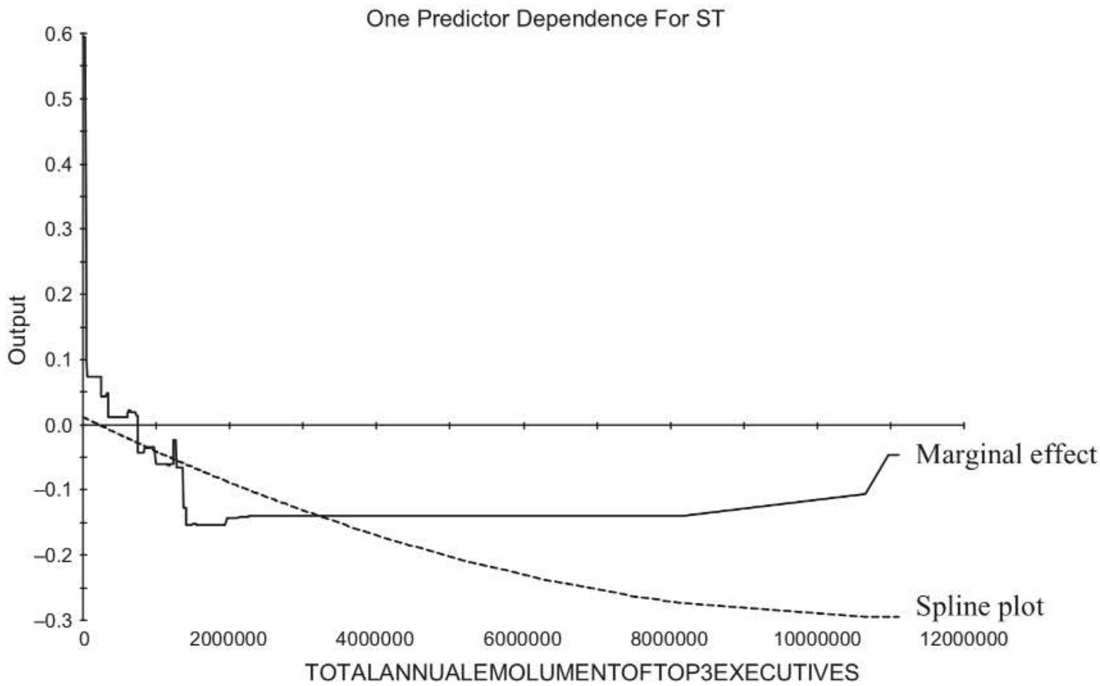

FIGURE 6.6: Partial dependency plot for executive compensation (top 3 executives)

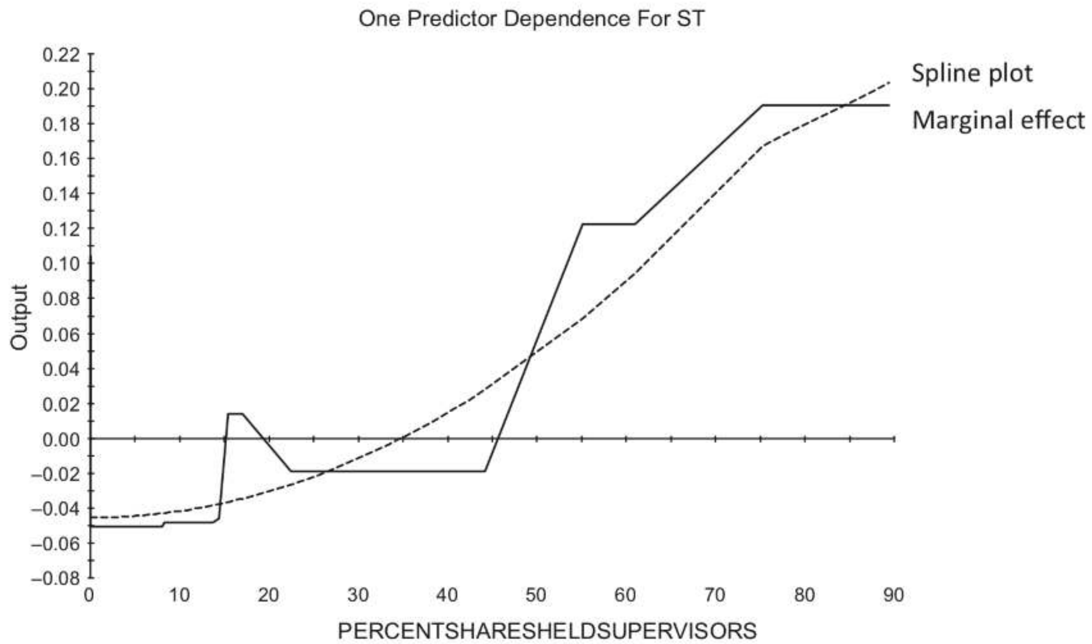

FIGURE 6.7: Partial dependency plot for percentage of shares held by all insiders (supervisors)

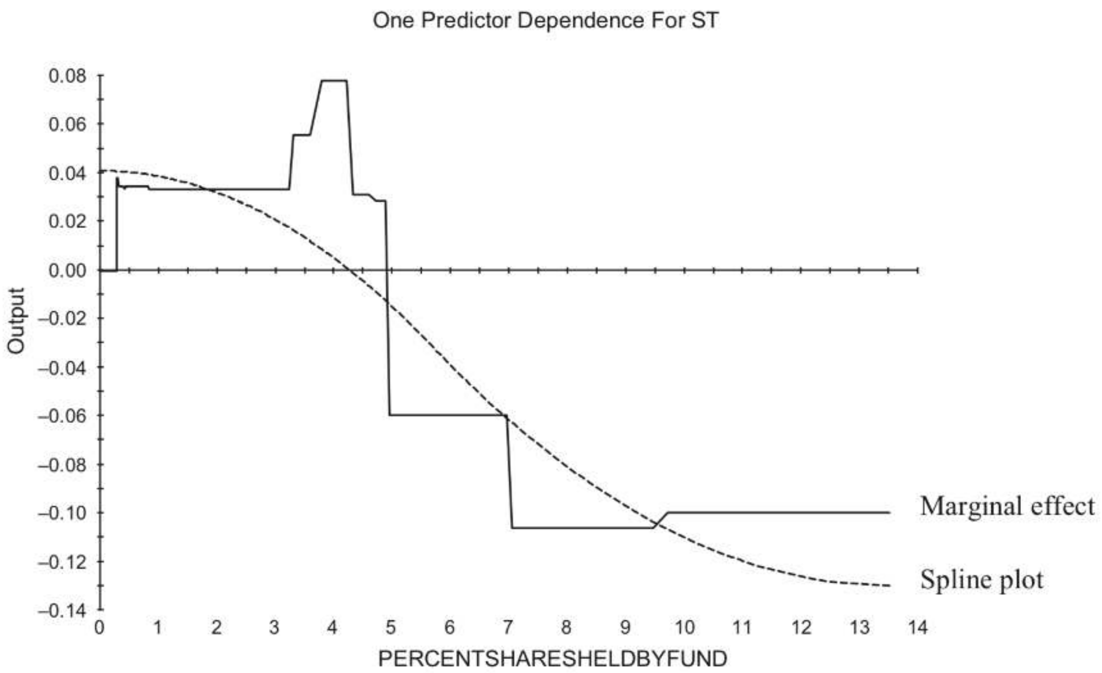

FIGURE 6.8: Partial dependency plot for percentage of shares held by institutions (funds)

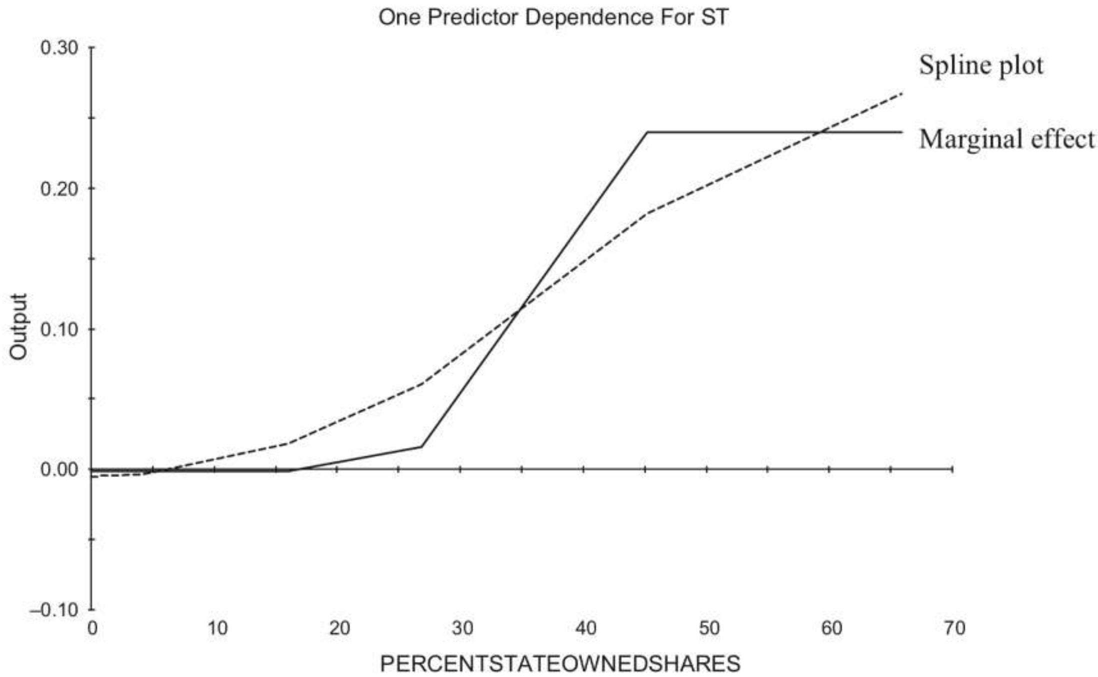

FIGURE 6.9: Partial dependency plot for state owned shares

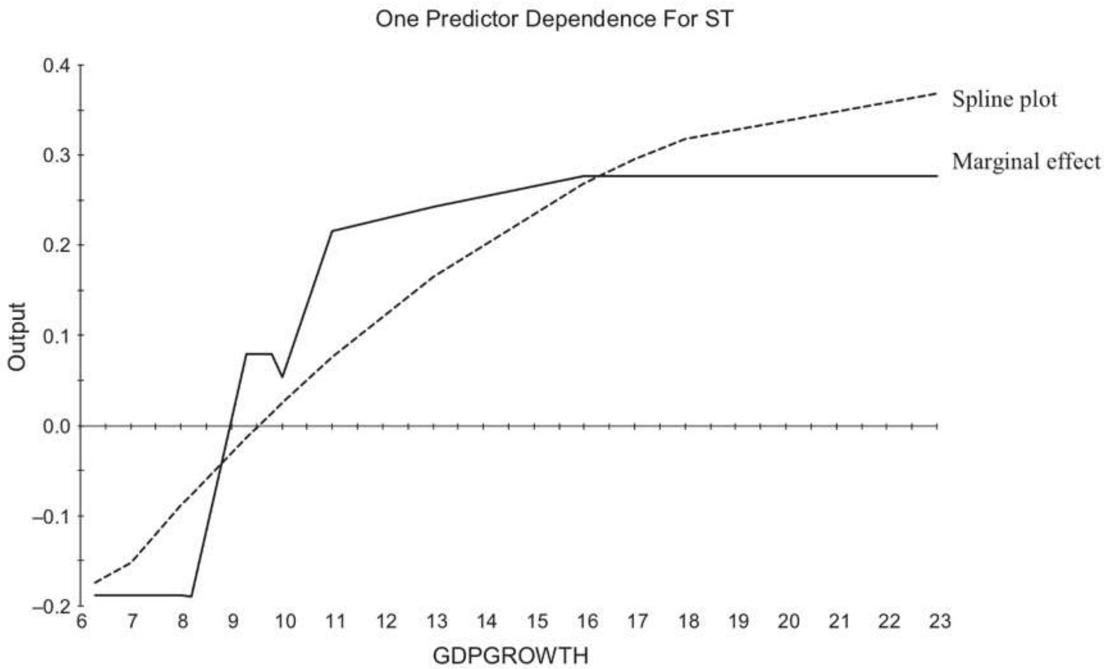

FIGURE 6.10: Partial dependency plot for gross domestic product growth

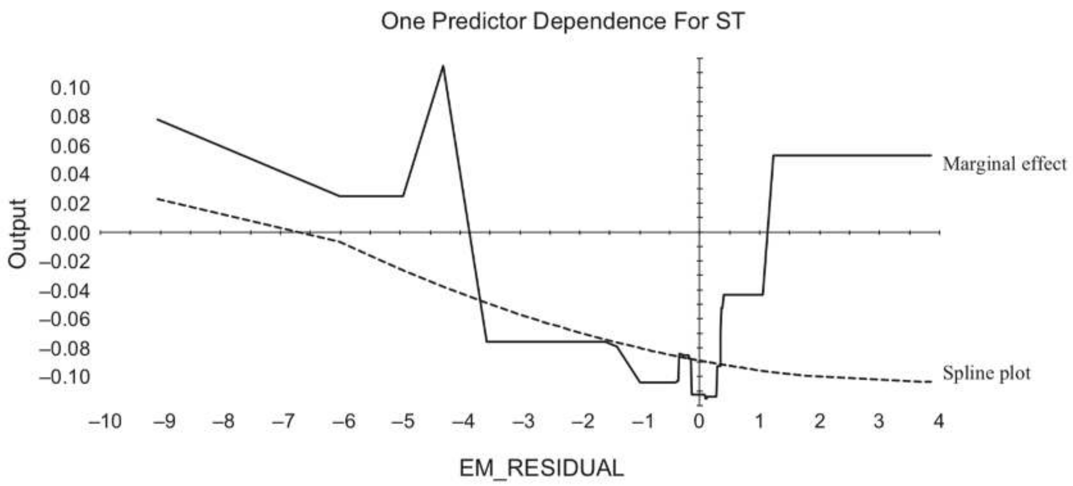

FIGURE 6.11: Partial dependency plot for earnings management proxy

6.5 Chapter conclusion

The empirical results of the binary TreeNet® model have been examined in this chapter. The binary TreeNet® model is interpreted through several outputs, including relative variable importances (RVIs), the confusion matrix, average log-likelihood, area under the ROC curve (AUC), and partial dependence analysis. Predictive performance of the binary TreeNet® model based on pooling all sampled observations is presented together with results on the predictive performance of the binary TreeNet® model 1 year, 3 years, and 5 years prior to the distress event. The TreeNet® model remains a very strong classifier across all time frames.

