An empirical diagnosis of multiple state financial distress in the Chinese equity market

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Stephen Iheanacho

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ABSTRACT

The Chinese equity market where firms *do not die* is saddled by an increasing number of *zombie* financially distressed firms resulting from a relatively low delisting rate, a weak Enterprise Bankruptcy Law process and a *profit-based* delisting system that is undermined by earnings management. As a result, it is difficult for investors and creditors to assess or predict the financial distress state of firms to reduce loss. This research uses panel data of 1,415 Chinese non-financial listed firms on the Shanghai and Shenzhen Stock Exchanges for the period 2009 to 2018. Using a two-stage multinomial logit model, this research models financial distress as a multiple state process of four financial distress states (NFDIS, FWEAK, FWEAK, FDIST) which is an improvement on the conventional binary state approach.

The empirical findings show a nonlinear relationship between financial ratios and corporate governance factors and financial distress. Specifically, a change in a firm's financial leverage and cash flow from finance has a significant positive effect on the probability of the firm in a financially distressed state: FDECL, FWEAK or the FDIST state. Inversely, a change in a firm's asset management efficiency, profitability, liquidity, cash flow from operations, dividend payment, market valuation, board structure or ownership structure has a significant negative effect on the

probability of the firm in a financially distressed state: FDECL, FWEAK or the FDIST state. Notably, the further a firm's financial health deteriorates, the lesser its probability of recovery.

Further to the two-year consecutive loss criteria, this research found that firms in the early FDECL state (ST firms) do experience distress *symptoms* of poor asset management efficiency, high cash flow from finance, low dividend pay-out, poor board structure and low percentage of institutional ownership. Firms in the FWEAK state also experience, in addition to the same *symptoms* as firms in the FDECL state, poor liquidity, cash flow from operations and poor market valuation. Firms in the terminal FDIST state experience the same *symptoms* as firms in the FDECL and FWEAK states in addition to high financial leverage. Although firms across the four financial distress states may experience similar distress *symptoms*, the magnitude of these *symptoms* at each distress state is significantly different as they are incremental.

The empirical findings imply that early financial distress may not be detected relying solely on accrual or market information as the case of the ST delisting criteria. This is because accrual-based ratios and market-based ratios are less effective in *diagnosing* the *symptoms* experienced by firms in the early FDECL state than they are in *identifying* the *symptoms* in the late FWEAK state or terminal FDIST state. Cash flow-based ratios and corporate governance factors improve the predictive and explanatory power of accrual and market-based ratios assessing aspects of financial distress not assessed by accrual-based ratios or market-based ratios.

Keywords: financial ratios, corporate governance factors, multiple state financial distress, multinomial logit regression, financial distress process

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DEDICATION

To the Almighty Jehovah to whom I owe everything

To my dearest wife Siony Iheanacho and our children; Sophie, Zoe and Stephanie Iheanacho who have shown amazing love to me throughout my PhD research journey.

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CHAPTER ONE

INTRODUCTION

The first section of this chapter introduces the concept of financial distress and provides some background to the Chinese equity market. Section 1.2 provides a discussion around the Enterprise Bankruptcy law in China and introduces the concept of financial distress in the context of the Chinese equity market including the Special Treatment delisting system. Section 1.3 presents the problem statement of this research and section 1.4 outlines the research objectives. Section 1.5 presents the motivation for undertaking this research and section 1.6 outlines the structure of the rest of the thesis.

1.1 Research Background

A firm is deemed financially healthy until the Court or some equity market framework (such as the Chinese delisting system) designates it as ‘financially distressed’. In the literature, several terms such as ‘financial distress’, ‘liquidation’, ‘default’, ‘insolvency’, ‘bankruptcy’ and ‘business failure’ have been used to describe the deteriorated state of a firm’s financial health. The lack of consensus in the literature as to the use of these terms is a source of concern as these terms have been used interchangeably. Muller, Steyn-Bruwer & Hamman (2009) express concern that the inconsistent application of fundamental terminologies could be a major shortcoming for several studies in this area. Although these terms have been used interchangeably in financial distress studies, in practice, these terms may not refer to the same thing (Jones & Hensher, 2004). The term used may also be influenced by the jurisdiction of the research or the financial distress state being referred to. Financial distress as a term has been used in the literature to define ‘a state’ of poor financial health (Binh & Duc, 2018; Brédart, 2014; Campbell, Hilscher & Szilagyi, 2011). The term has also been used to describe ‘a process’ (financial distress process) of a decline in the financial health of a firm from when a healthy firm begins displaying *symptoms* of poor financial health up to when the firm either recovers from those *symptoms* or deteriorates into a terminal distress state (Farooq, Qamar & Haque, 2018; Jones & Hensher, 2004; Outecheva, 2007; Pozzoli & Paolone, 2017). Before reaching a terminal distress state such as mergers, acquisition or liquidation, studies by Pozzoli & Paolone (2017) and Farooq et al. (2018) show that firms transverse through several other states. Legally, the court declares a firm with evidence of financial health deterioration 'insolvent' which is, the inability of the firm to settle its obligations as they fall due according to InsolvencyAct (1986). The insolvency status assigned to a firm by a court is equivalent to the *financial distress* status assigned to a firm by a given equity market system. For this research, the term 'financial distress' is used to define a 'state' where the financial health of a firm deviates from the norm as determined by a competent Court or equity market framework. Also, the 'financial distress process' is used to refer to several states a firm assumes from when it deviates from the financially healthy norm until it ceases to exist or recovers to a financially healthy state.

In general, when firms become financially distressed, the consequences for stakeholders are far-reaching. Shareholders risk losing the value of their investment, fund providers risk losing their loan advances, trade creditors risk losing their payables, employees (including management) risk losing their jobs, and the Government risks losing corporate tax revenue and risks spending more to resuscitate the ailing firms. Further consequences for investors include social cost, emotional cost, financial cost and loss of confidence in the market (Ucbasaran, Shepherd, Lockettand & Lyon, 2012). Firms do not operate in isolation, which theoretically implies that the failure of a firm may affect the firm's stakeholders which includes individuals and corporate entities. For instance, trade payables and loan payables in the books of financially distressed firms are receivables or an investment in the books of the creditor. Furthermore, purchases in the books of a financially distressed firm are sales in the books of another firm. Therefore, when a firm goes bankrupt, the domino effect could mean that some or all portions of the receivables of creditors become impaired and such impairment could result in financial distress. A study by Patau, Somoza & Torra (2020) found a significant impact on the capital structure and financing strategy of stakeholders of bankrupt firms, especially the creditors. Tan (2019) added that the management of financially distressed firms involves spending time and resources sourcing short-term and long-term liquidity rather than growing shareholders' wealth. Given the interrelationship between elements of financial statements, it suggests that deterioration in one aspect of firms could trigger deterioration in other aspects. For instance, declining sales and attendant liquidity squeeze could deter a firm from undertaking investment in growth opportunities.

The afore discussion on the consequences of financial distress emphasizes the importance of assessing the financial health of firms and diagnosing early warning signs of financial distress. The importance of research in this area is driving researchers' interest in the subject matter. A considerable amount of literature has addressed the subject, from the causes to explanatory variables that explain financial distress to models that predict financial distress. It is of immense benefit to all stakeholders if early *symptoms* of financial distress can be diagnosed or predicted. Early studies in financial distress such as those of Beaver (1966) Altman (1968) and Deakin (1972) used accrual-based ratios drawn from the income statement and balance sheet. The study by Altman (1968) appears to set the pace and influences the dominant use of accrual-based ratios in financial distress literature noting that cash flow-based ratios are sparingly considered (Casey & Bartczak, 1985). Studies such as those of Casey & Bartczak (1985), Gentry, Newbold & Whitford (1985), Gombola, Haskins, Ketz & Williams (1987) and Rodgers (2011) expanded the explanatory variables to include cash flow ratios in addition to accrual-based ratios in predicting firms' financial distress. Despite the possibility of determining financial distress with a combination of accrual-based and cash flow-based ratios, there have been criticisms by Shumway (2001) and Reisz & Perlich (2007) that the market perspective was neglected. The study by Shumway (2001) is amongst early studies to popularise the use of market-driven ratios in explaining financial distress. Studies integrating market information advanced the robustness of financial factors in explaining financial distress. Nonetheless, the susceptibility of financial factors to manipulation has encouraged researchers to include non-financial factors such as corporate governance and macro-economic factors as variables that explain financial distress (Tinoco, 2013). There have been notable advancements in the methods of predicting financial distress from pioneer discriminant analysis models to more advanced statistical methods such as logistic regression, survival analysis and a few other non-statistical methods including neural networks (Aziz & Dar, 2006; Sun & Li, 2008).

From pioneer studies by Fitzpatrick (1932), Beaver (1966) and Altman (1968) up to the recent study by Binh & Duc (2018), researchers are confident that financial distress can be predicted with reasonable accuracy ahead of terminal events such as the company failing or liquidation (Aziz & Dar, 2006). Despite advances in financial distress research, external factors such as the fast-changing corporate reporting framework, corporate practices and the business environment continue to challenge the validity of prior financial distress output. For instance, the conventional financial distress studies including those by Altman (1968), Ohlson (1980), El-Hannawy (1981), Gilbert, Menon & Schwartz (1990), Shumway (2001) and Binh & Duc (2018) suggest a sole terminal state for financially distressed firms that is bankruptcy and subsequently liquidation. This may be the case in the era of Altman (1968) and Beaver (1966) but not in recent times when firms explore several strategic options. Further, the endogenous selection of firms that take the liquidation route against other exit routes such as mergers or acquisitions raises the question as to the validity of the output of these studies. This is because firms in liquidation exit the market and cease to exist, just like firms that exit the market via a merger or acquisition, with the difference being the strategy used by firm management. Given the implications of these challenging factors, studies such as Grice & Dugan (2001) argue that *bankruptcy* cannot be validly predicted.

Financial distress research in emerging markets is key and challenging. Studies by Rommer (2005) found that firms in emerging markets are more likely to go financially distressed than their counterpart in developed markets due to unfavourable business environments in emerging markets. China as an emerging market is uniquely defined by its historical institutional background, State ownership and interference, weak bankruptcy process and a delisting system whose criteria is prone to manipulation (Lee, 2011). These factors drive the relatively low delisting rate compared to developed markets and a situation where firms typically 'do not die' (Cheng & Li, 2015a). Delisting is one of the mechanisms that equity market regulators use to ensure financially healthy stocks trade in the Exchange. According to (Xinhua, 2018), a relatively low delisting rate in the case of China is argued to immensely contribute to the increasing number of financially distressed firms in the Shenzhen and Shanghai Stock exchanges (hereafter collectively referred to as the "Chinese equity market"). Results from prior research in addressing the difficulties is undermined by the choice of research approach and explanatory variables. In addition to the research approach adopted by the literature, the unique corporate governance and market mechanism in the Chinese equity market also implies that financial distress explanatory factors that were significant elsewhere may not be relevant in the Chinese equity market (Li, 2014). For instance, state ownership and institutional ownership aspects of corporate governance are relatively stronger in the Chinese equity market compared to the Western markets (Cheung, Jiang, Limpaphayom & Lu, 2008).

The situation presents gaps in the literature that gets conspicuous in the context of China where financial distress research is currently at a growth stage according to (Zhang, Mahenthiran & Huang, 2012). Using China as a case study, this research investigates the effects and explanatory variables on financial distress by examining the nature of the association between the two factors. This research further seeks to understand different states in a financial distress continuum and therefore, model financial distress as multiple state processes following Lau (1987). Further, this research investigates financial and non-financial explanatory factors, less susceptible to manipulation, that could enhance the criteria of the delisting system. In fitting a robust model, consideration is made around possible endogeneity problems in modelling the relationship between financial distress and FR and CGI. The findings of this research will enable investors to make a well-informed investment decision to minimise the loss of investment. Where early warning signs of financial distress are foreseeable, regulators can make appropriate intervention strategies, and firm management teams would have the opportunity to correct their 'mistakes'.