In the full binary TreeNet® model, 87 out of the 94 predictor variables have nonzero RVI scores, which indicates that all 87 input variables contribute to the out-of-sample predictive performance in some way, although the predictive strength of different predictors varies. Because the RVI scores of the binary TreeNet® model are mostly nonzero and appear reasonably dispersed across a range of different predictor categories, this confirms the high dimensional nature of corporate financial distress observable across Chinese listed companies. The high dimensional nature of corporate financial distress on China's stock exchange suggests that distress predictors from dimensions other than accounting-based variables, such as market-price variables, executive compensation variables, macroeconomic variables, and shareholder ownership/control variables may also provide explanatory and predictive power in the Chinese setting. After comparing the RVI results from the binary TreeNet® model to the results of Jones (2017) based on a large sample of U.S. Chapter 11 filings, it concludes that a wide range of financial and non-financial 'Western-style' bankruptcy predictors are also found to be fairly predictive in the Chinese context.

Notwithstanding the fact that very limited research effort has been devoted to examination of the predictive performance of accounting-based variables versus market-price indicators, the RVIs of the binary TreeNet® model provide evidence that market-price indicators significantly outperform accounting-based variables in the context of Chinese distress prediction. In terms of the predictive power of other non-financial variables, the RVIs of the binary TreeNet® model support findings in previous research that some macroeconomic, ownership structure, and corporate governance variables contain predictive power regarding corporate financial distress in China (Wang and Li, 2007; Xie, Luo, and Yu, 2011). In addition, the RVIs of the binary TreeNet® model also provide evidence that some non-conventional variables, such as executive compensation measures, valuation multiples, and corporate social responsibility measures also contain predictive and explanatory power in Chinese distress prediction. Similar to the findings of Xie, Luo, and Yu (2011) and Wang and Li (2007) that distress prediction models combining financial and non-financial variables outperform those containing only financial ratios, the high dimensional nature of corporate financial distress in China as evidenced in this chapter also suggests that a prediction model combining different categories of predictor variables provides better predictive results than a model concentrating solely on a single type of variables.

The overall prediction accuracy of the binary TreeNet® model is 94.57 percent using the baseline threshold as the cut-off score. Furthermore, the binary TreeNet® model is 93.74 percent accurate in predicting distress (a Type I error rate of 6.26 percent) and 94.81 per- cent accurate in predicting active/healthy companies (a Type II error rate of 5.19 percent). The predictive performance of the binary TreeNet® model does not change significantly several years prior to the distress event. Having established that the binary TreeNet® model has very strong out-of-sample predictive performance, it is also important to assess whether the explanatory variables make sense in terms of their influence on the distress outcome. Analysis of the partial dependency plots displayed in Figures 6.1 to 6.11 indicates that while a majority of explanatory variables appear to have logical relationships with the distress outcome, there are also some significant tensions in the results. From the partial dependence analysis, three variables have somewhat counter intuitive marginal effects on the distress outcome: annual market returns, price-to-book ratio, and GDP growth.

Chapter 7

Empirical results – multi-state analysis

7.1 Chapter introduction

This chapter presents the empirical results of the multi-state TreeNet® models. The multi-state TreeNet® models are interpreted through several outputs, including relative variable importances (RVIs), the confusion matrix, average log-likelihood, area under the ROC curve (AUC), and prediction accuracy based on the baseline threshold. The empirical results of the five-state TreeNet® model is presented in Section 7.2 followed by empirical results of the three-state TreeNet® model in Section 7.3. Predictive results based on pooling all sampled observations are provided together with results on the predictive performance of the multi-state TreeNet® models 1 year, 3 years, and 5 years prior to the distress event. After presenting the empirical results of the binary (in Chapter 6), three-state, and five-state TreeNet® models, Section 7.4 compares the empirical results of the the binary and multi-state TreeNet® models. Section 7.5 concludes this chapter.

7.2 Empirical results of the five-state TreeNet® model

This section presents the empirical results of the five-state TreeNet® model. Section 7.2.1 explores the relative variable importances of the five-state TreeNet® model (reported in Table 7.1). Section 7.2.2 presents the confusion matrix and summary of predictive performance of the five-state TreeNet® model (reported in Table 7.2 and Table 7.3). As defined in Section 4.2.3, in the five-state TreeNet® model, the dependent variable is speficied in five states as: (1) State 0: ST=0 (if a company is active or healthy); (2) State 1: ST=0 (if a company has experienced only one ST event); (3) State 2: 1$<$ ST $<$4 (if a company has experienced more than one but less than four ST events); (4) State 3: ST $\geq$ 4 (if a company has experienced four ST events or more); and (5) if a company has been delisted as a result of ST events.

7.2.1 RVIs of the five-state TreeNet® model

Following the general approach of Chapter 6, a full five-state TreeNet® model[1] is estimated based on pooling all sampled observations. Table 7.1 displays the five-state TreeNet® model estimated on all explanatory variables defined in Appendix A using all sampled observations. As pointed out by Jones (2017), high dimensional models will typically involve many more variables, therefore increasing the number of variables with nonzero importance. Some of the very small RVI values can result from random noise. After re-estimating The five-state TreeNet® model on all variables with RVIs of at least 6 to eliminate potential noise effects, the ranking of RVIs does not substantially change following this treatment.

[1]The TreeNet® algorithm randomly partitions 80% of the total observations to the training sample and 20% of observations to the test sample.

It can be seen from Table 7.1 that 89 out of the 94 predictor variables have nonzero RVI scores. This means that all 89 input variables contribute to the out-of-sample predictive performance in some way, although the predictive strength of different predictors varies. Table 7.1 reveals that a diverse range of predictor variables dominate the five-state TreeNet® model, reflecting several different dimensions of corporate financial distress in the Chinese market setting. These different dimensions of financial distress are reflected in the dispersed RVI scores across a number of dimensions, such as financial variables, market-price variables, macroeconomic variables, executive compensation measures, shareholder ownership/concentration variables, valuation multiples, and other variables.

Similar to the results from the binary TreeNet® model in Table 6.1, Table 7.1 also generally confirms the high dimensional nature of corporate financial distress observable across Chinese listed companies from a multi-state perspective. As there are several different dimensions of corporate financial distress in China, Table 7.1 also indicates that a prediction model that combines different categories of predictor variables may provide better predictive results than a model concentrating on one type of variables (such as accounting-based variables). The predictor variables that feature most strongly in the five-state analysis (RVIs $>$ 40) include: (1) market-price variables including market capitalisation, annual market returns, and market capitalisation to total debt; (2) a range of accounting-based variables and financial ratios including return on assets, net profit margin, retained earnings to total assets, accounts payable to total liabilities, sales to total assets, intangible assets to total assets, inventory turnover, total assets, and return on equity; (3) executive compensation measures including total executive compensation (top 3 executives) and total director compensation (top 3 directors); and (4) macroeconomic variables such as GDP growth.

As Table 7.1 displays, the strongest predictor variable overall is market capitalisation with an RVI of 100. This is followed by return on assets (RVI = 56.63), net profit margin (RVI = 54.68) and retained earnings to total assets (RVI = 54.33). The next strongest variable is equal weighted annual market returns with an RVI of 49.77 followed by total executive compensation (top 3 executives) with an RVI of 49.53. The top ten contributing variables also include GDP growth (RVI = 49.06), market capitalisation to total debt (RVI = 46.85), accounts payable to total liabilities (RVI = 45.62), and sales to total assets (RVI = 45.59). Other variables with a strong influence include: intangible assets to total assets (RVI = 45.22), inventory turnover (RVI = 42.32), total assets (RVI = 41.52), total director compensation (top 3 directors) (RVI = 40.29), return on equity (RVI = 40.12), cash to current liabilities (RVI = 39.07), cash resources to total assets (RVI = 38.86), total operating revenue (RVI = 37.88), debt to tangible assets (RVI = 36.52), number of employees (RVI = 35.53), percentage of shares held by supervisors (RVI = 33.41), current assets to total liabilities (RVI = 32.85), registered unemployment rate in urban areas (RVI = 32.01), earnings per share (RVI = 31.34), and working capital to sales (RVI = 30.65).

After analysing the variables with strongest influence in the five-state TreeNet® model, in order to get a better sense of which group of predictors is actually driving the results, average RVIs across the different predictor categories are considered. The market-price variables have an average RVI of 65.54, ranking as the strongest predictor category overall. The second best predictor category comprises the executive compensation variables with an average RVI of 44.91. The third best predictor category is the macroeconomic variables, which have an average RVI of 34.13. Despite the fact that financial variables featured strongly among the top predictors, their average RVI is around 26.58 across the entire five-state TreeNet® model. In terms of the average RVIs of the market-price variables versus financial variables, similar to the results from the binary analysis in Table 6.1, market-price variables also perform significantly better than financial variables in this five-state prediction case. This is consistent with results found for the developed capital markets, where market-price indicators have stronger forecasting power than accounting-based measures (Hillegeist et al., 2004; Beaver, McNichols, and Rhie, 2005). Shareholder ownership/control variables also show comparable predictive strength in the model with an average RVI of 23.21, followed by valuation multiple variables with an average RVI of 17.23. The earnings management proxy variable also has reasonable predictive impact with an RVI of 13.09. Variables with the lowest impact in the five-state TreeNet® model include audit variables (average RVI = 10.37), and the corporate social responsibility variable (RIV = 5.24).

The results in Table 7.1 also have a number of similarities and dissimilarities with the findings of Jones (2017) based on a large sample of U.S. Chapter 11 filings. The RVI results of Jones (2017) are estimated on a binary TreeNet® model. Broadly speaking, a wide range of financial and non-financial predictors are found to be predictive in both the Chinese and U.S. context. While market-price variables ranked as the most predictive predictor category in the five-state TreeNet® model, they ranked in third place in Jones (2017). Further, while macroeconomic factors have relatively weak predictive power in Jones (2017), they ranked in third place in the current five-state TreeNet® model. Executive compensation variables and financial variables appear to have quite reasonable predictive power, which is broadly consistent with the findings of Jones (2017). However, shareholder ownership/concentration variables, which featured less significantly in the five-state TreeNet® model, comparatively rank the top in Jones (2017).

TABLE 7.1: RVIs of the five-state TreeNet® Model – All Data

Variable	Dimension	RVI Score (Av. All Classes)
Market capitalisation	Market/Size proxy	100.00
Return on assets	Financial	56.63

Continued on next page

Table 7.1 – *Continued from previous page*

Variable	**Dimension**	**RVI Score (Av. All Classes)**
Net profit margin	Financial	54.68
Retained earnings to total assets	Financial	54.33
Annual market returns (equal weighted)	Market	49.77
Total executive compensation (top 3 executives)	Executive compensation	49.53
GDP Growth	Macroeconomic	49.06
Market capitalisation to total debt	Market/Financial	46.85
Accounts payables to total liabilities	Financial	45.62
Sales to total assets	Financial	45.59
Intangible assets to total assets	Financial	45.22
Inventory turnover	Financial	42.32
Total assets	Financial	41.52
Total director compensation (top 3 directors)	Executive compensation	40.29
Return on equity	Financial	40.12
Cash to current liabilities	Financial	39.07
Cash resources to total assets	Financial	38.86
Total operating revenue	Financial	37.88
Debt to tangible assets	Financial	36.52
Number of employees	Size proxy	35.53
Percentage of shares held by supervisors	Shareholder ownership/control	33.41
Current assets to total liabilities	Financial	32.85
Registered unemployment rate (urban areas)	Macroeconomic	32.01
Earnings per share	Financial	31.34
Working capital to sales	Financial	30.65
Percentage of shares held by funds/institutions	Shareholder ownership/control	29.87
General consumer price index	Macroeconomic	29.25
Total assets to total liabilities	Financial	29.12
Total profit margin	Financial	28.55
Cash flow to debt	Financial	28.25
Operating cash flow to equity	Financial	27.80