1.2 Bankruptcy, Financial Distress and the Chinese Equity Market

1.2.1 The Bankruptcy Practice in China and the Enterprise Bankruptcy Law of China

The establishment of the People's Republic of China in 1949 was followed by the abolition of existing laws by the Nationalist Government and that included bankruptcy laws since they did not seem to have a place in a socialist country (Chen, Chen & Su, 2001). Under a planned economy, bankruptcy was never a concern since profits and losses by State-owned enterprises (SOEs) are centrally administered and losses are offset with subsidies by the respective State government (Yu, 2013). Transitioning to a market economy where investment is encouraged and market participants and enterprises are protected, necessitated a bankruptcy system and the establishment of the Enterprise Bankruptcy Law (EBL) of 1986 (Booth, 2008). The EBL of 1986 trial implementation was superseded by the EBL of 2006 with a broader application that covers not just SOEs (as in the 1986 EBL) but also non-SOEs, foreign-invested enterprises and private enterprises (Lee, 2011). The 2006 EBL ("EBL" draws from bankruptcy laws in the UK and US and includes a reorganisation system that mimics Chapter 11 of the U.S. bankruptcy law (Lee, 2011). The reorganisation plan (one of the two key components of the EBL) must be approved by the creditors and may linger for one or more years when they fail to obtain the approval of either of the two parties (Lee, 2011). The reorganisation process that firms on the ST and SST designations undertake commonly involves some combination of asset restructuring, ownership restructuring and debt restructuring (Lee, 2011).

However, the implementation of the EBL and indeed the bankruptcy process has been hindered in various ways. On one hand, there is the bankruptcy law whose implementation would bring firms with weak financial results to liquidation and on the other hand, there is the central and state government that are strongly motivated to protect ailing SOEs from going through liquidation (Wei, 2017). Studies have cited several rationales for protecting SOEs that are not economically viable by the Chinese Central and State government. Where SOEs that are usually large enterprises go into liquidation, there is a great risk of an economy-wide insolvency domino effect on the economy resulting from trade creditors losing unpaid invoices, customers losing input supplies and a huge portion of unpaid loans from banks going bad (Tang, 2018). The Chinese central Government disbursed funds to SOEs through the National and State banks who in return lend to SOEs thus, State banks are the biggest providers of funds to SOEs (Yu, 2013). There is also the social effect of SOE going *underground* and that includes the risk of social unrest that may result from the significant rise in unemployment that follows firm liquidation. Another rationale is that state governments pride themselves on listing SOEs from their region and the listing of an SOE implies continual access to public funding for state enterprises (Tang, 2018). In addition, State governments also want to avoid being criticized for lack of administrative efficiency by the public when state enterprises within their region go into liquidation. Rather than allow SOE to go into liquidation or get delisted from the equity market, it is a common practice for the Central and State governments to bail out state enterprises in financial distress and on the brink of liquidation (Tang, 2018). Bailout in the form of subsidies, grants and tax holidays often go with reorganisation plans which, in most cases, are structured to suit SOEs (Yu, 2013). Further, studies by Yu (2013) observed that government officials do actively interfere with the bankruptcy process of State enterprises within their region in a bid to protect them from liquidity. According to a national survey of large and medium-sized state enterprises in 1997, close to half of the 14,923 SOEs surveyed were loss-making firms (Booth, 2008). Despite their large non-performing loans and loss-making, distressed SOEs continue to receive funding from the Chinese government and loans from state banks that keep them afloat to continue servicing their debt (Booth, 2008). For these reasons, firms in the Chinese equity market *hardly demise* because they remain active and listed with active support from the central and state governments and, state banks. The insolvency/bankruptcy process in any jurisdiction influences the quality of firms listed on the Stock Exchanges. In the case of China, the challenge in implementing the EBL and bankruptcy process implies that firms with weak financials continue to trade in the equity market. Bankruptcy information such as details of firms that have been bankrupt or are currently going through bankruptcy is not readily available to the public, which contrasts with developed markets, for reasons such as privacy and protecting the firms in bankruptcy.

1.2.2 The Chinese Equity Market Structure and Institutional Background

The establishment of State-owned enterprises (SOEs) dates back to the 1940s when the Chinese Government implemented a centrally planned economy (Bian, 2014). SOEs are usually large enterprises with both social and community objectives alongside profit-making. As a result of the size and position of these firms, they can make a significant contribution to the growth of their respective industries, employ a significant portion of labour and account for a significant portion of the interest revenue of Chinese banks (Wang & Yung, 2011). A centrally planned economy implies that Government budgeting and funding of different sectors are centrally allocated to and administered through SOEs who dominate key sectors (Cheng, Yu & Ke, 2007). Being a Socialist State, China's economy was centrally planned and controlled and there were no real capital markets(Cheng & Li, 2015a). The Chinese economic reforms of the 1970s to open China's market to foreign investment gave rise to the emergence of the Chinese equity market. In a bid to transit from a planned economy to a market-driven economy and to enable SOEs to access funding from the public, the Government privatized SOEs by issuing SOE equity shares to the public (Bian, 2014). The privatization of SOE witnessed a decline in SOE from over 80% of listed Chinese firms in the 2000s to about 60% by 2016 (Cheng & Li, 2015a). Despite the privatization, most State governments still maintain control of the privatized SOEs (Tang, 2018). The essence of a market-driven economy is to open China's financial market and allow the market mechanism to influence investment rather than central planning.

Until the year 2000 when more than 80% of listed firms were SOEs, the issue of corporate governance was underplayed. Following the privatization of SOEs and the listing of more non-SOE firms, the subject of corporate governance has increasingly become of interest to investors and market regulators (Khaw, Liao, Tripe & Wongchoti, 2016). However, the state ownership concept makes corporate governance in SOEs more complicated. This is because even where the state is the controlling shareholder, it still acts as an agent of the real owner - the taxpayers and citizens (Yu, 2013). Likewise, (Cheng et al., 2007) expressed concern over the general corporate governance practice of listed Chinese firms, especially SOEs where controlling shareholders exercise a dominating influence over firm management.

The privatization of SOEs necessitated the establishment of the Shenzhen Stock Exchange (SZSE) and Shanghai Stock Exchange (SSE) in 1991 and 1990 respectively. One of the fundamental changes that came with the establishment of the two equity markets is the accounting reporting regulations in 1992, 1998, 2001 and 2006 towards converging the Chinese Generally Accepted Accounting Principles (Chinese GAAP) and the International Financial Reporting Standards (IFRS) (Peng et al., 2008). Listed Chinese companies could issue three kinds of shares: A shares, B shares and H shares (Cheng & Li, 2015b). Firms issuing B shares are required to report under IFRS, firms issuing A shares are required to report under Chinese GAAP while firms issuing both A and B shares must report under both IFRS and Chinese GAAP (Peng et al., 2008). From 2007, firms listed on either the SZSE or SSE must report under the converged Chinese GAAP and IFRS (Cheng & Li, 2015b)

Despite the privatization of SOEs, the manner of equity restructuring made provision for the state government to retain significant control of SOEs (Bian, 2014). This is achieved by a split-share structure where a portion of the stock is tradeable, and a portion is non-tradeable. A split-share structure is a system where outstanding shares of Chinese firms are split between tradeable and non-tradeable shares to protect state control in key industries of the Chinese economy. For States to retain control of SOEs, they own non-tradeable shares which are held back by market regulators from being traded publicly in the stock market (CSRC, 2014). On the other hand, tradeable shares are shares listed and publicly traded by private investors in the stock market (CSRC, 2014). The Split Share Reform of 2005- 2006 was aimed at reducing the volume of non-tradable shares, nonetheless, SOE ownership and control remain significant in the concerned firms (Yu, 2013, p.76). Considering the split-share structure, the market value of SOEs is misleading since not all outstanding shares are tradeable. Tradeable shares in the Chinese equity market can be A-shares, B-shares or H-Shares. A-Shares are shares issued by firms that operate in mainland China and trade on the Shenzhen Stock Exchange and/or the Shanghai Stock Exchange. Historically, the share structure served to ensure the ownership and trading of A-Shares were restricted to only mainland Chinese citizens and they are quoted in Chinese RMB. In contrast, B-shares are open to foreign investors and are quoted in US dollars. However since 2003, through the Qualified Foreign Institutional Investor (QFII) system, designated foreign investors can trade on A-Shares and ongoing reforms in the market have witnessed firms issuing both A and B shares (Cheng & Li, 2015b). H-shares are shares issued by Chinese mainland companies but denominated in Hong Kong dollars and traded on the Hong Kong Stock Exchange or other foreign exchange (Cheng & Li, 2014).

1.2.3 Financial Distress and the ST Delisting System

Over the past decade, China's economy has experienced rapid growth and globalization (Cheng & Li, 2015a). As a result, different aspects of the Chinese economy, such as the equity market, have experienced similar growth. For instance, China equity market is the largest behind the US equity market. Specifically, the SSE is the third-largest (behind NASDAQ and NYSE) while SZSE is the sixth-largest (behind Japan Exchange Group)(Wang, 2017). Although part of the drivers of growth in China's economy is the adaptation to global trends, the underlying institutional background and uniqueness of the Chinese equity market remain largely the same (Cheng et al., 2007). Since the establishment of the two equity markets, the number of listed firms has rapidly grown from 14 listed firms in 1990 to 3,776 firms in 2018 and there was an increasing need for regulation of the two equity markets (CSMAR, 2020). Subsequently, the China Securities Regulatory Commission (CSRC) was established in 1992 following the establishment of the SZSE and SSE. The main aim of the CSRC is to regulate and supervise listing and trading in both the SZSE and SSE Stock Exchanges. It is the responsibility of market regulators to protect the interest of investors by ensuring that financially healthy firms trade in the market. This is more so in the case of the Chinese equity market, considering the manipulation avenues and complexities created by the split-share structure and institutional ownership. Following irregularities in the Chinese equity market and in a bid to protect investors, in 1998 the market regulator - CSRC launched the Special Treatment delisting system (hereafter "delisting system") in the SSE and SZSE stock exchanges. The delisting system in the Chinese equity market is administrative with Government interference compared to the market-driven in developed markets (Cheng & Li, 2015a). The ST delisting system mimics the US Chapter IX Bankruptcy process. It assesses listed stocks to filter out financially unhealthy stocks from the market and to reduce the volatility in the markets by deterring speculators from cashing in fluctuating underperforming stocks (He, 2017). Although the ST delisting system was launched in 1998, stocks did not get ST designated until nine years later, in 2007.

The CSRC administratively reviews the published financial statements of listed firms on a proceeding year basis. According to Zhou (2013), a firm that meets any of the three key criteria below gets a Special Treatment (henceforth "ST") designation before their trading symbol:

1. Reported net loss for two consecutive financial years;
2. An adverse or disclaimer audit opinion on audited financial statements; and
3. Reported negative net equity for two consecutive financial years

Other reasons for an ST designation according to Zhou (2013) include:

4. The firm has ceased or will likely cease the main business operation for at least three months; and
5. Has other significant financial trading irregularities been decided by CSRC as an indication of financial distress.