Continued on next page

Table 7.1 – *Continued from previous page*

Variable	Dimension	RVI Score (Av. All Classes)
Operating cash flow to total assets	Financial	27.49
Total number of shareholders	Shareholder ownership/control	27.35
Growth net profit (1yr)	Financial	27.09
Number of directors	Other – governance	26.34
Operating cash flow to total revenue	Financial	26.31
GDP growth per capita	Macroeconomic	26.18
Book value per share	Financial	26.09
Chairman and general manager concurrent	Other – governance	26.01
Conglomerates industry	Industry	25.91
Working capital to total assets	Financial	25.90
Long term liabilities to total equity	Financial	25.52
Growth total liabilities (1yr)	Financial	24.45
Growth operating revenue (1yr)	Financial	24.06
Growth in equity (3yrs)	Financial	23.87
Growth net profit (3yrs)	Financial	23.81
Growth in equity (1yr)	Financial	23.48
Growth total assets (3yrs)	Financial	23.44
Working capital to total liabilities	Financial	23.26
Total liabilities to total equity	Financial	22.36
Price to book ratio	Valuation multiple	22.18
Total audit fees	Audit	22.16
Growth operating revenue (3yrs)	Financial	21.80
Growth in cash (1yr)	Financial	21.67
Growth working capital (1yr)	Financial	21.26
Growth earnings per share (1yr)	Financial	21.22
Growth operating cash flow (1yr)	Financial	21.00
Debt to equity	Financial	20.93
Growth total assets (1yr)	Financial	20.14
Growth working capital (3yrs)	Financial	19.80

Continued on next page

Table 7.1 – *Continued from previous page*

Variable	**Dimension**	**RVI Score (Av. All Classes)**
Analyst concern degree	Other – analyst coverage	19.60
Growth operating cash flow (3yrs)	Financial	19.41
Growth in long term debt (1yr)	Financial	19.20
Current ratio	Financial	19.13
Growth in cash (3yrs)	Financial	17.96
Percentage of shares held by brokers	Shareholder ownership/control	16.46
Research report concern degree	Other – Research coverage	15.82
Growth earnings per share (3yrs)	Financial	15.37
Growth in EBIT (1yr)	Financial	15.36
EBIT to operating cash flow	Financial	15.15
Growth total liabilities (3yrs)	Financial	14.24
Public utility industry	Industry	14.11
Earnings management proxy	Earnings Management Proxy	13.09
EBIT to total assets	Financial	12.46
Price earnings ratio	Valuation multiple	12.27
Operating cash flow per share	Financial	12.11
Industrial industry	Industry	11.75
Qualified audit opinion	Audit	11.70
Properties industry	Industry	10.60
Commercial industry	Industry	10.23
EBIT margin	Financial	9.25
Percentage of state owned shares	Shareholder ownership/control	8.97
Growth in EBIT (3yrs)	Financial	6.30
Growth in income (1yr)	Financial	6.05
Social contribution value per share	CSR	5.24
Growth in income (3yrs)	Financial	4.42
Disclaimer audit opinion	Audit	4.33
Finance industry	Industry	3.79
Audit from Big4 firm	Audit	3.29

7.2.2 Confusion matrix and summary of predictive performance of the five-state TreeNet® model

Table 7.2 reports the confusion matrix for the test sample of the five-state TreeNet® model. From Table 7.2, the overall prediction accuracy of the five-state TreeNet® model is 85.77 percent. The confusion matrix reported in Table 7.2 shows that the five-state TreeNet® model is 94.47 percent accurate in predicting active or healthy companies using the baseline threshold as the cut-off score. Table 7.2 also shows that the five-state TreeNet® model is 61.70 percent accurate in predicting state 1 distress (ST=1); 53.12 percent accurate in predicting state 2 distress ($1 < ST < 4$); 62.56 percent accurate in predicting state 3 distress ($ST \geq 4$); and 51.72 percent accurate in predicting state 4 distress (delisted).

When examining the results in Table 7.2, it is advisable to note that the predictive performance of a multi-state prediction model is not directly comparable to that of a binary prediction model. According to Lau (1987), multi-state classification models permit many more types of classification errors than are possible in the binary classification models. Therefore, as suggested by Johnsen and Melicher (1994), such a difference should be accounted for when analysing the predictive results of a multi-state prediction model. In a binary prediction model, there are only two types of misclassification errors – Type I error and Type II error. However, in a five-state prediction model, there are twenty different types of misclassification errors: (1) the misclassification of healthy firms as state 1 distress firms; (2) the misclassification of state 1 distress firms as healthy firms; (3) the misclassification of healthy firms as state 2 distress firms; (4) the misclassification of state 2 distress firms as healthy firms; (5) the misclassification of healthy firms as state 3 distress firms; (6) the misclassification of state 3 distress firms as healthy firms; (7) the misclassification of healthy firms as state 4 distress firms; (8) the misclassification of state

4 distress firms as healthy firms; (9) the misclassification of state 1 distress firms as state 2 distress firms; (10) the misclassification of state 2 distress firms as state 1 distress firms; (11) the misclassification of state 1 distress firms as state 3 distress firms; (12) the misclassification of state 3 distress firms as state 1 distress firms; (13) the misclassification of state 1 distress firms as state 4 distress firms; (14) the misclassification of state 4 distress firms as state 1 distress firms; (15) the misclassification of state 2 distress firms as state 3 distress firms; (16) the misclassification of state 3 distress firms as state 2 distress firms; (17) the misclassification of state 2 distress firms as state 4 distress firms; (18) the misclassification of state 4 distress firms as state 2 distress firms; (19) the misclassification of state 3 distress firms as state 4 distress firms; and finally (20) the misclassification of state 4 distress firms as state 3 distress firms. In addition, a cut-off score is usually computed in a binary classification setting by minimising the sample classification error. A sample can then be classified into one of the two states depending on the cut-off score. However, such optimisation procedure is not possible for a multi-state probabilistic prediction model (Lau, 1987).

In comparison with binary prediction models in which there are only two possible types of misclassification errors, five-state models permit 20 types of misclassification errors. This implies that a case could be far more easily misclassified in a five-state prediction model than in a binary prediction model. In terms of the misclassification costs, empirical evidence has shown that a missed crisis (Type I error) costs about three times more than a false alarm (Type II error) (Tsai, 2013). In practice, it is quite reasonable to presume the cost of Type I errors to be higher and more concerning than Type II errors. For example, from a debtor's perspective a misjudged investment in bankrupt firms may result in significant losses; however the consequence of an incorrectly missed lending opportunity merely represents forgone profits (Tsai, 2013). From Table 7.2, as the cost of

Type I errors (the cost of misclassifying distressed firms as healthy firms) is more concerning than that of Type II errors (the cost of misclassifying healthy firms as distressed firms), the results of predicted class 0 (healthy firms) is analysed. As Table 7.2 reports, 94.47% (2257/2389) of healthy firms are correctly classified. Further, 30.04% (16/47) of state 1 distressed firms are mistakenly classified as healthy firms (class 0); 8.01% (27/337) of state 2 distressed firms are mistakenly classified as healthy firms (class 0); no state 3 distressed firms are mistakenly classified as healthy firms (class 0); and 5.17% (6/116) of state 4 distressed firms are mistakenly classified as healthy firms (class 0). As the severity of financial distress (proxied in the current study as the number of times a company gets into the ST status) increases, the chance of more severely distressed firms being mistakenly classified as healthy firms decreases significantly. Furthermore, Table 7.2 also shows that it is the state 1 distress (in which companies have experienced only one ST event) that is the most difficult to be differentiated from the healthy companies. For companies that have been classified as state 1 distress, it is possible that they are only experiencing temporary distress, which would not affect their prospects. Therefore, it is possible that there are very limited fundamental differences between healthy companies and state 1 distress companies, leading to difficulties in differentiating between the two in the model.

Table 7.3 summarises predictive performance of the five-state TreeNet® model reported in Table 7.1. Panel A of Table 7.3 reports model performance based on all sampled data (five years of pooled observations). Panels B, C, and D of Table 7.3 presents predictive performance of the five-state TreeNet® model estimated on t-1[2] data (one year prior to the distress event), t-3 data (three years prior to the distress event), and t-5 data (five years prior to the distress event). Average log-likelihood (Negative), average ROC curve, and overall misclassification rates based on the baseline threshold for both the training and test samples are reported in Table 7.3.

[2]Time t represents the year of the distress event.

From Table 7.3, the predictive power of the five-state TreeNet® model is highest when estimated on t-1 data (one year prior to the distress event). The overall classification accuracy (baseline threshold) for the five-state TreeNet® model is 85.77% using five years of pooled observations. The classification accuracy (baseline threshold) for the five-state TreeNet® model when estimated using t-1 data (one year prior to the distress event) is 90.10%. It deteriorates slightly when estimated using t-3 data (three years prior to the distress event) and t-5 data (five years prior to the distress event). The prediction accuracy based on the baseline threshold for the model is 85.05% three years prior to the distress event and 88.50% five years prior to the distress event. From Table 7.3, the average ROC (Area Under Curve) remains very robust over all time frames. There is little evidence of deterioration in average ROC performance one year, three years, and even five years from the distress event. Again, this result corroborates the findings of the binary TreeNet® model presented in Chapter 6, Jones (2017), and other literature that the gradient boosting model and TreeNet® in particular is a highly accurate classifier.

TABLE 7.2: Confusion matrix – test sample (five-state model)

Actual class	**Total class**	**Percent correct**	**Predicted class**				
			0	1	2	3	4
			N=2306	N=128	N=302	N=247	N=109
0	2389	94.47%	2257	82	48	0	2
1	47	61.70%	16	29	2	0	0
2	337	53.12%	27	14	179	91	26
3	203	62.56%	0	0	55	127	21
4	116	51.72%	6	3	18	29	60
Total	3092						
Average		64.72%					
Overall % correct		85.77%					

TABLE 7.3: Summary of predictive performance for the five-state TreeNet® model

	Training sample	**Test sample**
Panel A (All Data)		
Average LogLikelihood (Negative)	0.34693	0.80693
Average ROC (Area Under Curve)	0.99666	0.98543
Classification accuracy (Baseline threshold)	0.93514	0.85770
Panel B (One year prior to distress (t-1))		
Average LogLikelihood (Negative)	0.45698	0.92963
Average ROC (Area Under Curve)	0.99900	0.99829
Classification accuracy (Baseline threshold)	0.95304	0.90088
Panel C (Three years prior to distress (t-3))		
Average LogLikelihood (Negative)	0.66899	1.21797
Average ROC (Area Under Curve)	0.99450	0.96562
Classification accuracy (Baseline threshold)	0.92010	0.85049
Panel D (Five years prior to distress (t-5))		
Average LogLikelihood (Negative)	0.61656	1.25165
Average ROC (Area Under Curve)	0.99332	0.94471
Classification accuracy (Baseline threshold)	0.95841	0.88498

7.3 Empirical results of the three-state TreeNet® model

This section presents the empirical results of the three-state TreeNet® model. Section 7.3.1 explorers the relative variable importances of the three-state TreeNet® model (reported in Table 7.4). Section 7.3.2 presents the confusion matrix and summary of predictive performance of the three-state TreeNet® model (reported in Table 7.5 and Table 7.6). As defined in Section 4.2.3, in the three-state TreeNet® model, the dependent variable is specified as three states : (1) State 0: ST=0 (if a company is active or healthy); (2) State 1: ST=0 (if a company has experienced only one ST event); and (3) State 2: ST $>$ 1(if a company has experienced more than one ST event including companies that have been delisted as a result of ST events).

7.3.1 RVIs of the three-state TreeNet® model

A full three-state TreeNet® model[3] is estimated based on pooling all sampled observations. Table 7.4 displays the three-state TreeNet® model estimated on all explanatory variables defined in Appendix A using all sampled observations. As pointed out by Jones (2017), high dimensional models will typically involve many more variables, therefore increasing the number of variables with nonzero importance. Some of the very small RVI values can result from random noise. Hence, it is advisable to re-estimate the three-state TreeNet® model excluding all variables with very small RVIs (close to zero). The three-state TreeNet® model is then re-estimated on all variables with RVIs of at least 6 to eliminate potential noise effects. The ranking of RVIs does not substantially change following this treatment.

It can be seen from Table 7.4 that 85 out of the 94 predictor variables have nonzero RVI scores. This means that all 85 input variables contribute to the out-of-sample predictive performance of the three-state TreeNet® model in some way, although the predictive strength of different predictors varies. The RVIs in Table 7.4 are ranked according to each predictor variable's contribution to the overall predictive success of the TreeNet® model. Similar to Table 7.1 for the five-state TreeNet® model and Table 6.1 for the binary TreeNet® model, Table 7.4 also reports that a diverse range of predictor variables dominate the three-state TreeNet® model, reflecting different dimensions of corporate financial distress in China.

The predictor variables that feature most strongly in the three-state TreeNet® analysis (RVIs > 20) include: (1) market-price variables including market capitalisation, annual market returns, and market capitalisation to total debt; (2) a range of accounting-based

[3]The TreeNet® algorithm randomly partitions 80% of the total observations to the training sample and 20% of observations to the test sample.

variables and financial ratios including retained earnings to total assets, return on equity, return on assets, net profit margin, accounts payable to total liabilities, total assets, total operating revenue, debt to tangible assets, intangible assets to total assets, cash to current liabilities, and three year growth in equity; (3) macroeconomic variables such as registered unemployment rate and GDP growth; (4) executive compensation measures including total executive compensation (top 3 executives) and total director compensation (top 3 directors); and (5) a variable concerning corporate governance, namely whether the chairman and general manager are concurrently held positions.

From Table 7.4, the strongest predictor variable overall is still market capitalisation with an RVI of 100. This matches the finding from the five-state TreeNet® model and the binary TreeNet® model, which confirms that market capitalisation is the single most important predictor variable in the case of corporate financial distress prediction in China. The second best performing variable is equal weighted annual market returns with an RVI of 49.56. This variable also features strongly (fifth place) in the five-state TreeNet® model. The third and fourth best performing variables are retained earnings to total assets (with an RVI of 48.16) and market capitalisation to total debt (with an RIV of 44.11). Retained earnings to total assets and market capitalisation to total debt are also top performing variables in the five-state TreeNet® model. The fifth and sixth contributing variables are return on equity (RVI = 36.01) and registered unemployment rate (RVI = 32.27), which are not featured strongly in the five-state TreeNet® model. The top ten contributing variables also include return on assets (RVI = 31.14), net profit margin (RVI = 29.24), accounts payable to total liabilities (RVI = 28.77), and total executive compensation of the top 3 executives (RVI = 26.04). These variables also feature significantly in the five-state TreeNet® model.

In comparison with the results from the five-state TreeNet® model, the top ten most contributing variables of the three-state TreeNet® model do not change significantly. The only two variables that do not feature in the five-state TreeNet® model but that appear as top performing variables in the three-state TreeNet® model are return on equity and registered unemployment rate. On the other hand, the only two variables that are not featured in the three-state TreeNet® model but appear as top performing variables in the five-state TreeNet® model are GDP growth and sales to total assets. Other than the aforementioned variables, the remaining variables are the same in both the five-state and three state TreeNet® models despite some slight change in RVI rankings. This implies that TreeNet® is quite robust no matter whether the model is estimated as a five-state or three-state model. Other variables with strong influence from the three-state TreeNet® model as shown in Table 7.4 include: total assets (RVI = 26.02), total operating revenue (RVI = 24.06), debt to tangible assets (RVI = 23.96), Chairman and general manager concurrent (RVI = 23.92), intangible assets to total assets (RVI = 23.68), cash to current liabilities (RVI = 23.23), GDP growth (RVI = 23.02), three years growth in equity (RVI = 22.06), and total director compensation of the top 3 directors (RVI = 21.88).

Average RVIs across different predictor categories are considered in order to get a better sense of which group of predictors is actually driving the results in the three-state TreeNet® model. Similar to the results from the five-state TreeNet® model and binary TreeNet® model, market-price variables also rank as the strongest predictor categories overall in the three-state TreeNet® model with an average RVI of 64.56. The second best performing predictor category comprises executive compensation variables with an average RVI of 23.96. The third best predictor category is macroeconomic variables with an average RVI of 21.02. Despite the frequency of being featured in the RVIs table, the average RVI of financial variables is 13.79 across the entire three-state TreeNet® model, ranking fourth place. Shareholder ownership/control variables also show comparable predictive strength in the three-state TreeNet® model with an average RVI of 12.97. Variables with the lowest impact in the three-state TreeNet® model include other variables (average RVI = 12.90), industry variables (average RVI = 7.69), audit variables (average RVI = 6.66), valuation multiple variables (average RVI = 12.90), earnings management proxy variable (RVI = 5.29) and the corporate social responsibility variable (RIV = 2.32).

In comparison with the average RVIs across different predictor categories from the five-state TreeNet® model, the predictor category rankings from the three-state TreeNet® model are broadly in consistent. The rankings of the top five contributing predictor categories are the same in both the five-state and three state TreeNet® models. They are: (1) market-price variables; (2) executive compensation variables; (3) macroeconomic variables; (4) financial variable; and (5) ownership/control variables. Because top performing predictor categories remain the same in both five-state and three-state TreeNet® models, the similarities and dissimilarities to the findings of Jones (2017) as discussed in Section 7.2.1 do not change in this three-state prediction case. In terms of the average RVIs of the market-price variables versus financial variables, market-price variables perform significantly better than financial variables in all cases. This again indicates that market-price variables are fairly predictive of corporate financial distress in the Chinese market.

The results in Table 7.1 also have a number of similarities and dissimilarities with the findings of Jones (2017) based on a large sample of U.S. Chapter 11 filings. The RVI results of Jones (2017) are estimated on a binary TreeNet® model. Broadly speaking, a wide range of financial and non-financial predictors are found to be predictive in both the Chinese and U.S. context. While market-price variables ranked as the most predictive predictor category in the five-state TreeNet® model, they ranked in third place in Jones (2017). Further, while macroeconomic factors have relatively weak predictive power in

Jones (2017), they ranked in third place in the current five-state TreeNet® model. Executive compensation variables and financial variables appear to have quite reasonable predictive power, which is broadly consistent with the findings of Jones (2017). However, shareholder ownership/concentration variables, which featured less significantly in the five-state TreeNet® model, comparatively rank the top in Jones (2017).

TABLE 7.4: RVIs of the three-state TreeNet® Model – All Data

Variable	**Dimension**	**RVI Score (Av. All Classes)**
Market capitalisation	Market/Size proxy	100.00
Annual market returns (equal weighted)	Market	49.56
Retained earnings to total assets	Financial	48.16
Market capitalisation to total debt	Market/Financial	44.11
Return on equity	Financial	36.01
Registered unemployment rate (urban areas)	Macroeconomic	32.27
Return on assets	Financial	31.14
Net profit margin	Financial	29.24
Accounts payables to total liabilities	Financial	28.77
Total executive compensation (top 3 executives)	Executive compensation	26.04
Total assets	Financial	26.02
Total operating revenue	Financial	24.06
Debt to tangible assets	Financial	23.96
Chairman and general manager concurrent	Other – governance	23.92
Intangible assets to total assets	Financial	23.68
Cash to current liabilities	Financial	23.23
GDP Growth	Macroeconomic	23.02
Growth in equity (3yrs)	Financial	22.06
Total director compensation (top 3 directors)	Executive compensation	21.88
Inventory turnover	Financial	19.19
Number of directors	Other – governance	18.32
Total number of shareholders	Shareholder ownership/control	18.07

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Table 7.4 – *Continued from previous page*

Variable	**Dimension**	**RVI Score (Av. All Classes)**
Cash flow to debt	Financial	17.56
Total assets to total liabilities	Financial	16.77
General consumer price index	Macroeconomic	15.80
Percentage of shares held by funds/institutions	Shareholder ownership/control	15.32
Operating cash flow to equity	Financial	15.29
Cash resources to total assets	Financial	15.12
Growth operating cash flow (1yr)	Financial	14.23
Operating cash flow to total revenue	Financial	14.12
Growth operating revenue (1yr)	Financial	13.08
GDP growth per capita	Macroeconomic	12.99
Conglomerates industry	Industry	12.70
Growth total assets (3yrs)	Financial	12.61
Number of employees	Size proxy	12.41
Total liabilities to total equity	Financial	12.12
Sales to total assets	Financial	12.06
Working capital to sales	Financial	12.02
Growth working capital (1yr)	Financial	11.56
Working capital to total liabilities	Financial	11.18
Percentage of shares held by supervisors	Shareholder ownership/control	11.08
Properties industry	Industry	10.74
Growth in equity (1yr)	Financial	10.63
Growth operating revenue (3yrs)	Financial	10.37
Growth in cash (1yr)	Financial	10.34
Qualified audit opinion	Audit	10.24
Total profit margin	Financial	9.61
Growth operating cash flow (3yrs)	Financial	9.56
Long term liabilities to total equity	Financial	9.15
Growth net profit (1yr)	Financial	9.09
Growth earnings per share (1yr)	Financial	8.88

Continued on next page

Table 7.4 – *Continued from previous page*

Variable	Dimension	RVI Score (Av. All Classes)
Growth in income (1yr)	Financial	8.72
Operating cash flow to total assets	Financial	8.71
Disclaimer audit opinion	Audit	8.54
Growth in cash (3yrs)	Financial	8.40
Growth in long term debt (1yr)	Financial	8.14
Growth earnings per share (3yrs)	Financial	8.08
Working capital to total assets	Financial	7.86
Percentage of state owned shares	Shareholder ownership/control	7.41
Growth total liabilities (3yrs)	Financial	7.34
Percentage of shares held by brokers	Shareholder ownership/control	7.00
Price earnings ratio	Valuation multiple	6.73
Current assets to total liabilities	Financial	6.68
Current ratio	Financial	6.54
Growth working capital (3yrs)	Financial	6.49
Debt to equity	Financial	6.43
Growth total assets (1yr)	Financial	6.35
Commercial industry	Industry	6.20
EBIT margin	Financial	6.03
Public utility industry	Industry	5.80
Research report concern degree	Other – Research coverage	5.62
Earnings management proxy	Earnings Management Proxy	5.29
Audit from Big4 firm	Audit	4.56
EBIT to operating cash flow	Financial	4.26
Price to book ratio	Valuation multiple	4.25
Growth total liabilities (1yr)	Financial	4.17
Book value per share	Financial	4.09
Analyst concern degree	Other – analyst coverage	3.74
Growth in EBIT (1yr)	Financial	3.61
Earnings per share	Financial	3.30

Continued on next page

Table 7.4 – *Continued from previous page*

Variable	Dimension	RVI Score (Av. All Classes)
Total audit fees	Audit	3.29
Growth in income (3yrs)	Financial	3.11
Industrial industry	Industry	2.99
Growth net profit (3yrs)	Financial	2.46
Social contribution value per share	CSR	2.32

7.3.2 Confusion matrix and summary of predictive performance of the three-state TreeNet® model

Table 7.5 reports the confusion matrix for the test sample of the three-state TreeNet® model. From Table 7.5, the overall prediction accuracy of the three-state TreeNet® model is 92.08 percent. The confusion matrix reported in Table 7.5 also shows that the three-state TreeNet® model is 96.82 percent accurate in predicting active or healthy companies using the baseline threshold as the cut-off score. From Table 7.5, the three-state TreeNet® model is 76.49 percent accurate in predicting state 1 distress (ST=1) and 73.28 percent accurate in predicting state 2 distress (ST $>$ 1). In comparison with the confusion matrix table of the five-state TreeNet® model as displayed in Table 7.2, the overall prediction accuracy improves significantly from 85.77 percent to 92.08 percent when estimated on the three-state TreeNet® model.

As discussed earlier in Section 7.2.2, while binary prediction models permit two types of misclassification errors, five-state models permit twenty types of misclassification errors. In a three-state prediction model, there are six different types of misclassification errors: (1) the misclassification of healthy firms as state 1 distress firms; (2) the misclassification of state 1 distress firms as healthy firms; (3) the misclassification of healthy firms as state 2 distress firms; (4) the misclassification of state 2 distress firms as healthy firms; (5) the misclassification of state 1 distress firms as state 2 distress firms; and (6) the misclassification of state 2 distress firms as state 1 distress firms. It is quite intuitive that the model predictive performance would improve when the number of states decreases. It is less likely for the model to make mistakes in discriminating among states when the number of states decreases from five states (which permits twenty types of misclassification errors) to the current three states (which permits six types of misclassification errors).

Again, as the cost of Type I errors (the cost of misclassifying distressed firms as healthy firms) is more concerning than that of Type II errors (the cost of misclassifying healthy firms as distressed firms) in terms of corporate financial distress prediction, the results of predicted class 0 (healthy firms) from Table 7.5 is analysed. As Table 7.5 reports, 96.82% (2312/2389) of healthy firms are correctly classified. Further, 11.06% (66/587) of state 1 distressed firms are mistakenly classified as healthy firms (class 0), and 4.31% (5/116) of state 2 distressed firms are mistakenly classified as healthy firms (class 0). Similar to the case of the five-state TreeNet® model, the state 1 distress group remains the most difficult to discriminate from the healthy group.

The predictive performance of the three-state TreeNet® model is summarised in Table 7.6. Table 7.6 displays average log-likelihood (Negative), average ROC curve, and overall misclassification rates based on the baseline threshold for both the training and test samples. Panel A of Table 7.6 reports model performance based on all sampled data (five years of pooled observations). Panels B, C, and D of Table 7.6 summarise predictive performance of the three-state TreeNet® model estimated on t-1 data (one year prior to the distress event), t-3 data (three years prior to the distress event), and t-5 data (five years prior to the distress event).

From Table 7.6, the predictive accuracy of the three-state TreeNet® model is the highest when estimated on t-1 data (one year prior to the distress event). The overall classification accuracy (baseline threshold) for the full three-state TreeNet® model is 92.08% on the test sample when estimated using five years of pooled observations. The classification accuracy (baseline threshold) for the three-state TreeNet® model when estimated on t-1 data (one year prior to the distress event) is 94.16%. The classification accuracy deteriorates slightly when estimated using t-3 data (three years prior to the distress event) to 93.40%. It deteriorates further to 92.25% when estimated on t-5 data (five years prior to the distress event). The predictive performance results of the three-state TreeNet® model as reported in Table 7.6 are largely in line with those of the five-state TreeNet® model reported in Table 7.3. In both cases, the predictive accuracy of the model is highest when estimated on t-1 data (one year prior to the distress event). The model predictive performance of the three-state and five-state TreeNet® models then deteriorates slightly when estimated on data three and five years prior to the distress event. In addiction, the average ROC (Area Under Curve) remains very robust over all time frames in both the three-state and five-state TreeNet® models. Again, this result corroborates the findings of the binary TreeNet® model presented in Chapter 6, Jones (2017), and other literature that the gradient boosting model and TreeNet® in particular is a highly accurate classifier.