A firm designated as ST could receive a further Star Special Treatment (henceforth SST) designation if, after their ST designation, the firm meets any of the following criteria:

1. Reported further net loss for one consecutive financial year;
2. Received a further adverse or disclaimer audit opinion on audited financial statements; and
3. Reported a further negative net equity for one consecutive financial year

From 2007, firms on ST or SST that fail to complete their equity division reform are further designated as 'SST' (Cheng & Li, 2015b). As of 2013, there were no ST or SST firms to complete equity division reform thus, the CSRC stopped designating firms with SST or S*ST from 2013 (Xinhua, 2018). For simplicity, the designation "*ST" will hereafter be referred to as "SST". The SST designation is informally known as a 'delisting warning', to warn investors of the risk associated with such a firm. The CSRC can suspend, at its discretion, a firm from the market in the first instance before delisting. The suspension provides ample time for these firms to complete necessary recovery strategies, which include restructuring or a merger or an acquisition. Where an SST firm on suspension fails to improve on the criteria upon which it was designated SST or suspended, such firm risks being permanently delisted from the equity market if the firm meets any of the following (Zhou, 2013):

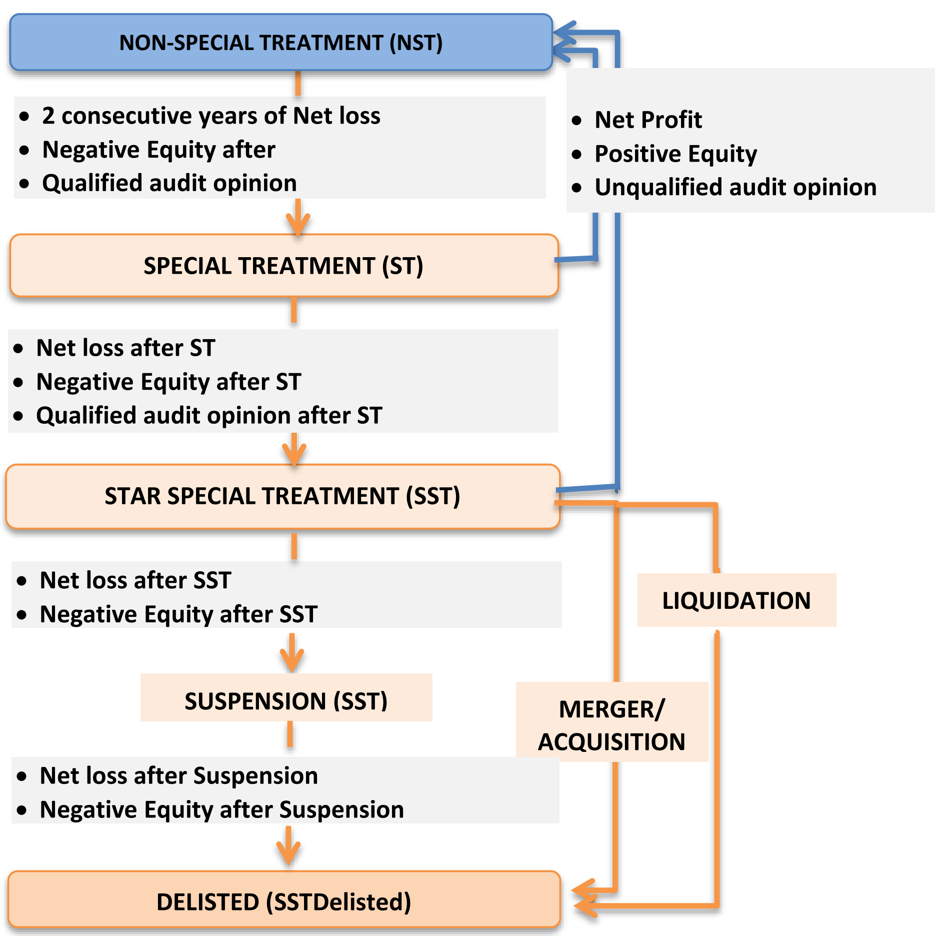
1. Fails to make good any of the criteria for which it was designated an SST within one year.
2. Fails to disclose first-year annual financial statement within the time stipulated.
3. Declared insolvent by the court or has gone into administration.
4. Equity shareholders resolve to delist the firm.
5. Rejects an application by CSRC to resume its normal listing status.
6. Any other criteria determined by CSRC as having significant financial risk

For simplicity, the delisted status would hereafter be referred to as "SSTDelisted". This is because these are SST firms that were delisted and the "SSTDelisted" designation help differentiate them from other SSTs that are not delisted over the research period. According to Zhou (2013), as a general rule, the CSRC will cancel and remove the ST or SST designation where the firm makes good the criteria upon which it was designated and these criteria include:

1. Reports a net profit in the financial year preceding the year under review
2. Receives an unqualified audit opinion on its audited financial statements.
3. Reports positive net equity for two consecutive financial years
4. All significant financial and trading irregularities decided by CSRC are cleared and no significant symptom of financial distress is present.

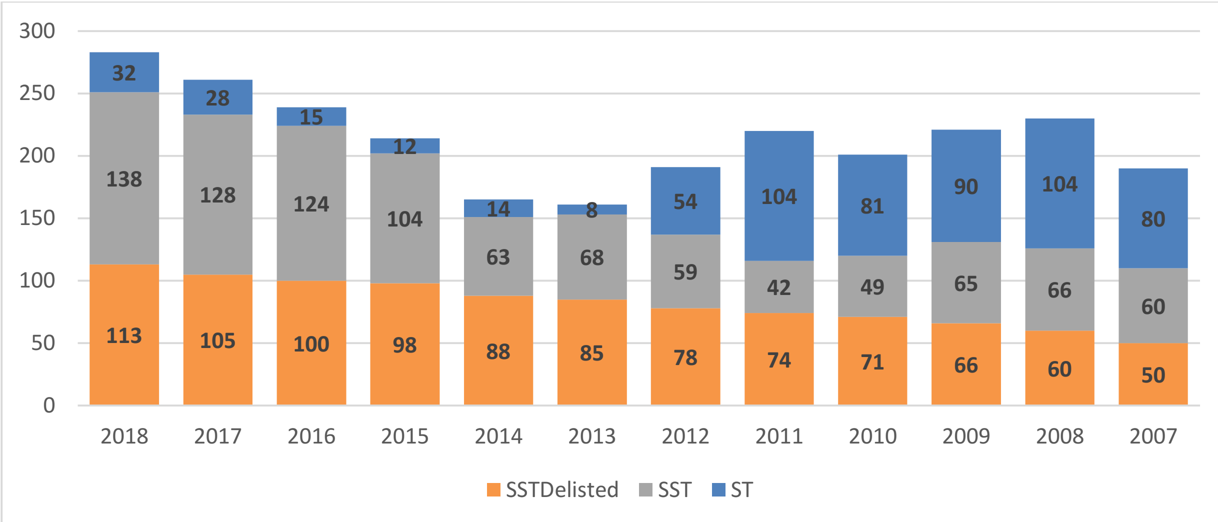
The expectation for firms with ST or SST designation is to address the criteria upon which they were designated and return to a normal Non-Special Treatment (NST) listing or risk being delisted from the Exchange (Zhou, 2013). Figure 1.1 shows the progression of firms in the Chinese equity market through different designations in the delisting system. In as much as the delisting system was instituted to provide a warning sign to investors on underperforming stocks, it was the Chinese equity market's unwritten rule for identifying financially distressed firms. However, studies by Kim, Ma & Zhou (2016) and Lai & Tam (2017) report that ST or SST firms are most likely to manipulate the delisting system criteria through earnings management to remove their designation and avoid being delisted. As a result, government influence on the bankruptcy process and the weakness of the delisting system appears to drive the increase in the heavily indebted SOEs that are not economically viable in the Chinese equity market (Kim et al., 2016). 'Zombie' stocks as they are referred to in the media continue to pose a problem for the government, market regulators and investors (Xinhua, 2018).

Figure 1.1: Chinese equity market delisting system



Source: Author's compilation, Wang & Deng (2006)

Figure 1.2: Number of ST, SST and SSTDelisted firms 2007-2018



Source: CSMAR (2020)

It is interesting to note that the equity market gives SOEs preference over other institutionally-owned or privately-owned firms (Cheng & Li, 2015a). For instance, Allen, Qian & Qian (2005) found greater flexibility and leniency in the application of market rules granted to financially distressed listed SOEs compared to other financially distressed listed firms. Figure 1.2 also reports a spike in the ST Pool during 2008/2009 following the global credit crunch and another steep increase from 2013. We selected our research period to commence from 2009 considering the convergence of Chinese GAAP and IFRS up to 2006 and the effective implementation of the ST delisting system from 2007.

From Figure 1.2, we observe a decrease in ST firms and an increase in SST firms between 2007 and 2018. From 2013, the increase in *financially distressed* firms has been driven by more firms on SST firms on *delisting warning* that are staying longer in the SST pool than they ought to remain there. We further observe from Figure 1.2 that a lesser number of firms on ST designation were delisted between 2013 and 2018 compared to the prior period. This adds to the Chinese equity market relatively low average delisting rate of 2% which compares poorly to that of 6% for NYSE, 8% for NASDAQ and 12% for the London Stock Exchange (Kim et al., 2016). Cheng & Li (2015a) in their study concluded that, although the Chinese equity market has made impressive progress at the macro-scale, there are still key problems at the micro-scale. At the micro-scale, problems such as the recurring phenomenon of booms and busts in the market and weak bankruptcy process (Allen et al., 2005), excessive speculation, market information and delisting criteria manipulation and misleading market information plagued the market (Cheng & Li, 2015b).

1.3 Problem Statement

Despite the massive growth and globalisation of the Chinese economy, financial distress research in the Chinese equity market is described as in the growth stage when compared to the mature stage in developed economies (Zhang et al, 2015). A significant amount of financial distress studies are based in the US, UK and European markets and adapting the output of these studies in the Chinese equity market could be practically questionable considering the uniqueness of the Chinese equity market. The inefficient dissemination of equity market information to individual investors (Chen et al, 2001) necessitates the need for a robust financial distress model that enables investors/creditors to effectively assess the financial health of firms. The issues surrounding the Chinese equity market as discussed in previous sections, coupled with limited financial distress research in that market, present gaps in research which this research aims to fill. Results from prior research in addressing these issues is undermined by the choice of research approach and explanatory variables.

The relationship between accrual-based ratios, cash flow-based ratios, market-based ratios and corporate governance and financial distress risk has been extensively researched in financial distress studies. However, the issue of endogeneity is often overlooked when constructing the relationships between the explanatory variables and financial distress in these studies, which questions the reliability of the results (Peel, 2018). Second, even where endogeneity is accounted for, most financial distress studies limit themselves to testing the linear relationship between explanatory variables and financial distress. The results of such studies provide an incomplete understanding of the dynamic nonlinear relationship that may exist between explanatory variables and financial distress. For instance, studies that find a negative relationship between profitability and financial distress fail to explain scenarios where a decrease in profitability do not suggest the presence of financial distress.

An underlying assumption of prior financial studies is that the effects of explanatory variables at different financial distress states are the same and constant throughout the financial distress process. This assumption is not consistent with the reality of financially distressed firms nor is it consistent with Lau (1987) that found that the financial health of a firm is not stagnant but changes as the firm transverse the financial distress process. For instance, prior studies associate poor profitability with firms in financial distress. What we do not know is whether the poor profitability situation at the early distress state of the firm is the same as when the firm is in a terminal liquidation state. The scarce research in this area results in a poor understanding of the nature of the effects of explanatory variables at diverse financial distress states what explanatory variables drive each financial distress state. In the case of China, the delisting system designate firms into the ST and SST pool mainly on profitability (consecutive net losses) however we do not know what other *symptoms* are exhibited by firms in the ST, SST and SSTDelisted pools. The scarce research in this area makes it challenging to differentiate firms at different financial distress states and makes it even more challenging to observe the financial health of firms as they progress through the diverse states of the financial distress process.

Likewise, studies in a developed market such as Ohlson (1980), Shumway (2001) and Binh & Duc (2018), and most studies in the Chinese equity market including Zhou, Kim & Ma (2012), Ruibn, Bose & Chen (2014) and Minhaz (2017) assume the financial distress is a binary process. These studies assume firms are either 'failed' or 'non-failed', 'financially healthy or bankrupt/insolvent. This is not consistent with the reality that financially distressed firms may traverse from being financially healthy to being bankrupt/insolvent as observed by Lau (1987). Moreover, firms are not simply either "non-distressed" or "distressed" but embody various magnitudes of financial distress that vary from one period to another (Ward, 1994). The binary state financial distress process approach provides an incomplete understanding of the financial distress process and other states that may exist between a financially healthy state and a terminal distress state. The binary state distress approach also hinders the study or prediction of early financial distress states. In addition, where investors could only predict a firm's terminal distress states, there is little time to respond with appropriate decisions to mitigate investment loss. This is because financially distressed firms lose a significant portion of shareholder wealth in the few years preceding the *terminal stage* as shown by Johnsen & Melicher (1994). In the context of the Chinese equity market where the system provides insufficient data on firms at terminal distress states and indeed discourage firms from advancing to terminal distress states, it is more challenging to adopt a binary state distress process approach.

The shortcomings of accrual accounting information in assessing and predicting financial distress have been researched by Grice & Dugan (2001). In the Chinese equity market, Yang, Chi & Young (2012) and Lai & Tam (2017) found that firms do engage in earnings management practices that enable them to manipulate the *profit-based* delisting criteria and avert the ST designation and delisting. This poses a question as to whether accrual-based ratios alone can effectively explain diverse financial distress states especially, early financial distress states. Fawzi, Kamaluddin & Sanusi (2015) argue that cash flow accounting and non-financial information are less susceptible to manipulation compared to accrual accounting data. Likewise, Atieh (2014), Barua & Anup (2015) and Laitinen (1994) show that accrual-based liquidity ratios and cash flow-based ratios measure distinctively different perspectives of a firm's liquidity. However, the cash flow aspect of liquidity is often neglected in research where accrual-based liquidity ratios are used in place of cash flow-based ratios. In a study of the value added by cash flow information in the Australian market by Sharma (2001), the study recommended investigating how the relationships between investing, financing, and operating cash flows could indicate a firm's liquidity levels and financial health. Further, empirical studies such as Hu & Zheng (2015), Li, Crook & Andreeva (2015) and Rezaee, Zhang, Dou & Gao (2016) researched the role of non-financial factors such as corporate governance in diagnosing and predicting the risk of financial distress. Notably, these have mainly been concerned with the isolated assessment of the effect of corporate governance factors on financial distress risk while financial factors such as financial ratios are left out. However, Black, Jang & Kim (2006), Bhagat & Black (2002) and Himmelberg, Hubbard & Palia (1999) argue that corporate governance factors alone do not sufficiently predict that the risk of financial distress notwithstanding, best serves as a strong complement to financial factors. There is limited research in the Chinese equity market extending the traditional financial ratios with non-financial factors such as corporate governance. Thus, there is an opportunity to investigate the added information that cash flows and corporate governance indicators introduce in explaining multiple state financial distress.

This research uses multinomial logit regression to investigate the financial ratios and corporate governance indicators that explain different financial distress states and their effects on the probability of multiple state financial distress. This research attempts to bridge the gaps in prior literature by providing a more comprehensive understanding of the association between explanatory variables and financial distress, the financial distress process, additional information provided by cash flow variables and corporate governance indicators. The output of this research would include a model that predicts the probability that a firm belongs in each financial distress state rather than predicting whether or not the firm "fails" as found in most financial distress studies.

1.4 Research Objectives

This research aims to achieve the following objectives:

1. *To examine the effects of financial ratios and corporate governance indicators on the probability of multiple state financial distress for non-financial listed firms in the Chinese equity market*

This objective is to examine the association between financial ratios and, corporate governance indicators and multiple financial distress states while controlling for firm-level and industry-level heterogeneity and confounding external factors. Explanatory factors include accrual-based ratios, cash flow-based ratios, market-based ratios and corporate governance indicators. Accrual-based ratios include asset management efficiency, profitability, liquidity and financial leverage ratios while corporate governance indicators board structure, ownership structure and management compensation. Part of this objective is to examine the effect of these explanatory variables, at different values, different financial distress, states using predicted probabilities and marginal effect analysis.

2. *To determine whether explanatory factors and their effects on each of the four financial distress states of a multiple state financial distress model are different for non-financial listed firms in the Chinese equity market.*

The first step in this objective is to test whether the median distributions of the four financial distress states are statistically different using non-parametric tests. The second step is to determine whether significant explanatory variables at each of the financial distress states relative to the reference state are the same from the multinomial logit regression results. The third step is to determine whether the effects of financial ratios and corporate governance indicators on each financial distress state are different using a post-multinomial logit regression second difference test analysis.

3. *To determine whether explanatory variables and their effects on financial distress in a binary state distress model and multiple state distress models are different for non-financial listed firms in the Chinese equity market.*

This objective compares the relationship between explanatory variables and financial distress in the binary state financial model and the multiple state financial model in terms of the sign and significance of the log coefficient and the magnitude of effects. The binomial logit regression is used to model binary state financial distress consisting of non-financially distressed (NFDIS) and financially distressed (FDIST). The multinomial logit regression is used to model multiple state financial distress consisting of mutually exclusive states; non-financially distressed (NFDIS), financial decline (FDECL), financially weak (FWEAK) and financially distressed (FDIST).

4. *To examine what influence cash flow-based ratios and corporate governance indicators have on the effects and explanatory power of accrual-based and market-based ratios of non-financial listed firms in the Chinese equity market.*

This objective is achieved by fitting the base multiple state financial distress model which consists of accrual-based ratios and market-driven ratios only and is referred to as the "accrual model". The "accrual model" is extended to include cash flow-based ratios to arrive at the "cash flow model" to evaluate the incremental explanatory and predictive power of cash flows. Likewise, the "accrual model" is extended to include corporate governance indicators to arrive at the "corporate governance model" to evaluate the incremental explanatory and predictive power of corporate governance indicators. Further, the "accrual model" is extended to include cash flow-based ratios and corporate governance indicators to arrive at the "full model". This is to evaluate the incremental predictive powers introduced by cash flow ratios and corporate governance indicators and how they influence accrual-based and market-based ratios.

1.5 Motivation of the Study

First, this research is motivated by the scarce research in multiple state financial distress process and the need to contribute to contemporary research approach to financial distress study that model financial distress as a multiple state process. This research attempts to provide a strong understanding of the financial distress process and the nature of financial distress symptoms across different financial distress states as it relates to the Chinese equity market. Such understanding is invaluable to the investors, creditors, the CSRC and other stakeholders in promoting the diagnosis of financial distress symptoms exhibited by firms at different financial distress states in the Chinese equity market. Seeing that the ST delisting system provides limited information on the financial health of listed firms in the Chinese equity market, this research seeks to explore the other factors that explain the financial health of firms at different designations of the ST delisting system.

In addition, this research is motivated by the lack of extension of accrual-based information with cash flow statement components and corporate governance indicators. The poor choice of explanatory variables makes an adequate assessment of financial distress challenging which results in poor financial distress prediction. The delisting system, for instance, has been criticised by several studies such as Liu & Lu (2007), Jiang & Wang (2008), Wang & Yung (2011) and Lai & Tam (2017) for its over-reliance on accrual-based profitability criteria which makes it is prone to manipulation. This research investigates how other explanatory factors including cash flow factors and corporate governance indicators that are less susceptible to manipulation could improve the assessment of firm financial health and prediction of financial distress in the Chinese equity market

1.6 Contribution of the Study

Finally, this study contributes to the growing financial distress research by examining the impact of financial ratios and corporate governance on the financial distress of nonfinancial firms in the Chinese Equity market with strong institutional background and unique market practices. The research contributes to the literature on the association between financial ratios and corporate governance and financial distress. This is achieved by investigating the non-linear associations between these variables especially in a multiple state financial distress context.

This research contributes to empirical research on multiple state financial distress process. First, this research shows how approaching financial distress as multiple states rather than binary states improves the understanding of the financial distress process. Further, the research provides an understanding of explanatory variables (symptoms), driving diverse financial distress states which is relevant when determining a firm’s financial distress state within the financial distress process.

1.7 Structure of the Study

Chapter Two reviews the literature on the concept of financial distress, the financial distress process and explanatory variables in the financial distress study. The chapter develops the hypotheses tested in this research and reviews of each explanatory factor. Chapter three discusses methods of data collection, sample selection and outcome and explanatory variables specification. The chapter discusses endogeneity in the context of this research and empirical estimation models and estimator used in this research. Chapter four details the empirical results analysis and discussion of the main findings of this research. Chapter five summarises the main findings of this research, highlights the implications and limitations of the research and gives suggestions for future research.

CHAPTER TWO

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 The Concept of Financial Distress and Insolvency

Although this research focuses on explanatory variables and methods used in estimating financial distress, it is essential to clarify the terminologies used in financial distress studies and this research. Terms used in financial distress studies have been used interchangeably however, these terms may not mean the same thing. There appears to be no generally accepted theory behind the use of terminologies and concepts of financial distress in the literature. The closest theory is the theory of organisational contingency which relates management decisions to firm performance and financial health. In the literature common terms that have been used to describe a financially unhealthy firm include financially distressed, default, insolvent, bankrupt, business failure. In some cases, it is a matter of the terminology used in different jurisdictions. For instance, in the US, bankruptcy is used to describe the terminal state that an insolvent firm falls into as adjudicated by a competent court (U.S.Courts, n.d.). Thus, insolvency precedes bankruptcy in the financial distress process as defined in the U.S jurisdiction. However, this is different in the UK jurisdiction where insolvency is used to refer to a terminal state of a financially unhealthy firm which is analogous to bankruptcy in the U.S. It does appear studies use the terms default, insolvency, bankruptcy and corporate failure interchangeably to define a terminal state where a financially unhealthy firm exits the market and ceases to exist. Beaver (1966), Deakin (1972), Rose, Andrews & Giroux (1982), Sharma (2001), Balcaena & Ooghe (2006), Ahmed (2014) and Almany, Aston & Ngwa (2015) used the term “corporate failure” (or failure) to refer to firms in a terminal state of financial distress. On the other hand, Altman (1968), Ohlson (1980) and Shumway (2001), Rodgers (2011)and Stewart (2016) used the term “bankruptcy” while Bharath & Shumway (2008) used the term “default” to refer to firms at a terminal state of financial distress.

The term ‘financial distress’ is not defined by jurisdiction in the U.S. or the UK and appears to gain its origin in the corporate finance world and popularized by Altman (1983). Altman (1983) used the term financial distress to cover the whole journey of a firm from when it is deemed to be financially unhealthy up to when it either recovers or deteriorates into terminal states such as liquidation or merger & acquisition. Legislations such as Section 123(2) of the InsolvencyAct (1986) of the UK did not define any of the terms that have been used in financial distress literature except for ‘insolvency’ (bankruptcy) which is defined as:

(i) “*a situation of a company’s inability to settle its obligations as they fall due and payable within the ensuing six months”, or*

(ii) “a reasonable probability that a company will become insolvent and fall into the definition in (i) above within the ensuing six months”, or

(iii) “a situation where it is evident that the value of its assets is less than the value of its liabilities including any contingent liabilities”.

The above definitions of the InsolvencyAct (1986) connect to the US Bankruptcy Act definition of *bankruptcy*. Insolvency definition anchors on *inability to pay* which in financial terms implies *default*. In other words, an insolvent firm defaults on its debt obligations. Thus, we could say insolvency is used to refer to a firm that is financially unhealthy in the legal world, while financial distress is used to refer to the same situation in the corporate finance world. Abou (2008), Sori & Jalil (2009), Beaver, McNichols & Correia (2010) and May (2013) identified two perspectives to the definition of insolvency, *cash-flow insolvency* and *balance sheet insolvency* (or technical insolvency) alongside interpretations by the UK Court of Law.