TABLE 7.5: Confusion matrix – test sample (three-state model)

Actual class	**Total class**	**Percent correct**	**Predicted class**		
			0	1	2
			N=2384	N=547	N=161
0	2389	96.82%	2313	72	4
1	587	76.49%	66	449	72
2	116	73.28%	5	26	85
Total	3092				
Average		82.20%			
Overall % correct		92.08%			

TABLE 7.6: Summary of predictive performance for the three-state TreeNet® model

	Training sample	**Test sample**
Panel A (All Data)		
Average LogLikelihood (Negative)	0.35630	0.46232
Average ROC (Area Under Curve)	0.98655	0.98206
Classification accuracy (Baseline threshold)	0.93764	0.92076
Panel B (One year prior to distress (t-1))		
Average LogLikelihood (Negative)	0.18451	0.48354
Average ROC (Area Under Curve)	0.99970	0.99866
Classification accuracy (Baseline threshold)	0.98301	0.94159
Panel C (Three years prior to distress (t-3))		
Average LogLikelihood (Negative)	0.33387	0.63091
Average ROC (Area Under Curve)	0.99636	0.97111
Classification accuracy (Baseline threshold)	0.97451	0.93398
Panel D (Five years prior to distress (t-5))		
Average LogLikelihood (Negative)	0.31910	0.69634
Average ROC (Area Under Curve)	0.99445	0.94829
Classification accuracy (Baseline threshold)	0.97348	0.92254

7.4 The binary TreeNet® model versus the multi-state TreeNet® models

This section compares the empirical results of the binary TreeNet® model presented in Chapter 6 and the empirical results of the five-state TreeNet® model and three-state TreeNet® model presented in the current chapter (Chapter 7). Section 7.4.1 compares the relative variable importances (RVIs) of the binary TreeNet® with those of the multi-state TreeNet® models. This is followed by a comparison of the predictive performance of the binary TreeNet® model versus that of the multi-state TreeNet® models in Section 7.4.2.

7.4.1 The RVIs of the binary versus multi-state TreeNet® models

In comparison with the RVI results from the five-state TreeNet® model, the top ten contributing variables of the the binary TreeNet® model do not change significantly. In both of the five-state TreeNet® model and binary TreeNet® model, market capitalisation ranks as the best performing variable overall. While equally weighted annual market returns ranks in second place in the binary TreeNet® model, it ranks in fifth place in the five-state TreeNet® model. The RVI ranking of retained earnings to total assets does not change significantly between the binary and five-state TreeNet® models; while it ranks in third place in the binary TreeNet® model, it is the fourth contributing variable in the five-state TreeNet® model. GDP growth, featured as the fourth best performing variable in the binary TreeNet® model, is ranked seventh in the five-state TreeNet® model. Net profit margin ranks fifth in the binary TreeNet®model; however, it is the third contributing variable in the five-state TreeNet® model. Despite return on assets being the second best performing variable in the five-state TreeNet® model, it ranks in eighth place in the binary TreeNet® model. While executive compensation of the top 3 executives is featured in sixth place in the five-state TreeNet® model, it ranks in tenth place in the RVI rankings of the binary TreeNet® model. Three variables that do not feature significantly in the five-state TreeNet® model but that appear as top performing variables in the binary TreeNet® model are registered unemployment rate in urban areas, three year growth in equity, and one year growth in earnings per share. On the other hand, variables that are not featured strongly in the binary TreeNet® model but that appear as top performing variables in the five-state TreeNet® model are market capitalisation to total debt, accounts payable to total liabilities, and sales to total assets.

In comparison with the RVI results from the five-state TreeNet® model, the top ten contributing variables of the the binary TreeNet® model are more similar to those of the three-state TreeNet® model. The rankings of the top three most contributing variables (market capitalisation, equally weighted annual market returns, and retained earnings to total assets) are the same in both the binary TreeNet® model and three-state TreeNet® model. While net profit margin ranks in fifth place in the binary TreeNet® model, it ranks in eighth place in the three-state TreeNet® model. Registered unemployment rate in urban areas ranks in sixth place in both the binary TreeNet® model and the three-state TreeNet® model. Despite return on assets being featured as the eighth best performing variable in the binary TreeNet® model, it ranks in seventh place in the three-state TreeNet® model. Executive compensation of the top 3 executives is ranked in tenth place in the RVI rankings of both the the binary TreeNet® model and three-state TreeNet® model. Three variables that are not featured significantly in the three-state TreeNet® model but that appear as top performing variables in the binary TreeNet® model are GDP growth, three year growth in equity, and one year growth in earnings per share. On the other hand, variables that are not featured strongly in the binary TreeNet® model but that appear as top performing variables in the three-state TreeNet® model are market capitalisation to total debt, return on equity, and accounts payables to total liabilities. It is noted that market capitalisation to total debt and accounts payable to total liabilities are two variables that are not featured strongly in the binary TreeNet® model but that appear as two of the top 10 best performing variables in both the five-state TreeNet® model and three-state TreeNet® model.

The relative variable importances (RVIs) of the five-state, three-state, and binary TreeNet® models all confirm the high dimensional nature of corporate financial distress observable across Chinese listed companies. This is again evidenced by the fact that the RVI scores are mostly nonzero and appear reasonably well dispersed across a range of different predictor categories. As there are several different dimensions of corporate financial distress, the RVIs of the five-state, three-state, and binary TreeNet® models indicate that a prediction model that combines different categories of predictor variables might provide better predictive results than a model concentrating solely on a single type of variable such as accounting-based variables. This finding is consistent with prior research by Xie, Luo, and Yu (2011) and Wang and Li (2007) that there are different dimensions of corporate financial distress in China and prediction models that combine financial and non-financial variables provide better predictive results than models estimated on financial variables only. To date, the majority of Chinese distress prediction studies have developed prediction models based only on financial variables. The high dimensional nature of corporate financial distress in China as evidenced in both the binary and multi-class prediction cases suggests that variables from other dimensions such as market-price variables, macroeconomic variables and shareholder ownership/control variables may also provide explanatory and predictive power in the Chinese setting.

In terms of the predictive performance of accounting-based versus market-price indicators in the context of China, very limited research effort has been devoted to examining this issue. The average RVI results from the five-state TreeNet® model, three-state TreeNet® model, and binary TreeNet® model all indicate that market-price indicators significantly outperform accounting-based variables in terms of Chinese distress prediction. This finding that market-price variables contribute more predictive power than accounting-based variables in Chinese distress prediction contradicts the finding of Kim, Ma, and Zhou (2016). As discussed in Section 3.4.1, in the turnaround prediction of ST firms, Kim, Ma, and Zhou (2016) suggest that non-accounting variables such as market-driven and institutional variables do not provide incremental predictive power in determining the turnaround probability of ST firms. They further conclude that accounting-based variables are the most influential predictors in predicting the turnaround probability for a distressed firm to get their ST status revoked and return to normal listing status (Kim, Ma, and Zhou, 2016). However, it is noted that according to the ST regime on China's stock market, ST companies cannot be restated to normal trading status unless they return to profitability. Because the determinant of the turnaround probability of ST firms is profitability, which is directly reflected in companies' financial statements, the finding of Kim, Ma, and Zhou (2016) that accounting-based variables are the most influential predictors in predicting the turnaround probability of ST firms make sense. On the other hand, listed companies can get into ST status for a number of reasons, such as poor financial performance, financial abnormality, and other events.

One possible explanation of the relatively lower predictive ability of accounting-based predictors as identified in the current study is that accounting-based variables are sourced from financial statements that tend to be manipulated in order to conceal financial problems. As a consequence, the manipulated financial ratios carry less information about the company and therefore reduce the value relevance of accounting-based variables in distress prediction. Given the unique features of the Special Treatment policy on the Chinese stock exchanges, empirical evidence indicates that listed companies tend to engage in earnings manipulation when they are confronted with the risk of being delisted (Jiang and Wang, 2008; Chen, Chen, and Huang, 2010; Yang, Chi, and Young, 2012). Similar findings have also been found in Taiwan-listed companies where manipulated financial variables carry less information about the underlying performance of the company and therefore lack predictive power of financial distress. In Tsai (2013) a multinomial logit model is estimated to measure the extent to which financial ratios and corporate governance factors predict financial distress in Taiwan-listed companies. Financial distress is defined as two states: slight distress events and reorganisation and bankruptcy events. The findings of Tsai (2013) suggest that financial ratios are more predictive of reorganisation and bankruptcy events than slight distress events whereas corporate governance variables are more predictive of slight distress events than reorganisation and bankruptcy events.

Managers tend to manipulate financial statements to conceal slight financial difficulties and therefore financial variables do not truly reflect the underlying performance of the company and are less predictive of slight distress events. However, managers are largely unable to manipulate financial statements to conceal prominent operational deteriorations that signal serious financial crisis prior to the occurrence of reorganisation and bankruptcy events (Tsai, 2013).

7.4.2 Predictive performance of the binary versus multi-state TreeNet® models

There are only two types of misclassification errors in the binary prediction setting; however, as has explained in Section 7.2.2 and Section 7.3.2, a five-state model permits 20 types of misclassification errors and a three-state model permits 6 types of misclassification errors. This implies that the predictive performance of the binary TreeNet® model is not directly comparable to the predictive results of the three-state and five-state TreeNet® models (Lau, 1987; Johnsen and Melicher, 1994). However, following the approach of Cortes, Martinez, and Rubio (2007), a more meaningful comparison can be made between the predictive results of the binary TreeNet® model as reported in Table 6.2, the five-state TreeNet® model (if analysed from a binary prediction perspective by combining state 1 to state 4 distress classes as one distressed state) and the three-state TreeNet® model (if analysed from a binary prediction perspective by combining state 1 and state 2 distress classes as one distress class).

The predictive performance of the multi-state TreeNet® models if analysed from a binary prediction perspective is reported in Table 7.7 for the five-state TreeNet® model and Table 7.8 for the three-state TreeNet® model. From Table 7.7, if Table 7.2 were to be analysed from a binary prediction viewpoint, the model is 93.03 percent accurate in predicting distress (a Type I error rate of 6.97 percent) and 94.47 percent accurate in predicting active/healthy companies (a Type II error rate of 5.53 percent). From Table 7.8, if Table 7.5 were to be analysed from a binary prediction viewpoint, the model is 89.90 percent accurate in predicting distress (a Type I error rate of 10.1 percent) and 96.82 percent accurate in predicting active/healthy companies (a Type II error rate of 3.18 percent). Recall that from Table 6.2, the binary TreeNet® model is 93.74 percent accurate in predicting distress (a Type I error rate of 6.26 percent) and 94.81 percent accurate in predicting active/healthy companies (a Type II error rate of 5.19 percent). Therefore, the predictive performance of the five-state and three-state TreeNet® models if analysed from a binary prediction perspective is quite comparable to the predictive performance of the binary TreeNet® model.

The results in Table 7.7 indicate that the majority of misclassification errors in the five-state TreeNet® model are attributable to the fact that it is extremely difficult to discriminate among state 1 to state 4 distress classes. Similarly, the results in Table 7.8 indicate that the majority of misclassification errors in the three-state TreeNet® model are attributable to the fact that it is extremely difficult to discriminate between state 1 and state 2 distress. This finding confirms that the majority of the misclassification errors in the multi-state TreeNet® models are attributable to the fact that it is extremely difficult to discriminate among distress states. Both the multi-state TreeNet® models and binary TreeNet® model have excellent predictive power in distinguishing between 'healthy' and 'distressed' groups. Zhou, Tam, and Fujita (2016) find that that in comparison with distinguishing between ST (companies with other risk warnings) and healthy companies and *ST companies (companies with delisting risk warnings) and healthy companies, it is more difficult to distinguish the ST and *ST companies.

Notwithstanding the predictive performance of distress prediction models, as Jones and Hensher (2007) suggest some emphasis should also be placed on the theoretical and explanatory values of the multi-state models. In the distress prediction literature, to date a large number of studies have modelled distress in terms of a dichotomous bankrupt or non-bankrupt response measure. Nonetheless, according to Ward (1994, p. 548), 'a dichotomous measurement of financial distress is an overly simple representation of the financial distress process and is unlikely to capture the true underlying construct'. The financial health of companies cannot be simply classified as bankrupt or non-bankrupt. Indeed, firms possess certain degrees of financial distress that vary over time (Ward, 1994). Multi-state distress prediction models that define distress in terms of different severity levels of financial distress can better approximate the continuum of corporate financial health (Lau, 1987). Furthermore, in the setting of the Chinese stock market, companies with different levels of severity of financial distress are associated with different levels of risks, such as volatility risks, liquidity risks and delisting risks (Zhou, Tam, and Fujita, 2016). Predicting the likelihood that a listed company will enter different distress states could help investors to manage stock portfolio risk and assist creditors suppliers and customers to better evaluate a company's credit risk (Zhou, Tam, and Fujita, 2016).

TABLE 7.7: Confusion matrix – test sample by joining state 1 to state 4 (five-state model)

Actual class	**Total class**	**Percent correct**	**Predicted class**	
			0	1
			N=2306	N=786
0	2389	94.47%	2257	132
1	703	93.03%	49	654
Total	3092			

TABLE 7.8: Confusion matrix – test sample by joining state 1 and state 2 (three-state model)

Actual class	Total class	Percent correct	Predicted class	
			0	1
			N=2384	N=708
0	2389	96.82%	2313	76
1	703	89.90%	71	632
Total	3092			

7.5 Chapter conclusion

The empirical results of the multi-class TreeNet® models including the empirical results of the five-state TreeNet® model and three-state TreeNet® model have been examined in this chapter. The multi-state TreeNet® models are interpreted through several outputs, such as relative variable importances (RVIs), the confusion matrix, average log-likelihood, area under the ROC curve (AUC), and prediction accuracy based on the baseline threshold. After presenting the empirical results of the binary TreeNet® model (in Chapter 6), three-state TreeNet® model, and five-state TreeNet® model, a comparison is made between the empirical results of the the binary and multi-state TreeNet® models.

In the five-state TreeNet® model, 89 out of 94 predictor variables have nonzero RVI, which indicates that all 89 input variables contribute to the out-of-sample predictive performance in some way, although the predictive strength of different predictors varies. From the RVIs measure, which rank orders variables according to each predictor variable's contribution to the overall predictive success of the TreeNet® model, a diverse range of predictor variables dominate the model, reflecting different dimensions of corporate financial distress in China. The predictor variables which feature most strongly in the five-state TreeNet® analysis (RVIs $>$ 40) include: (1) market-price variables including market capitalisation, annual market returns, and market capitalisation to total debt; (2) a range of accounting-based variables and financial ratios including return on assets, net profit margin, retained earnings to total assets, accounts payable to total liabilities, sales to total assets, intangible assets to total assets, inventory turnover, total assets, and return on equity; (3) executive compensation measures including total executive compensation (top 3 executives) and total director compensation (top 3 directors); and (4) macroeconomic variables such as GDP growth.