Cash flow insolvency test

Parts i) and ii) of the Act’s definition of insolvency relate to cash flow insolvency since they deal with the inability to settle the due obligation. In determining an inability to pay the debt, the Act takes into consideration debts that have fallen due and are payable (short term obligations) and those falling due in the near future - long term obligations (InsolvencyAct, 1986). A firm experiencing a decline in sales is at high risk of a decline in profitability and a decline in profitability puts a firm at further risk of a decline in operating cash flow. A poor cash flow puts a firm at risk of not paying its obligations as they fall due. A firm that is cash flow insolvent is at a higher risk of borrowing as a result of its inability to generate liquidity internally through sales and supplier credit. A declining sales and profitability (Equity) coupled with increasing financial leverage (Liabilities) may result in negative equity (which is balance sheet insolvency). It thus appears firm cash flow insolvency holds the default definition of 'insolvency' and precedes balance sheet insolvency.

Balance sheet insolvency test (Technical insolvency)

Section 123(2) of InsolvencyAct (1986) provides for what is commonly referred to as a *balance sheet insolvency* test or which is also referred to as 'negative equity in the literature. Slaughter & May (2013) argue that the balance sheet insolvency expression cannot be satisfied simply because a corporate entity's balance sheet shows negative equity but must be interpreted in the context of inability to pay the debt – cash flow insolvency. An instance of balance sheet insolvency occurs commonly in share repurchase which is a common trend for US-listed firms to repurchase their shares from the market (Lv, Li & Gao, 2012). Share repurchase (treasury stocks) provides immediate benefits for both corporate entities and investors and has been a proven corporate strategy for fighting off impending forceful acquisition (Beaver, Kettler & Scholes, 1970). However, the exercise may result in a decrease in shareholders' equity which commonly results in 'negative equity. Negative equity in this sense might then be misinterpreted as balance sheet insolvency on the side of the firm. In this light, it can be argued that Balance sheet insolvency can only be confirmation of an existing cash flow insolvency.

In terms of the financial distress process, the path travelled by distressed firms from when they are declared *insolvent* by the court or *financially distressed* by the market framework until it is *dissolved* or recovers, is clear and well documented in the bankruptcy process in different jurisdictions. This part of the financial distress process is what we refer to as the *post-insolvency* period in this research. May (2013) elaborated on different exit routes or options open for a firm from when it is declared insolvent and these options include merger, acquisition, company voluntary arrangement, administration and receivership. However, it is a bit unclear both in corporate finance and the legal world what term is to be used to describe states that distressed firms transverse from when they are deemed *financially healthy* until the point when they are declared *insolvent* by the court or designated *financially distressed* by a framework. This part of the financial distress process is what we refer to as the *pre-insolvency* period in this research. Any creditor or investor whose aim is to minimize losses would likely focus on early financial distress symptoms. In this research, early financial distress symptoms are observed in the pre-insolvency part of the financial distress process and this would be the focus of this research.

2.2 Causes of Financial Distress and Research Framework

Investigating the causes of financial distress is not the focus of this research. However, a review of the literature on causes of financial distress provides some foundation to the conceptual framework of this research. This section identifies and discusses causes of financial distress as identified by prior studies. Being an subjective area, studies on the causes of financial distress have been criticised for high subjectivity going as far as pointing at factors such as 'bad luck' as a cause of financial distress (Dempster & Isaacs, 2014). This appears to have resulted in fewer researches in this area as noted by Beaver (2016). Argenti (1976) is among the pioneer attempts to identify causes and symptoms of financial distress into what he termed the business failure process.

Figure 2.1 draws the relationship between causal and explanatory factors and the outcome financial distress. The research framework - the explanatory factors and outcome financial distress is present in orange. Figure 2.1 is derived from Argenti (1976) business failure process model and the wider organisational contingency theory by Donaldson (2006). The focus of this research is on financial and non-financial symptoms of financial distress as indicated in the orange section of Figure 2.1. In Figure 2.1, Donaldson (2006) classified causes of business failure into factors exogenous to the firm and factors endogenous to the firm. According to Donaldson (2006), *exogenous causes* influence *endogenous causes* although both can independently cause firm *symptoms of financial distress. Management actions* and *firm attributes* are contingent on *exogenous causes* while financial and non-financial symptoms of financial distress are contingent on management actions and firm attributes.

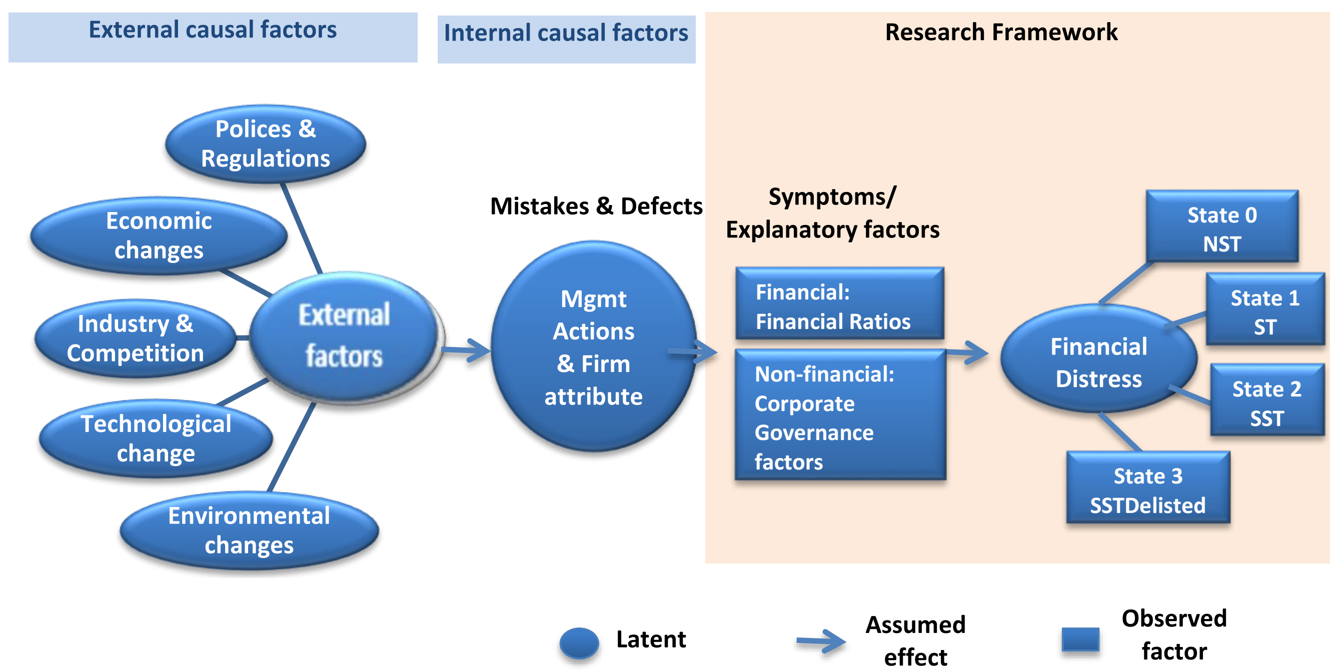
External exogenous causes

From Figure 2.1, we observed the root causes of financial distress are sourced from external exogenous factors. The theory that external factors impact the firm management decisions is established in studies by Brown & Caylor (2009), Memba & Job (2013), Beaver (2016) and Mahtani & Garg (2018) and Sami, Wang & Zhou (2011) in China. For instance, Mahtani & Garg (2018) found government policies and economic conditions to significantly impact airline operating profit performance by way of decisions made by management. Including external factors in the conceptual framework helps to trace the root cause of financial distress which is an extension of Argenti's model. External factors are exogenous to the firm and include variables such as policies and regulations by the Government, changes in the environmental elements, technological innovations, macroeconomic variables and industry regulation and forces of competition. The laws and regulations that firms must adhere to have a significant impact on firm performance particularly revenue and profitability through management actions (Donaldson, 2006).

Internal endogenous causes

Figure 2.1 show that management actions (mistakes) and firm attributes (defects) as endogenous causes of financial distress and this finding agrees with Kenney, LaCava & Rodgers (2016) who found that 40% of business failure was a result of poor strategic management.

Figure 2.1: Causes of Financial Distress and Research Framework



Source: Author's compilation, Donaldson (2006)

The management of a firm makes decisions and strategies which significantly determine the success or failure of a firm's operations. The influence of management actions on a firm draws from the organisational contingency theory that defined these relationships (Donaldson, 2006) and concurred by Agrawal & Knoeber (2012), Memba & Job (2013) Dalwai, Basiruddin & Rasid (2015) and Malik & Makhdoom (2016). Management actions come in the form of corporate policies, business strategies and daily management decisions. According to Argenti (1976), *firm attributes* (defects) are inherent characteristics of a firm such as business model, organisation structure, organisation culture, systems, size and industry. Management actions and firm attributes directly result in financial distress *symptoms* exhibited by the firm (Argenti, 1976).

2.3 Financial Ratios, Corporate Governance Factors and Financial Distress

To provide empirical evidence on the effect of determinant symptoms of financial distress, this section reviews financial ratios and corporate governance factors according to the categorization by Kenney et al. (2016).

2.3.1 Financial Ratio Determinants of Financial Distress

Studies such as El-Hannawy (1981) and Harrison (2005) show that the success and failure of a firm as well as its financial health are evident in the financial statements. This argument concurs with the statutory definition of financial distress (Insolvency), which makes references to the financial statement items. Based on this, it thus appears any study of financial distress that omits accounting data (financial ratios) will suffer significant shortcomings as observed by Harrison (2005). However, the use of financial statement items in predicting financial distress does not draw from a known theory that should specify what financial ratios and the number of financial ratios to use. Rather than theories, there has been an overwhelming volume of studies that connect financial distress to financial ratios drawn from financial statements. One of the earliest use of financial statement items to assess financial distress is by Fitzpatrick (1932) where thirteen financial ratios were used in a dichotomous bankruptcy prediction study using forty firms matched into twenty pairs. In the study by Baumol (1952), financial statement items were employed in building a financial distress theoretical model. In the inventory model by Baumol (1952), a firm is viewed as having a reservoir of liquid assets supplied by the inflow of liquid assets and drained by the outflow of liquid assets. Financial distress is modelled as a state in which the firms' reservoir goes dry and at which state the firm is unable to pay its obligations. Hypothetically, the larger a firm's reservoir, the less likely it is for the firm to become financially distressed and vice versa. Second, the larger a firm's cash outflow is, the more likely it is for the firm to go into financial distress. Third, the larger a firm's cash inflow is, the less likely it is for the firm to go into financial distress. Liquid asset inflow mainly refers to cash and cash equivalent while outflow liquid assets are short-term and long term obligations to pay cash or cash equivalent. Baumol (1952)'s reservoir model revolves around the cash flow statement while relating to revenue in the income statement in addition to assets and liabilities in the balance sheet. While the study by Fitzpatrick (1932) mainly pointed to the use of financial statement items in assessing the financial health of a firm, the study by Baumol (1952) emphasized modelling financial distress by highlighting key financial statement items and their role in assessing financial distress.

Beaver (1966) contributed to both Fitzpatrick (1932) and Baumol (1952) on the significance of financial ratios in the financial distress study, by studying wider aspects of the financial statements using thirty financial ratios. The thirty financial ratios were narrowed to five financial ratios, one for each financial statement performance area: cash flow-to-total liabilities (CFOTL) for cash flow, working capital-to-total assets (WCTA) for liquidity, net income-to-total assets (NITA) for profitability, current assets-to-current liabilities (CR) ratio for liquidity and total liabilities-to-total assets (TLTA) for financial leverage. The study found cash flow to total debt (total liabilities) as having the highest discriminant power to discriminate between "failed" firms and "non-failed". Although Beaver (1966) did not model the financial ratios, the study is consistent with the reservoir model by Baumol (1952). *Liquid assets inflow*" is represented by "*cash flow from operations*" while "*liquid assets outflow*" is captured in the "*total liabilities*. Beaver (1966) identified profitability, liquidity and financial leverage and cash flow as key financial statement areas that are critical in assessing financial distress. Recent studies such as Tinoco, Holmes & Wilson (2018) used financial leverage ratios (total assets to total liabilities and interest coverage) and cash flow ratios (cash flow from operations to total liabilities) which emphasize the relevance of the research by Beaver (1966).

Altman (1968) assessed twenty-two financial ratios selected from a similar financial statement area as Beaver (1966). Altman (1968) extended the profitability and liquidity aspects of financial statements studied by Beaver (1966) with asset management efficiency and market-based ratios.

Notably, financial leverage and cash flow-based ratios were not significant in the study by Altman (1968). The five financial ratios significant in Altman (1968) are sales to total assets (TATURN) for asset management efficiency, WCTA ratios for liquidity, retained earnings to total assets (RETA), earnings before interest and taxes to total assets or profitability and market value of equity to total liabilities (MVTL) for market valuation. The Altman Z score model with five financial ratios achieved a classification accuracy of 72% in the estimation sample and 80% to 90% in the subsequent test compared to 78% by Beaver (1966)'s CFOTL ratio. Based on this comparison, Altman (1968) argue that employing financial ratios that assess different aspects of the financial statement *at the same time* performs better at assessing financial distress than a single financial ratio. Yap, Helmi, Munuswamy & Yap (2011) replicated the study by Beaver (1966) using fourteen financial ratios fitted in a financial distress model. The study found that a single CFOTL ratio achieved better classification power of 81% and 94% in estimation and holdout sample than a multivariate model with several financial ratios.

Following afore discussed pioneer studies, a host of studies have employed financial ratios in studying financial distress. These studies include Deakin (1972), Ohlson (1980), Hensher, Jones & Greene (2007), Farooq et al. (2018), Tinoco et al. (2018), Tan (2019), Barbuta-Misu & Madaleno (2020). Based on the findings of prior literature, we hypothesize that financial ratios significantly influence a firm's financial distress status. In reviewing the role financial ratios play in assessing financial distress we explore the firm performance aspects in both Beaver (1966) and Altman (1966) and these are asset management efficiency, profitability, liquidity/working capital, market valuation and cash flow.

2.3.1.1 Asset Management Efficiency and Financial Distress

The asset management efficiency aspect of firm performance is considered in this research following the findings by Palinko & Savoob (2016) that strongly suggest operating inefficiency as a symptom of early financial distress. Further, revenue measured in asset management efficiency is the source of internally generated liquidity for the firm. Asset management efficiency ratios or activity ratios are a group of financial ratios that measure a firm's ability to efficiently utilize its assets: fixed assets, accounts receivables and inventory (Beaver et al., 2010). The focus of the asset management efficiency ratio is to relate revenue or turnover that represents a firm's financial performance in the income statement to assets in the balance sheet since key activities of a firm are driven by assets. The significance of asset management efficiency draws from studies such as Palinko & Savoob (2016) who found the early "symptoms" of financial distress in operational inefficiency. Beaver (2016), Gilbert et al. (1990) and Turetsky & McEwen (2001) cited one of the symptoms of operational inefficiency is an inefficient use of assets. We believe that where a firm is unable to efficiently utilize its fixed assets to general revenue then this could not be a symptom of financial health deterioration but an early one. Other evidence that points to the inability to generate revenue as an early aspect of firm performance to watch out for is that several other areas of a firm performance including profitability, liquidity and cash flow depend on revenue. Thus, we believe asset management efficiency will have a meaningful effect in assessing the financial distress state of firms in the Chinese equity market. It is also expected that a firm with increasing revenue and asset management efficiency is less likely to become financially distressed. On one hand, it is expected that the delisting criteria that depend on the ability of a firm to generate revenue and profits will drive the significance of the asset management efficiency ratio in the Chinese equity market. On the other hand, the potential significance of asset management efficiency ratios in the Chinese equity market may be undermined where financially distressed firms do manipulate their revenue. This is because the *profit-based* delisting system creates an incentive for firms (especially SOE firms on ST or SST designation) to manipulate their revenue and earnings to stay listed (Lai & Tam, 2017). The situation makes it interesting to research the effects of asset management efficiency on different financial distress states in the Chinese equity market. We are interested in observing the effect of asset management efficiency in the unique situation of the Chinese equity market after we control for factors that could influence the variable such as State ownership. We, therefore, hypothesize as to the following:

Hypothesis H2.1: *Asset management efficiency has a significant effect on the probability of multiple financial distress states of non-financial listed firms in the Chinese equity market.*

2.3.1.2 Profitability and Financial Distress

Profitability ratios measure the ability of a firm to retain profit (Axel, 2012). Typically, a profitability ratio is a measure resulting from the comparison of a profit item with another financial statement item. In measuring profitability, profit or retained earnings has been commonly compared to three main financial statement items directly related to profit including revenue, assets and shareholders' equity. When profit is compared to revenue, the ratio measures the ability of the firm to retain profit from the revenue it generated. This ratio is borne out of the concept that profit is net of revenue after deducting cost or cost and tax. When profit is compared to assets, the ratio measures the ability of a firm to generate profit from assets it holds. This ratio follows the concept that assets generate revenue for a firm and from revenue, a firm retains profit Beaver, McNichols & Rhie (2005). Profit compared to shareholders' equity measures how much profit a firm generates from invested shareholders' equity which is assets net of liabilities. Cash flow underlines the definition of cash flow insolvency (financial distress) by the InsolvencyAct (1986), however a firm's source of cash flow is its revenue and profit from operations. It then follows that profitability is a fundamental determinant of financial distress. Following this relationship, it is assumed that firm with poor profitability will have a high risk of financial distress. This finding is consistent with Pozzoli & Paolone (2017) and Laitinen (1991) who found poor profitability as the sole determinant factor for firms in early-stage financial distress. Similarly, to asset management efficiency, the profit-based delisting system of the Chinese equity market is expected to drive the effects of profitability in our research. Therefore, the expectation is that profitability would have a negative association with financial distress and that is, the more profitable a firm the less probable it is that it would become financially distressed. Although evidence from prior studies points to the strong significance of profitability ratios, we observe the influence of possible earnings manipulation, which Lai & Tam (2017) found common amongst ST and SST firms. Prior financial distress studies have been concerned with testing the linear effect of profitability on a single pooled financial distress state (dichotomous approach). We progress this approach by observing the non-linear association between profitability and different financial distress state in the case of China. To test the effect of profitability on the probability of financial distress, the following hypothesis is established:

Hypothesis H2.2: *Profitability has a significant effect on the probability of multiple state financial distress of listed non-finance firms in the Chinese equity market.*

2.3.1.3 Liquidity and Financial Distress

Liquidity ratios from accrual accounting data measure the ability of a firm to pay its short-term obligations (Altman, 1968). In financial distress studies, liquidity has been measured by comparing the current liquid assets to the current liquid liabilities of the firm or by comparing the working capital to the total assets of the firm (Altman, 1968). Liquidity ratios are considered a fundamental determinant of financial distress considering the underlying definition of insolvency and findings from empirical studies such as those of Campbell et al. (2011) and Atieh (2014). Liquidity is related to financial distress to the extent that a firm needs liquid assets to settle its financial obligations, especially short-term obligations. Where insolvency is the inability to pay short term obligations, it follows that the weaker the liquidity ratio of a firm, the more the firm is susceptible to cash flow insolvency. In day-to-day operations, a firm is expected to hold sufficient short-term liquidity (liquid assets) to settle its short term obligations as they arise (Atieh, 2014). When the ability to generate and hold sufficient or positive working capital is impaired then it is likely the firm will be unable to settle its obligations as they fall due, that is, become financially distressed. The consequence for a firm not maintaining a positive or sufficient working capital is the inability of the firm to adequately finance its operations and invest in future business growth opportunities. Kenney et al. (2016) cited poor funding of operations and attendant operational inefficiency as a key endogenous driver of financial distress. When a firm is experiencing short term insolvency (for instance, in the case of negative working capital), there is pressure to raise additional capital either from equity or debt or both according to the Pecking Order (Alzomaia, 2014).

Liquidity ratios were found to be significant and used in modelling financial distress by studies such as Altman (1968), Altman, Haldeman & Narayanan (1977) Charitou, Neophytou & Charalambous (2004) and Rommer (2005). Drawing from prior studies, liquidity ratios and financial distress are expected to have a negative relationship. It is expected that as the liquidity of a firm deteriorates, the firm advances towards financial distress. This is because, in a poor liquidity situation such as a negative working capital situation, there is evidence the firms are unable to settle their short-term financial obligations as they fall due from their short-term liquid assets. It is important we separately assess liquidity using accrual-based ratios and liquidity using cash flows as argued by (Sharma, 2001). Beyond testing the linear associations, we are interested in observing the non-linear association between liquidity and different financial distress state in the case of China. To test the effect of liquidity on the probability of financial distress, the following hypothesis is established:

Hypothesis H2.3: *Liquidity has a significant effect on the probability of multiple state financial distress of non-financial listed firms in the Chinese equity market.*

2.3.1.4 Financial Leverage and Financial Distress

The financial leverage aspect of firm performance is considered for this research following the significance of external debt borrowing and capital structure of a firm in the definition of insolvency (especially balance sheet insolvency) by InsolvencyAct (1986). Financial leverage ratios measure a firm's ability to settle its long term financial obligations and also tell how much a firm relies on external borrowing sources for capital (Axel, 2012). Alzomaia (2014) observed two main sources of a firm's financing, internal and external funding sources. Internal funds include short-term financing such as working capital and long-term reserves such as retained earnings (revenue reserve) while external funds could be debt or equity. The Pecking Order of sourcing finance prioritizes internal sources first, then external sources such as debt and then the equity in the order these sources are influenced by information symmetry (Alzomaia, 2014). It follows that a firm that is experiencing financial distress would likely assess funding in the manner of the pecking order. When a firm is experiencing poor profitability and subsequently cash flow and liquidity squeeze, the expectation as per pecking order is that they will resort to external financing from equity or debt. However, debt financing is relatively quicker than equity financing in the Chinese equity market (Cheng et al., 2007). Since a firm experiencing financial distress does not have time on its side, debt financing becomes more attractive. Long-term borrowing in this case helps to fund the negative working capital or deficiency of liquid assets to settle short term obligations. A firm with high financial leverage may have higher cash flow from external sources (cash flow from financing) as borrowing increases. However, such a firm runs a higher risk of experiencing a negative net asset where total liabilities exceed total assets.