The overall prediction accuracy of the five-state TreeNet® model is 85.77 percent. The five-state TreeNet® model is 94.47 percent accurate in predicting active or healthy companies using baseline threshold as the cut-off score; 61.70 percent accurate in predicting state 1 distress (ST=1); 53.12 percent accurate in predicting state 2 distress (1$<$ ST $<$4); 62.56 percent accurate in predicting state 3 distress (ST $\geq$ 4); and 51.72 percent accurate in predicting state 4 distress (delisted). Following the approach of Cortes, Martinez, and Rubio (2007), if the five-state TreeNet® model is analysed from a binary classification viewpoint, the model is 93.03 percent accurate in predicting distress (a Type I error rate of 6.97 percent) and 94.47 percent accurate in predicting active/healthy companies (a Type II error rate of 5.53 percent).

In the three-state TreeNet® model, 85 out of 94 predictor variables have nonzero RVI scores, which indicates that that all 85 input variables contribute to the out-of-sample predictive performance of the three-state TreeNet® model in some way, although the predictive strength of different predictors varies. The predictor variables that feature most strongly in the three-state TreeNet® analysis (RVIs $>$ 20) include: (1) market-price variables including market capitalisation, annual market returns, and market capitalisation to total debt; (2) a range of accounting-based variables and financial ratios including retained earnings to total assets, return on equity, return on assets, net profit margin, accounts payable to total liabilities, total assets, total operating revenue, debt to tangible assets, intangible assets to total assets, cash to current liabilities, and three year growth in equity; (3) macroeconomic variables such as registered unemployment rate, and GDP growth; (4) executive compensation measures including total executive compensation (top 3 executives) and total director compensation (top 3 directors); and (5) a variable concerning corporate governance, namely Chairman and general manager concurrent.

The overall prediction accuracy of the three-state TreeNet® model is 92.08 percent. The three-state TreeNet® model is 96.82 percent accurate in predicting active or healthy companies using the baseline threshold as the cut-off score; 76.49 percent accurate in predicting state 1 distress (ST=1); and 73.28 percent accurate in predicting state 2 distress ($ST > 1$). Following the approach of Cortes, Martinez, and Rubio (2007), if the three-state TreeNet® model is analysed from a binary classification viewpoint, the model is 89.90 percent accurate in predicting distress (a Type I error rate of 10.1 percent) and 96.82 percent accurate in predicting active/healthy companies (a Type II error rate of 3.18 percent).

After comparing the predictive results of the the binary and multi-state TreeNet® models, this chapter reveals that the predictive performance of the five-state and three-state TreeNet® models if analysed from a binary prediction perspective is quite comparable to the predictive performance of the binary TreeNet® model. This indicates that the majority of the misclassification errors in the multi-state TreeNet® models are attributable to the fact that it is extremely difficult to discriminate among distress states. Despite the model predictive performance, Jones and Hensher (2007) suggest that some emphasis should also be placed on the theoretical and explanatory values of the multi-state models. Multi-state distress prediction models that define distress in terms of different distress states could better approximate the continuum of corporate financial health (Lau, 1987), as companies are not simply healthy or distressed but possess certain degrees of financial distress that vary over time (Ward, 1994).

Chapter 8

Conclusions

8.1 Chapter introduction

Chapter 1 provided an introduction and background to this thesis. In particular, Chapter 1 highlighted China's unique historical, institutional, and socio-political background that is distinctive from that of Western economies. Given China's historical, social, and cultural intolerance towards corporate failure, explored in Chapter 2 together with the legislative development of the bankruptcy law in China, this thesis models corporate financial distress in China based on the Special Treatment (ST) system. Chapter 3 reviewed prior literature by four themes – developments in distress prediction modelling, alternative distress predictors, research on multi-state distress prediction, and research on Chinese distress prediction. This discussion confirmed the choice of the TreeNet® as the appropriate empirical framework for this study, which was further explored in Chapter 4 in addition to a description of the data and variable definitions used in this thesis. The discussion of alternative distress predictors provided motivation for variable selection of this thesis. The review of prior Chinese distress prediction studies revealed some limitations that this thesis overcomes. The empirical findings of this thesis were presented in Chapters 5 –

7. Chapter 5 described summary statistics of the study sample, which forms the basis of analysis of the empirical results in Chapter 6 and Chapter 7 of this thesis. Chapter 6 presented the empirical results of the binary TreeNet® model, while Chapter 7 presented the empirical results of the five-state TreeNet® model and three-state TreeNet® model. After presenting the empirical results of the binary and multi-state TreeNet® models, some comparisons among the binary, five-state and three-state TreeNet® models are also provided in Chapter 7.

This final chapter (Chapter 8) of the thesis provides a summary and concluding remarks. Section 8.2 summarises the research setting of this thesis. As this thesis models corporate financial distress in China based on its unique Special Treatment (ST) system, Section 8.3 revisits the ST system unique to the Chinese context. Section 8.4 summarises the research design of this thesis, followed by the empirical findings in Section 8.5. Section 8.6 summarises the main contributions of this thesis. This thesis concludes with a discussion of limitations as well as directions for future research in Section 8.7.

8.2 Summary of research setting

The research setting of the current study is China. Unlike the New York Stock Exchange (NYSE) that has a long trading history dating back to 1908, the Chinese stock market was only recently established at the end of 1990 under the guidelines of Deng Xiaoping Theory following China's economic reform and opening-up. In contrast to the Western notion of bankruptcy, China as a socialist economy is more concerned with maintaining social stability and employment (Jiang, 2014). Given China's historical, social and cultural intolerance towards corporate failure, there have been few bankruptcies and liquidations. To protect domestic and overseas investors' interests, the 'Chinese equivalent of U.S. Chapter 11', namely the Special Treatment (ST) system was introduced in 1998 with an aim to identify distressed companies and provide investors and creditors with an early warning system. Despite the implementation of the ST system, the annual average delisting rate of China's stock market is only 2 percent, which is significantly lower than that of NYSE (6 percent), NASDAQ (8 percent) and AIM (12 percent) (Cheng, 2014). The low delisting rates on China's stock market may indicate some implementation problems of the ST system. In addition, there are also a series of other problems underlying the recently established China's stock market, such as insider trading, financial fraud, market manipulation, and excessive speculation (Cheng, 2014). Due to the loosely implemented ST system and other problems of the stock market, corporate distress prediction modelling in the Chinese context not only appeals to investors and creditors for risk management purposes, but it also appeals to regulators and practitioners due to its policy ramifications.

Given China's growing importance in the world economy and the relevance of distress prediction in the Chinese context, this study has been undertaken with four main research objectives. First, considering the social and cultural complexities of the Chinese system of corporate failure, it attempts to develop a class of accurate distress prediction models based on China's unique Special Treatment system. The distress prediction models in this study have been estimated on a large sample of Chinese corporate financial distress data. The sample of this study includes all listed companies on both the Shanghai and Shenzhen stock exchange from 1998 to 2016. Second, in addition to conventional binary distress modelling setting, this study also aims to model corporate financial distress in a multi-state setting. Although the relevance and utility of multi-state distress prediction models has been largely appreciated, to date very limited research effort has been devoted to developing such models. Unlike binary distress prediction models that are subject to oversimplification of the underlying economic reality of firms, multi-state models can better approximate the continuum of corporate financial health observable across Chinese listed companies. Third, this study is also designed to examine the predictive and explanatory power of a wide range of financial and non-financial variables, including accounting-based variables, market-price indicators, shareholder ownership/concentration variables, corporate governance proxies, macroeconomic variables, executive compensation variables, corporate social responsibility (CSR) variables, valuation multiples, industry background, and other variables. A large number of studies in the distress prediction literature have focused solely on the predictive ability of accounting-based measures. This is especially the case with regards to Chinese distress prediction research. This study evaluates and compares how well these 'Western-style' bankruptcy predictor variables apply to the unique context of China's ST system. Finally, following the approach of Jones (2017), this study employs an advanced machine learning technique – TreeNet Gradient Boosting Machine (TreeNet®) to examine the predictive performance of over 90 financial and non-financial variables. TreeNet® is one of the most powerful commercial machine learning models available and it is particularly useful for empirical investigations that involve large numbers of input variables (Hastie, Tibshirani, and Friedman, 2009; Jones, 2017).

8.3 The Special Treatment regime revisited

Unlike Western economies such as the U.S. and Eurozone, China as the largest developing country has a unique institutional cultural and socio-political background. These distinctive features of the Chinese economy are what make the current Chinese distress modelling study novel in the distress prediction literature, as the majority of the literature focuses on a Western economy perspective. Arguably one of the most distinct features of the Chinese economy in comparison with Western countries is the Special Treatment (ST) system. Despite some recent bankruptcy reforms, the Chinese bankruptcy regime is considerably less developed than other major industrialised nations. In fact, one of the most important issues that has hindered the bankruptcy law development is the concern of social disruption through displacement of workers in bankrupt SOEs. To date, there have been few bankruptcies and liquidations in China. The most important reason for China's inactive bankruptcy practices is that the Communist government prioritises the maintenance of social stability, taking collectivist approaches over individual concerns, and allocating more power to the courts and government in such disputes (Jiang, 2014). China is still strongly influenced by the communist ideology, a philosophy that commits to a fully employed and egalitarian society.

Given the historical, social, and cultural complexities of the Chinese system of corporate failure, this study models distress according to China's unique Special Treatment (ST) system. The ST system has been enforced in China's stock market since 1998 with a major objective to identify and single out poorly performing stocks as an early warning signal to firms, investors, and creditors. Under the ST system, the China securities regulatory commission (CSRC) assigns ST status to listed companies for poor financial performance, financial abnormality, and other events. Companies with ST status face a two-way street. They must either take remedial action to have their ST status revoked (and return to normal listing status), or face delisting as a result of persistent financial distress. Another important objective of the ST system is to provide a regulatory mechanism by which struggling companies can improve their performance over time. Usually companies with ST status adopt a series of restructure and/or reorganisation programs to improve their financial health so that they can retrieve normal listing status.

Arguably there exists a unique 'Chinese phenomenon' behind the ST regime that not only the management of ST companies but also external parties (such as the provincial government and other private companies wishing to go public) are strongly motivated to bail out financially struggling ST companies. There are at least three important reasons behind bailing out ST companies. First, ST companies are usually rescued through support from their SOE backed parent companies or bailouts from state-owned banks. Second, a number of capital hungry companies wishing to be publicly listed find ST firms attractive for merger or acquisition purposes, as listing through a 'shell' purchase provides a path to access China's capital markets due to China's highly competitive Initial Public Offering (IPO) regime. ST firms are usually perceived as profitable investment targets by investors and valuable 'shell' opportunities by other non-listed companies. Finally, bailing out ST companies can help maintain employment and stimulate local economic growth and development (Kim, Ma, and Zhou, 2016), a reflection of the administrative ability and political achievement of provincial government officials.

In comparison with distress prediction modelling studies undertaken from developed economies' perspectives, dating back to at least the 1930s (see e.g., Fitzpatrick (1932)), similar studies are of relatively recent origin in China. The history of Chinese distress prediction modelling is less than 20 years, with one of the first studies appearing in 1999 (see e.g., Chen (1999)). The main reasons for the late start of Chinese distress prediction modelling is attributable to a lack of proper market exit mechanisms and bankruptcy regulations that lagged behind real-world practice. Arguably the ST system remedies such a situation by providing a regulatory mechanism through which distressed companies can be suspended and terminated and viable companies can improve their financial performance and return to normal listing status. More importantly, the ST system provides a useful framework for the development of Chinese distress modelling studies. This is especially meaningful considering China's historical, social, and cultural intolerance towards corporate failure as a result of the government's collectivist priorities for social stability and full employment.

8.4 Summary of research design

After an extensive review of the financial distress prediction literature in Chapter 3, this study has identified how distress prediction modelling techniques have evolved over time from simple statistical methods (such as MDA and logit) to conventional machine learning models (such as NN and SVM) and then to more advanced 'new age' machine learning techniques (such as boosting and random forest). With the evolution of distress prediction modelling techniques, some strict assumptions of statistical models that are difficult to meet in practice, such as independent and identically distributed (IID) errors and independence of irrelative alternatives (IIA), are gradually relaxed with the development of machine learning techniques. One important issue associated with conventional statistical methods such as logit is that they use maximum likelihood to optimise parameters jointly, which implies that conventional statistical models are generally only capable of handling a small number of variables because too many variables usually leads to model overfitting that reduces the overall validity of the model (Jones, 2017). As statistical distress prediction models become unstable as the number of predictor variables increase, they are not suitable for the current study which aims to evaluate and compare how well over 90 'Western-style' bankruptcy predictor variables apply to the unique context of China's ST system.