Drawing from the findings of prior literature, it is expected that a firm with increasing financial leverage is more likely to become financially distressed. Yet, the relationship between financial leverage and financial distress does not appear linear as reported in several financial distress studies. This is because “financially healthy” firms may also experience increasing external borrowing. It is in our interest to observe the non-linear effects of financial leverage especially when firms are in different financial distress states. To test the influence of financial leverage on the probability of financial distress, the following hypothesis is established:

Hypothesis H2.4: *Financial leverage has a significant effect on the probability of multiple state financial distress of non-finance listed firms in the Chinese equity market.*

2.3.1.5 Market Ratios and Financial Distress

Traditionally, market-driven ratios have been used to compare firm market valuation (market risk) to the firm financial performance of the firm (financial risk)(Altman, 1968). Studies such as Dichev (1998) argue that market risk is different from financial risk and there is no association between the two. Nonetheless, we consider the market valuation aspect of firm performance based on its significance in prior financial distress studies such as Shumway (2001), Zhang, Altman & Yen (2010) and Malik, Aftab & Noreen (2013). A key item used in computing market ratios is share prices and because share prices are a reflection of an investor’s current and future valuation of a firm (Wang, 2017). Similarly to financial ratios, there is no known theory around the use of market-based ratios in studying financial distress. The use of market-based ratios became famous over perceived shortcomings of financial ratios some of which are highlighted by Reisz & Perlich (2007) and Agarwal & Taffler (2008). Although some studies such as Zhang et al (2010) classified market ratios as financial ratios, market-based ratios use a quotient of the market-driven element such as stock prices, stock returns and balance sheet items. Market-based ratios aim to relate the market performance of a firm to financial statement performance. Traditionally, market-driven ratios have been used to compare firm market valuation to total liabilities (Altman, 1968) or to compare firm market valuation with firm book (financial statement) valuation (Beaver et al, 1970). Stock prices are the key measure of the market value of a firm since they reflect investor expectations about future cash flows from the firm (Rees, 1995). Stock prices are expected to capture the fundamentals of a firm and the expectation of investors accordingly, there has been overwhelming research on the association between the market value of a firm and firm financial health. Empirical studies by Chan, Nai-fu & David (1985), Fama & Kenneth (1992), Shumway (2001), Bharath & Shumway (2008) found a significant influence of market-driven factors on

financial distress. Lindsay & Campbell (1996) and Clark & Weinstein (1983) both found that firms approaching bankruptcy showed negative stock returns up to three years before failure. Shumway (2001) and Bharath & Shumway (2008) fitted a financial distress prediction model combining market-driven variables such as firm stock returns and standard deviation of stock returns with financial ratios used in Altman (1968) and Zmijewski (1984). Shumway (2001) found that the efficacy of financial ratios to predict financial distress risk is improved by market-based ratios. He (2002) found that market-driven factors work better as complementary variables in the diagnosis and prediction of financial distress risk which agrees with the finding of Shumway (2001). Aharony, Jones & Swary (1980) found that firms at terminal financial distress states have significantly different market returns compared to other listed firms generally. Further Clark & Weinstein (1983) found that firms at terminal financial distress states (three years before bankruptcy) perform in the equity market and experience negative market returns.
In contrast, studies by Altman (1968), Ohlson (1980) models and Dichev (1998) argues that bankruptcy risk is a systematic risk because financial distress risk is not compensated with higher stock returns. Consequently, these studies argue that market-based ratios such as the book value to the market value used in prior studies are unlikely to be relevant to financial distress risk. Notably, the same market-driven indicators that Shumway (2001) found to complement financial ratios in predicting distress risk were found not to relate to financial distress risk when tested alone by Dichev (1998). Further, Dichev (1998) argued that firm market risk as measured by market-based ratios appears different from financial distress risk as measured by financial ratios. Bharath & Shumway (2008) and Merton (1974) noted that the incremental information provided by market-based ratios concerning diagnosing financial distress risk is under the assumption of efficient markets. However, emerging markets like China are still on their way to market efficiency which implies that market-based ratios may not be as significant in the Chinese equity market as they are in studies in developed markets.

Despite a large body of literature on the effects of market-based ratios on financial distress, there are several aspects of the association between the two factors that remain unclear. A host of studies by Shumway (2001), Bharath & Shumway (2008) and Malik et al. (2013) that find the effects of market valuation significant are based on a sample of firms in terminal financial distress state such as bankruptcy. However, these studies do not show whether market valuation is significant for firms in the pre-insolvency period including early financial distress states. This research wishes to observe the association between market valuation and financial distress in the face of China unique market mechanism, retail and block shareholding structures and weak market regulation. Therefore, the following hypothesis is established:

Hypothesis H2.5: *Market valuation has a significant effect on the probability of multiple state financial distress of non-finance listed firms in the Chinese equity market.*

2.3.1.6 Cash Flow and Financial Distress

The cash flow liquidity aspect of firm performance is considered for this research as a result of its significance to the definition of insolvency (especially cash flow insolvency) by InsolvencyAct (1986). In the literature, cash flow-based ratios compare the cash flow items to different financial statement items typically total assets, total liabilities, total liabilities current liabilities or outstanding shares. Several cash flow-based ratios have been used in the literature notwithstanding, cash flow from operations remains the most referenced proxy for cash flow (Hossari & Rahman, 2005). The CFOTL ratio compares a firm's cash flow from operations to the total liabilities. The ratio was popularized by Beaver (1966) as a single ratio as powerful as multivariate ratios in discriminating between financially distressed and non-financially distressed firms. The importance of this ratio is that it draws from two financial statement items directly related to financial distress, which are cash flow from operations and debt.

Cash flow-based ratios are a measure of how much cash liquid a firm is and how well a firm generates cash flow from its operations to pay short-term obligations and finance working capital (Beaver, 1966). Cash flow has a direct association with financial distress drawing from the definition of cash flow insolvency. The definition of cash flow insolvency refers to cash flow from operations since the ability to settle obligations depends on the firm's ability to internally generate cash flow from operations rather than the cash flow from financing. However, both aspects of the cash flow information assess diverse levels of firm liquidation. Several studies in the Chinese equity market such as those of Zhou, Kim & Ma Tang (2012), Yu (2013) and Tang (2018) cited China's state government and state banks providing continued "bailout" and financial support to SOEs on ST and SST designations even when these state enterprises are not economically viable. Although the literature points to absolute cash flow information as a strong factor in diagnosing financial distress, cash flow information appears less researched in the Chinese equity market. The traditional measure for liquidity from Altman (1966) has been the accrual-based liquidity or working capital ratios and most studies in financial distress measure liquidity using accrual-based liquidity ratios while neglecting cash flow ratios. Atieh (2014), Barua & Anup (2015) and Laitinen (1994) show that accrual-based and cash flow-based liquidity ratios measure distinctively different aspects of a firm's liquidity. Laitinen (1994) also argue that accrual-based liquidity ratios may not adequately assess the insolvency level of a firm especially with regards to the definition of financial distress by the InsolvencyAct (1986). In emerging markets such as China where market regulations are less tight, there are increased concerns as to the reliability of accrual accounting data due to increased risk of manipulation and earnings management (Guilford, 2018; Liu & Lu, 2007). This is a major limitation of financial distress studies in the Chinese market such as those of (Ding, Song & Zen, 2008; Kam, 2007; Qian, Feng & Zhou, 2007; Wang & Li, 2007) where cash flow data is largely omitted. This poses a question as to whether accrual-based ratios alone can effectively be used to measure firm liquidity while predicting financial distress. We observed that several factors such as poor profitability precede cash flow problems however, financial distress studies have not shown how these factors play out for firms in different financial distress states. Further, prior financial distress studies have been primarily concerned with testing the linear effects of the cash flow-based ratio. Beyond this aim, this research is interested in understanding the non-linear association between cash flow and firms in a different financial distress state. Therefore, we establish the following hypothesis:

Hypothesis H2.6: *Cash flow has a significant effect on the probability of multiple state financial distress of non-finance listed firms in the Chinese equity market.*

2.3.2 Corporate Governance Factor determinants of Financial Distress

According to Liang, Lu, Tsai & Shih (2016) corporate governance is widely described as the whole body of practices, rules and systems by which a firm is governed. Interest in corporate governance research has been fueled by ongoing concerns over the agency problem – conflict of interest between shareholders ('principal') and management ('agent') (Liang et al., 2016). Although research in corporate governance has lasted several decades, the collapse of large US corporations such as WorldCom in 2002 followed by Enron in 2007 emphasized the role corporate governance plays in ensuring business success or failure. Also, the use of corporate governance indicators in financial distress research has received massive attention following the need for non-financial factors that are less susceptible to manipulation.

Diverse empirical research has researched the influence of corporate governance on various aspects of a firm - market value, firm performance, financial distress and earnings management. The relationship between corporate governance and firm performance was explored extensively by Li & Naughton (2007); Xu & Wang (1999) and Bai, Lui, Lu, Song & Zhang (2004). If corporate governance could influence firm performance, it is assumed that a firm with good corporate governance is less likely to enter financial distress. other studies by Lee & Yeh (2004), Wu (2007), Lin et al. (2010), Zhang et al. (2012), Brédart (2014) and Rezaee et al. (2016) show that corporate governance indicators (CGIs) play an important role in predicting financial distress and corporate failure. Empirical studies such as Agrawal & Knoeber (2012) and Dalwai et al. (2015) found that companies with strong corporate governance performed better than companies with poor corporate governance. Jaikengkit (2004), Lee & Yeh (2004) found that board composition, ownership structure and management compensation had a significant impact on the risk of the firm becoming financially distressed. Corporate governance mechanism was also the focus of several financial distress studies on the Chinese equity market including Liu, Uchida & Yang (2012) and Li (2014). To the researcher's knowledge, these studies have not been concerned with studying the effects of corporate governance components at different financial distress state. Also, a good number of these studies such as Elloumi & Gueyle (2001) and Brédart (2014) focus on assessing the relationship between corporate governance mechanisms and financial distress while neglecting financial ratios. This research investigates the association between corporate governance mechanisms (board structure and ownership structure) combined with financial ratios and, different financial distress states These corporate governance mechanisms are consistent with those of Elloumi & Gueyle (2001) Bai et al. (2004) Jaikengkit (2004), Wu (2007) and Chen (2008).

2.3.2.1 Board Structure and Financial Distress

Board composition or structure is an important aspect of corporate governance considering that governance and control of a firm lie with the boards. Empirical research found that board independence, separation of position of Chairman and CEO and board size are key indicators of strong board structure (Ashbaugh-Skaife, Collins & LaFord, 2006; Bredart, 2013; Brédart, 2014; Huang, Mahenthiran & Zhang, 2011; Malik & Makhdoom, 2016). These three proxies are also relevant in the guideline by OECD (2015) and therefore used in this research.

Board Independence

Board independence as a proxy for measuring the effectiveness of board structure and corporate governance draws from the argument that the board of directors are the instrument through which equity holders of a company control the company and influence management. Going by agency theory, the board of directors is the *principal* acting on behalf of the shareholders while the board of management is the *agent* (Brédart, 2014). It is further argued that the board of directors needs to be independent of management to effectively function as the principal for shareholders. Also, for the function of being a principal to be effective, the board of directors should be composed of more non-executive directors, in other words, it should not be dominated by executive directors (Brédart, 2014; Santen & Soppe, 2009b). Therefore, for the board of directors to be truly independent of the management board, Malik & Makhdoom (2016) argue that both boards be headed by different persons. While empirical research agrees that the effectiveness of the board of directors is fostered by its independence, findings on the impact of board independence on financial distress are mixed. Studies by Lee & Yeh (2004) and Li et al. (2015) argue that firms whose boards of directors are headed by the chairman and constitute more non-executive directors (NEDs) are less likely to go into financial distress than firms without such board. On the other hand, Li (2014) did not find board independence to significantly influence the risk of financial distress.

Board Size

Some empirical studies argue that relatively smaller board size significantly gives rise to management effectiveness, improved firm performance and reduced risk of financial distress, while other studies argue otherwise. Lipton & Lorsch (1992) conducted a study on 86 financially distressed firms and found that firms whose board is small were less likely to go through financial distress than firms with larger board sizes. These studies further argue that the small size of the board ensured more effective and quicker decision making especially in a fast-changing business environment. Adams & Ferreira (2007) studied the relationship between board size and board director quality and risk of financial distress and found that larger board size was positively and significantly related to the risk of financial distress. On the other hand, Pearce & Zahra (1992) studied the board size of 88 financially distressed and 112 non-financially distressed firms and found that small board size is significantly related to the risk of financial distress. Pearce & Zahra (1992) argue that a large board size allows for more skills and experience which may be lacking in small size boards. Further, Simpson & Gleason (1999) argue that smaller boards are relatively easier to dominate by the CEO compared to larger board sizes. Furthermore, Brédart (2014) and Daily, Dalton & Cannella (2003) pointed out that a larger board is less likely to become financially distressed since they offer more disciplinary control and advice to the CEO and management board. The influence of board size as a corporate governance indicator on the probability of financial distress continues to be a source of debate in the literature. Also, it is not clear from previous literature what the impact would be on different financial distress states where a firm board size changes or remain the same. For instance, we do not know whether the impact of board size would be different for firms on NST status and those on ST status and whether the impact of board size would remain the same for a firm that is about to be delisted.