The TreeNet® model has been selected as the empirical framework of this thesis among numerous machine learning techniques because it has several appealing properties that are best suited to fulfilling the research objectives of this thesis. First, the TreeNet® model provides an effective method for comparing the predictive performance of a wide range of financial and non-financial predictors in a single statistical framework. Rather than optimising parameters jointly, the predictive ability of TreeNet® is achieved through a stage-wise process by optimising parameters one at a time (Jones, 2017). In this way, TreeNet® provides very accurate prediction outcomes while remaining highly resilient to model over-fitting (Friedman, 2001; Schapire and Freund, 2012). Second, unlike other machine learning models that generally suffer from the ‘black box’ criticism as a result of a lack of interpretability, the TreeNet® model provides outputs which allow the researcher to see through the ‘black box’, particularly through relative variable importances (RVIs) and partial dependence plots (or marginal effects). The RVI metrics rank order all input variables based on their relative contribution to the overall predictive success of the model. The RVI metrics are useful for evaluating the predictive power of alternative distress predictors. In addition, the RVI metrics also help identify non-conventional distress predictors not widely explored in prior literature. Partial dependence analysis shows the direction of a predictor variable’s influence (whether positive or negative) on the dependent variable as well as the magnitude of the effect. Third, as the TreeNet® model is not restricted to binary settings, it can be applied to model corporate financial distress in a multi-state setting.

Another theme in the distress prediction modelling literature relates to the role and predictive power of alternative distress predictors. In addition to financial indicators, Jones (2017) finds that many non-conventional bankruptcy predictors, especially some non-financial measures, such as market-price indicators, shareholder ownership/ concentration variables, executive compensation measures, macroeconomic variables and other variables also have a high degree of predictive power in bankruptcy prediction. However, to date the majority of Chinese distress prediction studies have only investigated a limited range of financial predictor variables. The predictive performance of non-financial variables has attracted little research attention in the context of Chinese distress prediction modelling. A wide range of financial and non-financial variables such as accounting-based variables, market-price indicators, shareholder ownership/concentration variables, corporate governance proxies, macroeconomic variables, executive compensation variables, corporate social responsibility (CSR) variables, valuation multiples, industry background, and other variables have been examined in this thesis, which arguably captures more comprehensive dimensions of corporate financial health of listed companies on China's stock exchange than financial variables alone.

Chapter 3 of this thesis also reviewed recent studies on Chinese distress prediction modelling. In comparison with the development of distress prediction modelling in Western countries, Chinese distress prediction modelling is of very recent origin, with one of the first studies only appearing in 1999. As a consequence of the limited research attention on Chinese distress prediction modelling, it has been 'under-researched' with some limitations that the current study overcomes. First, the majority of Chinese distress prediction studies have relied on matched-pair sample selection design, which can result in choice-based sample biases, overstated parameters, and misleading classification accuracy. Second, many Chinese distress prediction models have been estimated on small sample sizes, which can limit generalisability. In the Chinese distress modelling literature, the sample period usually only spans three to five years, which represents a short sample period for an adequate distress sample. However, it is noted that the issue with small sample size and short sample period is to some extent unavoidable in Chinese distress prediction modelling as the ST system was only introduced in 1998 and it has taken some years for an adequate sample of Chinese ST firms to emerge. As discussed in Chapter 4, this study uses a much larger sample drawn over a longer time frame (over 18 years). The sample of this study includes all listed companies on both the Shanghai (SSE) and Shenzhen stock exchange (SZSE) from 1998 to 2016. Up to five annual reporting periods of data are collected on all ST firms prior to their first year of ST designation. The same procedure is applied to the control (healthy/active) group from the most recent year.

8.5 Empirical findings of this thesis

In the unique Chinese setting where the Chinese system of corporate failure is distinct from the bankruptcy system of Western economies, empirical findings are gathered in Chapter 5, Chapter 6, and Chapter 7 of this thesis. The preliminary empirical findings are presented in Chapter 5, detailing the descriptive statistics. Chapter 5 not only provided some insightful information on some of the early symptoms of financial distress among Chinese listed companies, it also formed the basis of analysis of the empirical results in Chapter 6 and Chapter 7 of this thesis. The analysis of how distress symptoms have developed over time sheds light on the usefulness of predictor variables as early warning signals of financial distress in China. It is important to understand the development of distress symptoms over time as this can assist the diagnosis of Chinese financial distress from an early stage. Although some distressed firms begin to show distress symptoms as early as five years prior to the occurrence of the distress event, on average, the distress symptoms become more prominent from 3 years prior to the distress event onwards (from t-3 to t-0) in the sample. Generally speaking, some early warning signals of financial distress include a sharp decrease in return on assets, the ratio of retained earnings to total assets, and the ratio of working capital to total assets. Furthermore, the early symptoms of financial distress also include a gradual decline in the current ratio, the ratio of cash resources to total assets, and the ratio of sales to total assets. In comparison with the active group, on average the distressed group is less profitable and less liquid. In addition, the distressed group tends to rely excessively on debt financing and they hold significantly less cash resources on hand.

Independent sample t-tests for equality of means between the active and distressed group was also conducted in Chapter 5. Statistically significant differences have been found between the active and distressed group in the majority of firm-specific predictor variables. The relative role and performance of over 90 financial and non-financial predictor variables are further explored in Chapter 6 and Chapter 7 using TreeNet® model as the empirical framework from binary and multi-state distress modelling perspectives. Overall, from the the independent sample t-tests, the distressed group have lower operating cash flow per share, lower ROA, significantly lower retained earnings to total asset ratio, lower cash flow returns to total assets, lower current ratio, higher debt to asset ratio, significantly lower cash resources to total assets ratio, lower asset turnover ratio, and significantly lower working capital to total asset ratio. In comparison with the active group, the distressed group also have significantly higher levels of state owned shares to total shares out- standing, lower percentage of shares held by institutions/funds, higher percentage of shares held by brokers, lower social contribution value per share, lower social donations, higher levels of earnings management, and higher annual market returns.

While Chapter 6 presented the empirical results of the binary TreeNet® model, the empirical results of the five-state TreeNet® model and three-state TreeNet® model are presented in Chapter 7. All data for this study has been collected from the China Stock Market & Accounting Research (CSMAR) database. The sample of this study included a total of 15,504 firm-year observations (12,156 active firm years and 3348 distressed firm years) between the sample period of 1998 and 2016. In comparison with previous Chinese distress prediction studies, the TreeNet® models of the current study have been estimated on a significantly larger distressed sample which spans over as long as 18 years. In this study, the TreeNet® algorithm randomly allocates 80% of the sampled observations for model estimation and 20% of the sampled observations to the test sample (or holdout sample).

Arguably one of the most important outputs of the TreeNet® model is the Relative

Variable Importance (RVI) metrics from which the relative role and performance of different input variables can be determined. In the RVIs measure, each predictor variable is rank ordered based on its weighted classification accuracy averaged across all predictors in the model. The variable that contributed the most predictive power to the overall prediction accuracy is scored 100 and all other variables are scored relative to the top performing predictor. Variables with lower RVIs add little to the model's overall prediction power in comparison with variables with higher RVIs. In addition to the RVI metrics, confusion matrix and summary of predictive performance of the TreeNet® models have also been presented. In addition to the predictive performance of the TreeNet® models based on pooling all sampled observations, it is equally important to evaluate how far ahead the model can predict Chinese financial distress with acceptable discrimination. As such, predictive performance of the TreeNet® models is also estimated on t-1 data (one year prior to the distress event), t-3 data (three years prior to the distress event), and t-5 data (five years prior to the distress event), respectively.

From Chapter 6 and Chapter 7, the empirical results from the binary TreeNet® model, five-state TreeNet® model, and three-state TreeNet® model all support the high dimensional nature of corporate financial distress observable across Chinese listed companies. The high dimensional nature of Chinese financial distress is evidenced by mostly nonzero RVI scores which appear to be reasonably dispersed across a range of different predictor categories. The high dimensional nature of Chinese financial distress also suggest that variables from dimensions other than financial ratios such as market-price variables, executive compensation variables, macroeconomic variables, and shareholder ownership/control variables also provide explanatory and predictive power in the Chinese setting. Furthermore, the empirical results from TreeNet® models also confirm that a wide range of financial and non-financial 'Western-style' bankruptcy predictors are also fairly predictive of corporate financial distress in China.

From the analysis of RVIs of the binary TreeNet® model, three state TreeNet® model and five-state TreeNet® model, variables with the strongest predictive value included: (i) market-price variables, particularly market capitalisation and annual market returns; (ii) executive compensation measures, such as total compensation of the top three executives and total compensation to the top three directors; (iii) macroeconomic variables, notably GDP growth, GDP per capita, and unemployment rates; (iv) financial variables, particularly retained earnings to total assets, net profit margin, ROA, ROE, and market capitalisation to total debt; and (v) shareholder ownership/concentration, notably percentage of shares held by insiders. In terms of the predictive performance of accounting-based variables versus market-price indicators in the context of Chinese financial distress prediction, the average RVI results from the binary, three-state, and five-state TreeNet® models all indicate that market-price indicators significantly outperform accounting-based variables in the Chinese setting. Given the unique features of the Special Treatment system on the Chinese stock exchanges, one possible explanation of the relatively lower predictive ability of accounting-based predictors is that financial statements tend to be manipulated in order to conceal financial problems. As empirical research reveals that Chinese listed companies tend to engage in earnings manipulation when facing the risk of being delisted, the value relevance of accounting-based variables in Chinese distress prediction is therefore reduced.

Based on the large sample of ST events, the TreeNet® models have produced very accurate out-of-sample prediction results. Based on pooled observations and assigning 20 percent of observations to the test (holdout) sample, the overall prediction accuracy of the binary TreeNet® model is 94.57 percent using baseline threshold as the cut-off score. The binary TreeNet® model is 93.74 percent accurate in predicting distress (a Type I error rate of 6.26 percent) and 94.81 percent accurate in predicting active/healthy companies (a Type II error rate of 5.19 percent). The overall prediction accuracy of the three-state

TreeNet® model is 92.08 percent. The three-state TreeNet® model is 96.82 percent accurate in predicting active or healthy companies; 76.49 percent accurate in predicting state 1 distress (ST=1); and 73.28 percent accurate in predicting state 2 distress (ST $>$ 1). The overall prediction accuracy of the five-state TreeNet® model is 85.77 percent. The five-state TreeNet® model is 94.47 percent accurate in predicting active or healthy companies; 61.70 percent accurate in predicting state 1 distress (ST=1); 53.12 percent accurate in predicting state 2 distress (1$<$ ST $<$4); 62.56 percent accurate in predicting state 3 distress (ST $\geq$ 4); and 51.72 percent accurate in predicting state 4 distress (delisted).

Despite the predictive success of the binary TreeNet® model, which seems to be significantly better than that of the three-state and five-state TreeNet® models, it is noted that the predictive results of the binary distress prediction models are not directly comparable to the predictive results of multi-state models. This is because the number of possible misclassification errors is notably larger in multi-state models than in binary models, which implies that a case could be far more easily misclassified in a multi-state prediction model than in a binary prediction model. While binary predictive models permit only two types of misclassification errors, five-state models permit twenty types of misclassification errors and three-state models permit six types of misclassification errors as has discussed in Chapter 7.

Following the approach of Cortes, Martinez, and Rubio (2007), a more meaningful comparison can be made among the predictive results of the binary TreeNet® model, three-state TreeNet® model, and five-state TreeNet® model if the predictive results of the multi-state TreeNet® models are analysed from a binary prediction point of view. The five-state TreeNet® model can be analysed from a binary prediction perspective by combining state 1 to state 4 distress classes as one distressed state, whereas the three-state

TreeNet® model can be analysed from a binary classification perspective by combining state 1 and state 2 as one distress class. As reported in Chapter 7, if the five-state TreeNet® model is analysed from a binary classification viewpoint, the model is 93.03 percent accurate in predicting distress (a Type I error rate of 6.97 percent) and 94.47 percent accurate in predicting active/healthy companies (a Type II error rate of 5.53 percent). Similarly, if the three-state TreeNet® model is analysed from a binary classification viewpoint, the model is 89.90 percent accurate in predicting distress (a Type I error rate of 10.1 percent) and 96.82 percent accurate in predicting active/healthy companies (a Type II error rate of 3.18 percent). This comparison confirms that the majority of the misclassification errors in the multi-state TreeNet® models are attributable to difficulties in discriminating among distress states. Overall, both the multi-state TreeNet® models and binary TreeNet® model have excellent predictive power in distinguishing between 'healthy' and 'distress' groups.

Having established that the TreeNet® models produced very accurate out-of-sample predictive results, it is also important to assess whether the explanatory variables make sense in terms of their influence on the distress outcome. The RVIs are scalars that measure the predictive ability of explanatory variables on the overall model classification success; however, they provide no indication of the direction of the explanatory variable on the distress outcome. Chapter 6 provided the results of partial dependence analysis on several variables from the binary TreeNet® model. Analysis of the partial dependency plots (marginal effects) indicated that many of the predictor variables have nonlinear relationships with the distress outcome. While the broad directions of the partial dependency plots seem both logical and interpretable in the majority of cases, there are also several significant tensions in the results.

One of the tensions in partial dependence analysis is annual market returns, which appear to increase in the direction of higher distress probabilities. One possible explanation of the higher market returns in distressed firms is that ST firms are attractive investment targets as the majority of ST companies resume normal trading status within 2 to 3 years. In fact, ST companies are often rescued by administrative interventions such as through support from their SOE backed parent companies or bailouts from state-owned banks. In addition, ST companies are also attractive investment targets by other non-listed companies wishing to go public via a 'shell' purchase. The 'shell' value of ST companies represents the valuable stock listing right as a result of China's highly competitive and highly strict IPO scheme. Another tension in partial dependence analysis is that GDP growth appears to increase with the probability of distress. This again is somewhat counter intuitive as strong GDP growth is generally expected to lead to a lower incidence of corporate distress. One of the possible explanations is that because the reported GDP numbers from China remain unreliable and are possibly severely overstated due to the challenges in effectively capturing GDP growth in transitioning China, this marginal effect is at least partially spurious and may not truly reflect the underlying influence. Another potential explanation is that high GDP growth itself 'contributes' to more economic distress such as capital reallocation away from the manufacturing and infrastructure sectors to the services sector as the Chinese economy transitions to a services based economy.

8.6 Summary of contributions of this thesis

This study has three key contributions. First, it extends the growing literature on corporate financial distress prediction by considering the case of China, where the institutional background is distinctly different from that of Western economies and there is historical social and cultural intolerance towards corporate failure. The class of financial distress prediction models developed in this thesis based on the unique ST system adds a novel dimension to the current financial distress prediction literature. Second, it also contributes to the distress prediction literature by comparing and evaluating the predictive and explanatory power of a large number of 'Western-style' bankruptcy predictor variables based on China's unique ST system. In addition to the conventional accounting-based variables and market-price indicators, this study also includes a wide range of 'non-conventional' bankruptcy predictor variables, such as corporate governance proxies, ownership concentration/control variables, macroeconomic variables, executive compensation variables, corporate social responsibility variables, valuation multiples and other control variables. Finally, it also contributes to the financial distress modelling literature from a multi-state prediction perspective. As TreeNet® is not restricted to binary settings, this study has also examined the predictive performance of TreeNet® in a three-state and five-state setting.

8.7 Limitations and directions for future research

This research has employed TreeNet® to evaluate and compare the predictive power of a wide range of financial and non-financial 'Western-style' bankruptcy predictors in distress prediction of Chinese listed companies based on China's unique ST system. The empirical results of TreeNet® from a binary prediction perspective as well as a multi-state prediction perspective have been examined. Like all other distress prediction models, TreeNet® also has its strengths and limitations. A frequent criticism of advanced machine learning models is the lack of interpretability (the black box effect). One limitation associated with the TreeNet® model is its limited interpretability as a result of the complex model structure that involves many potential nonlinear relationships and interactions among the large number of predictor variables. However, some outputs from the TreeNet® model, such as relative variable importances (RVIs) and partial dependency plots (marginal effects), allow the role and influence of different variables to be more readily interpreted.

Another limitation of this thesis relates to the data used for distress prediction modelling. The Special Treatment (ST) regime has been introduced by the CSRC as an attempt to remedy the situation in China where as a result of historical, cultural, and social intolerance towards corporate failure there have been few bankruptcies and liquidations. The distressed sample used in this study has been collected based on the ST system, which arguably is not as severe as the 'bankruptcy' sample typically used in other distress prediction modelling studies. However, given the constraints, obtaining a sizeable bankruptcy sample in China is not always possible. In addition, the empirical results of the binary and multi-state TreeNet® models, including the reported model predictive performance and the relative role and performance of different input variables, ultimately depends on the reliability of data collected from the CSMAR database. If there are deficiencies in the Chinese financial reporting data, this can clearly have implications for the empirical results of this thesis. However, to date there is limited empirical evidence on this issue.

There are also several suggestions for future research. First, despite TreeNet® being one of the most recognised machine learning methods available, the predictive performance of TreeNet® could be compared with other advanced machine learning techniques, such as deep learning (Goodfellow, Bengio, and Courville, 2016) and random forests (Breiman, 2001). Second, as suggested by Jones (2017), machine learning techniques such as TreeNet® could work as a 'bias eliminating framework' to enhance the predictive and explanatory performance of conventional parametric models such as logit. TreeNet® could be applied to identify the most contributing predictors among a potentially very large number of predictors, including the impacts of nonlinearities and interaction effects among these variables.

Appendix A

Definition of Study Variables

Variable	**Definition (Based on the CSMAR database)**
Accounting Variables and Financial Ratios:	
TotalAssets	The sum of all asset items.
TotalOperatingRevenue	The sum of all income arising from operating business of the company.
EarningsPerShare (EPS)	Net profit or loss for the current period attributable to ordinary shareholders/ weighted average number of ordinary shares outstanding.
CFOperShare	Cash flow from operations / total number of shares.
BookValuePerShare	Total shareholder's equity / total number of shares.
CashResources_TA	Cash and short term investments / total assets.

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Variable	**Definition (Based on the CSMAR database)**
NegativeCFO	A dummy variable coded ‘1’ if annual operation cash flow is positive and zero otherwise.
EBIT_OperatingCashFlows	Earnings before interest and taxes / cash flow from operating activities.
TotalLiabilities_TotalEquity	Total liabilities / total shareholder’s equity.
Netprofitmargin	Net profit / total revenues.
Interest_Cover	Earnings before interest and taxes / interest expenses.
Intangibleassets_TA	Intangible assets / total assets.
Debt_Equity	Total liabilities / total shareholder’s equity.
Cashflow_TotalRevenue	Operating cash flow / total revenue.
CurrentAssets_TL	Current assets / total liabilities.
Cash_TA	Cash and cash equivalents / total assets.
AR_TA	Accounts receivables / total assets.
Cash_CurrentLiab	Cash and cash equivalents / current liabilities.
WC_TL	(Current assets − current liabilities) / total liabilities.

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Variable	Definition (Based on the CSMAR database)
GrowthCFO1YR	Operating cash flow (t)− Operating cash flow (t-1) / Operating cash flow (t-1).
GrowthCFO3YR	Operating cash flow (t)− Operating cash flow (t-3) / Operating cash flow (t-3).
GrowthLTD1YR	Long term debt (t)− Long term debt (t-1) / Long term debt (t-1).
GrowthLTD3YR	Long term debt (t)− Long term debt (t-3) / Long term debt (t-3).
GrowthEbit1YR	Earnings before interest and taxation (t)− Earnings before interest and taxation (t-1) / Earnings before interest and taxation (t-1).
GrowthEbit3YR	Earnings before interest and taxation (t)− Earnings before interest and taxation (t-3) / Earnings before interest and taxation (t-3).
GrowthOperatingRevenue1YR	Revenue (t)− Revenue (t-1) / Revenue (t-1).
GrowthOperatingRevenue3YR	Revenue (t)− Revenue (t-3) / Revenue (t-3).
GrowthNetProfit1YR	Net profit after tax (t)− Net profit after tax (t-1) / Net profit after tax (t-1).

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Variable	**Definition (Based on the CSMAR database)**
GrowthNetProfit3YR	Net profit after tax (t)− Net profit after tax (t-3) / Net profit after tax (t-3).
Growthequity1YR	Total Equity (t)− Total Equity (t-1) / Total Equity (t-1).
Growthequity3YR	Total Equity (t)− Total Equity (t-3) / Total Equity (t-3).
GrowthTotalLiabilities1YR	Total Liabilities (t)− Total Liabilities (t-1) / Total Liabilities (t-1).
GrowthTotalLiabilities3YR	Total Liabilities (t)− Total Liabilities (t-3) / Total Liabilities (t-3).
Growthcash1YR	Cash Resources (t)− Cash Resources (t-1) / Cash Resources (t-1).
Growthcash3YR	Cash Resources (t)− Cash Resources (t-3) / Cash Resources (t-3).
GrowthWC1YR	Working Capital (t)− Working Capital (t-1) / Working Capital (t-1).
GrowthWC3YR	Working Capital (t)− Working Capital (t-3) / Working Capital (t-3).
Growthincome1YR	Operating Income (t)− Operating Income (t-1) / Operating Income (t-1).
Growthincome3YR	Operating Income (t)− Operating Income (t-3) / Operating Income (t-3).

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Variable	**Definition (Based on the CSMAR database)**
GrowthTotalAssets1YR	Total Assets (t)− Total Assets (t-1) / Total Assets (t-1).
GrowthTotalAssets3YR	Total Assets (t)− Total Assets (t-3) / Total Assets (t-3).
GrowthEPS1YR	Earnings per Share (t)− Earnings per Share (t-1) / Earnings per Share (t-1).
GrowthEPS3YR	Earnings per Share (t)− Earnings per Share (t-3) / Earnings per Share (t-3).
ARturnover	Net credit sales / average accounts receivable.
ROA	Net income / total assets.
ROE	Net income / total shareholder's equity.
CFO_TA	Cash flow from operations / total assets.
CFO_E	Cash flow from operations / total shareholder's equity.
LTL_E	Long term liabilities / total shareholder's equity.
Debt_TangibleAssets	Total Debt / total tangible assets.
TotalProfitMargin	(Total revenue− Cost of goods sold) / total revenue.
Cashflow_Debt	Cash flow from operations / Total debt.

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Variable	**Definition (Based on the CSMAR database)**
WC_TA	(Current assets−current liabilities) / total assets.
RE_TA	Retained earnings / total assets.
EBIT_TA	Earnings before interest and taxes / total assets.
Sales_TA	Sales revenue / total assets.
EBIT_Margin	Earnings before interest and taxes / net revenue.
TA_TL	Total assets / total liabilities.
AP_TL	Accounts payable / total liabilities.
CurrentRatio	Current assets / current liabilities.
Debt_Equity	Total liabilities / total shareholder's equity.
WC_Sales	(Current assets− current liabilities) / Sales revenue.
InventoryTurnover	Cost of goods sold / average inventory.
Shareholder ownership/control variables:	
PercentSharesHeldSupervisors	Number of shares held by supervisors including Chairman of the board / total number of shares.

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Variable	**Definition (Based on the CSMAR database)**
PercentStateOwnedShares	Ratio of state owned shares to total shares outstanding. State owned shares: shares held by governmental agencies or institutions, which are authorised to invest on behalf of the state, including state shares and state-owned legal person shares.
PercentSharesHeldbyBroker	Ratio of shares held by securities brokers to total shares outstanding.
PercentSharesHeldbyFund	Ratio of fund/institutional shareholding to total shares outstanding.
TotalNumberofShareholders	Total number of shareholders disclosed by listed company.
Other governance style variables:	
ChairmanGMcocurrent	Whether the board chairman and the general manager is the same person: 1 = The Same Person; 2 = Different Persons.
NumberofDirectors	Total number of directors (including board chairman), excluding advisors to the board of directors, secretary of board of directors, etc.
Executive compensation variables:	

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Variable	**Definition (Based on the CSMAR database)**
TotalAnnualEmolumentofTop3Directors	Total annual emolument of top 3 directors excluding allowance received by directors.
TotalAnnualEmolumentofTop3Executives	Total annual emolument of top 3 executives excluding allowance received by executives.
Valuation multiples:	
PBRatio	Price to book value per share.
PERatio	Price to earnings per share.
Market price variables:	
AnnualMarketReturns	The equal-value weighted average market returns as defined in CSMAR.
MarketCapitalisation	The total market capitalisation of all individual shares. It is calculated by the total number of share multiplied by its closing price in the year.
MarketCapitalisation_Debt	Market capitalisation / total debt.
Corporate social responsibility variables:	
SocialDonation	Annual donations of the company.

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Variable	**Definition (Based on the CSMAR database)**
SocialContributionValueperShare	Social contribution value per share = Earnings per share + (Total tax + Employee costs + Interest expenses + Total contributions to public welfare funds - Social costs) / Total capital stock at the end of period.
Macroeconomic variables:	
GDPGrowth	GDP reflects the value of all goods and services produced by a nation. GDP growth indicates how much a country's production has increased or decreased compared to the previous year. GDP is reported by The National Bureau of Statistics of China.
GDPGrowthperCapita	GDP growth / total population. Total population is reported by The National Bureau of Statistics of China.

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Variable	**Definition (Based on the CSMAR database)**
RegisteredUnemploymentRate	Registered urban unemployment rate = number of registered urban unemployed people / (number of urban employed people + number of registered urban unemployed people) $\times$100%. Unemployment rate is reported by The National Bureau of Statistics of China.
GeneralConsumerPriceIndex	CPI reflects the trend and degree of changes in prices of consumer goods and services purchased by urban and rural residents. CPI is reported by The National Bureau of Statistics of China.
Coverage variables:	
AnalystConcernDegree	Number of analysts (teams) who have conducted tracking analysis on the company in a year; one team presented as 1, not counting the number of its members.
ResearchReportConcernDegree	Number of research reports that have released a tracking analysis of the company in a year.
Audit variables:	
TotalAuditFees	Total reported audit-related fees.

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Variable	**Definition (Based on the CSMAR database)**
Qualifiedauditopinion	A dummy variable coded '1' if the firm has received some type of qualified audit opinion, zero otherwise. A qualified opinion includes: a qualified opinion; a qualified opinion with an emphasis of matter paragraph; a qualified opinion with explanation notes.
Disclaimerauditopinion	A dummy variable coded '1' if the firm has received a disclaimer audit opinion, zero otherwise.
Auditbig4	A dummy variable coded '1' if the firm was audited by a Big4 audit firm, zero otherwise.
Auditoverseas	A dummy variable coded '1' if the firm was audited by an overseas audit firm, zero otherwise.
Other variables:	

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Variable	**Definition (Based on the CSMAR database)**
EM_Residual	An earnings management proxy measured by the Kothari et al. (2005) model which matches accruals to return on assets according to the following well known formula: $\text{Accruals}_{it} = \alpha + \beta_1 \Delta \text{REV}_{it} + \beta_2 \Delta \text{PPE}_{it} + \beta_3 \Delta \text{ROA}_{it} + \varepsilon_{it}$.
Firm Size	Measured by market capitalisation, total employees and total assets. Total number of employees of a listed company, which refers to the number of employees who are registered in the company or hold positions in the listed company disclosed in the annual report.
Firm Age	Firm age is proxied by Retained Earnings /Total Assets. Industry/sector variables Six major industry groups defined by CSRC (China Securities Regulatory Commission) including finance, utilities, properties, conglomerates, industrial, and commerce.

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