CEO Duality

The separation of Chief Executive Officer (CEO) and Chairman roles (duality) has been widely debated in corporate governance literature and is among good corporate governance guides by the OECD (2015). The concept of separation of the positions of the CEO and the Chairman draws from agency theory that states that having both positions handled by one person results in reduced board independence (Fama & Jensen, 1983; Osma & Guillamón-Saorín, 2011). In a dual board structured firm, the CEO oversees the daily management of a firm while the chairman oversees the board of directors of which the CEO is a member. The board of directors represents the interest of the shareholders and is overseen by the Chairman who is considered as the principal (Jensen & Meckling, 1976). On the other hand, the CEO oversees the management board as well as running the company thus, is considered the agent. In an agency relationship, Jensen & Meckling (1976), argue that there is a potential for conflict of interest that may give rise to an agency problem, that is where the objective of the principal varies from that of the agent. Several empirical studies such as Bredart (2013) and Brédart (2014) found CEO duality to significantly explain financial distress. The CEO duality is also relevant in the Chinese equity market as opined by Chen (2008), Li et al. (2015), Rezaee et al. (2016) and Jiang & Kim (2015). These studies argue that CEO duality is negatively correlated with financial distress. This is because where the positions of the CEO and Chairman are handled by different individuals, there are more chances than not that the independent oversight function of the board of directors would be more effective in checking the CEO excesses. Secondly, having a separate individual for the CEO and Chairman positions helps avoid situations where one person dominates board decisions. We measure board structure using board size, board independence and CEO duality as proxies.

2.3.2.2 Ownership Structure and Financial Distress

Empirical studies argue that the ownership structure of a firm goes a long way in influencing long term firm performance. For instance, Himmelberg et al. (1999) studied the relationship between ownership structure and firm performance and found a strong relationship between the two because the ownership of a firm influences who runs the firm which in turn determine how a firm is managed. Sami et al. (2011) and Rezaee et al. (2016) and Hu & Zheng (2015) found state ownership and institutional ownerships as significantly impacting financial distress in the Chinese equity market. For this research, we observe institutional ownership in assessing the probability of financial distress while using state ownership as a corporate governance control variable.

Institutional Ownership

In China, institutional owners are legal persons holding concentrated shareholding in firms which they leverage to facilitate an IPO for a newly listed firm by purchasing block amounts of equity shareholding (Cheng & Li, 2015b). There have been empirical studies on the impact of institutional investors (mutual funds, investment banks, pension managers, equity stockbrokers) on corporate governance effectiveness and firm performance. Daily et al. (2003) studied the board quality and institutional ownership percentage for 57 failed and 57 non-failed firms. The study found a significant positive relationship between institutional ownership and financial distress.

Furthermore, Mangena & Chamisa (2008) had a similar finding from their research on 81 firms in the Johannesburg Stock Exchange between 1999 and 2005. This study used audit quality and institutional ownership proxies while controlling for firm size and age and found that institutional ownership enhances board effectiveness and was positively related to the risk of financial distress. Li, Wang & Deng (2008) and Daily et al. (2003) Joseph, Fan, Huang & Ning Zhu (2013) and Hu & Zheng (2015) further linked the relationship between institutional ownership and financial distress and found that firms that are owned by institutions are less likely to become financially distressed. These studies argue that having a reasonable or significant amount of shareholding facilitates quicker and more precise decision making which is an advantage in a fast-changing business environment. Furthermore, Daily et al. (2003) show that institutional ownership of a firm means that it fosters relatively quicker and more strategic decision making by the board. This results in corporate governance efficiency that positions the firm to achieve better performance, thereby reducing the risk of financial distress. Also, institutions such as pension funds and insurance have access to relatively huge amounts of funds that the firm can leverage in times of financial crisis.

However, Donker, Santen & Zahir (2009) and Donker et al. (2009) could not find a significant relationship between institutional ownership and the risk of financial distress. Cheung et al. (2008) reveal that over 70% of the shareholding in the Chinese equity market is held by individual retail investors and not concentrated ownership as in the case of State or institutional ownership. Considering its unique market structure, the impact of institutional ownership on financial distress in the Chinese equity market may differ from findings elsewhere. The literature is split on the effect of institutional ownership. On one hand, Han (2014) argues that firms with large institutional ownership is a disincentive to produce a quality financial statement and are more likely to engage in earnings management. On the other hand, Jiang & Kim (2015) show that institutional ownership reinforces corporate governance practice best practices that reduce mismanagement, thereby reducing financial distress risk. In the context of the strong institutional background, retail and block ownership practice in the Chinese equity, this research investigates the effects of institutional ownership on multiple state financial distress. We measure ownership structure as the percentage of block equity shares held by institutions such as insurance companies, pension and investment firms or financial institutions.

To determine the effect of corporate governance factors- board structure, ownership structure, on the probability of financial distress we establish the following hypothesis:

Hypothesis H2.7: *Board structure and ownership structure has a significant effect on the probability of financial distress of non-finance listed firms in the Chinese equity market.*

2.4 Multiple State Financial Distress Process

This subsection reviews the literature on the concept of the financial distress process and seeks to understand different states a firm transverse from financially healthy to being financially distressed.

Pioneer studies in financial distress such as Altman (1968) and Beaver (1966) and most recent studies such as Minhaz (2017) and Binh & Duc (2018) have built on the concept of a binary financial distress process. The binary financial distress process is dichotomous and assumes firms move from being *financially healthy* to being insolvent or financially distressed. These studies have been criticized for not reflecting the business reality of what transpires throughout the financial health of firms (Jones & Hensher, 2004), poor contextual applications (Pindado, Rodrigues & De la Torres, 2008) and ex-post approach. This suggests that the output of these studies does not predict such early warning symptoms of financial distress as they claim as shown by Opuko, Amon & Arthur (2015).

Turetsky & McEwen (2001) researched the financial ratios of sample firms and found that the financial ratios of a firm change as the firm transverses through different states of the financial distress process. Outecheva (2007), Haber (2005) and Pozzoli & Paolone (2017) expanded on the study by Turetsky & McEwen (2001) and found that firms do not suddenly get financially distressed but transcend through different distress states in the financial distress continuum. These studies observed that each distress state is evidenced by symptoms that become more evident (in virtually all aspects of the firm) as the firm approaches terminal states (Lau, 1987). The multiple state financial distress process research contradicts earlier dichotomous financial distress process concepts that assume firms become financially distressed or liquidate "within a snap of a finger”. Hensher et al. (2007) and Farooq et al. (2018) argue that a financial distress prediction model that captures multiple states of the financial distress continuum produces a real-life scenario closer to that which firms go through. Pioneer studies such as that of Argenti (1976) did not identify different states in the financial distress process, however, he points to the fact that the time from when firms make ‘mistakes’ until the time symptoms of distress become evident is five years or more. Lau (1987) was amongst pioneer studies to counter the ‘failed’ and ‘non-failed dichotomous research, arguing that firms go through a financial distress continuum from when they are healthy until when they exit the market or cease to exist.

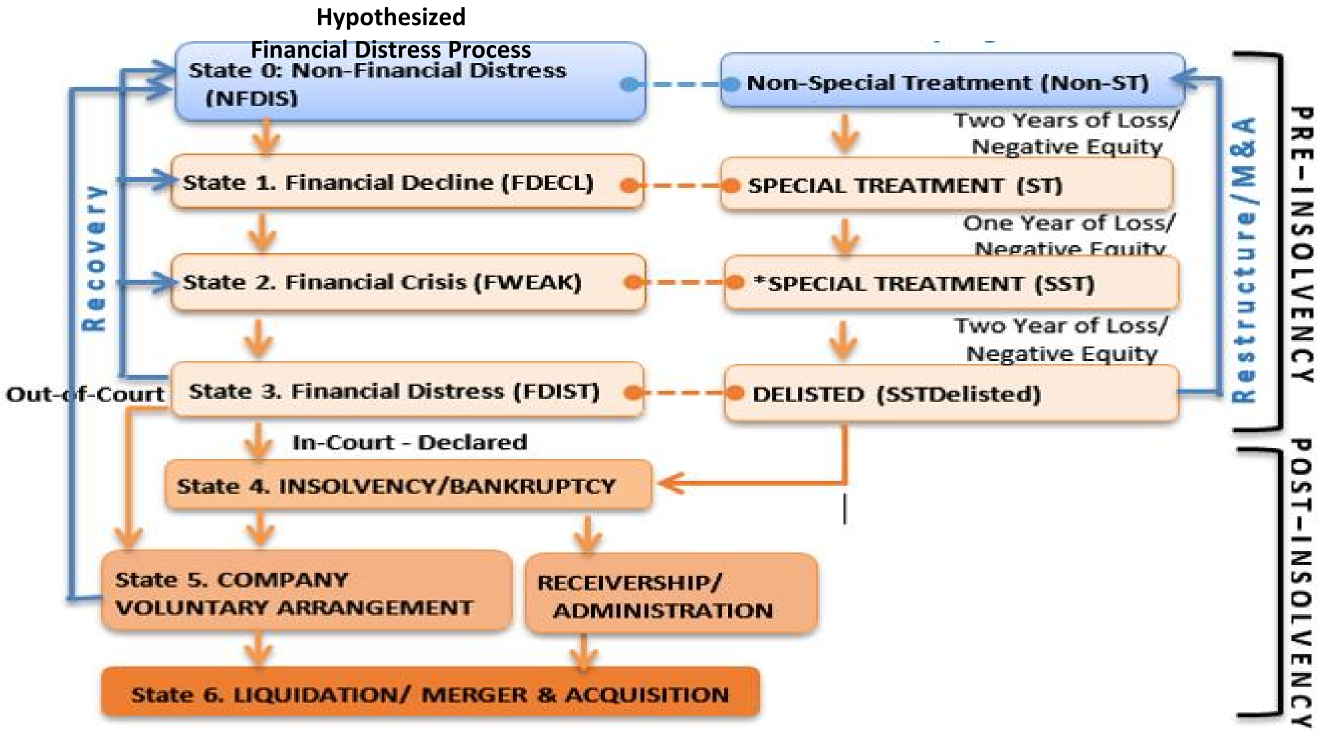
Table 2.1 report studies that adopted the multiple state financial distress process approach, the explanatory variables and methods used and the gaps in the studies. Notably, the gaps in these studies major in excluding key explanatory variables, lack of comparison between different financial distress states and lack of control for endogeneity. These gaps are areas that this research intends to fill in the financial distress process literature. Studies using the multiple state financial distress process have uniquely defined each distress state using similarity of explanatory variables or symptoms experienced by the firm within a given distress state. Financial distress *symptoms* such as declining dividend, loan default, declining profits and events such as delisting, restructuring, reorganisation, administration, receivership, bankruptcy/insolvency have been used. This research models the multiple state financial distress process, defining each distress state according to the designation criteria by the Chinese equity market Delisting system. A few financial distress studies such as Johnsen & Melicher (1994) assigned time to the financial distress process. The heterogeneity of firms suggests that over time firms will react differently through the financial distress process. In addition, a firm’s attributes and management decisions may influence the magnitude of impact from external factors. For instance in the Chinese equity market, as a result of preferential treatment SOEs receive, SOEs on ST or SST status may stay longer in the Chinese equity market compared to their non-SOE counterparts (Wang & Yung, 2011). As a result, time as a factor is not the focus of the financial distress process developed in this research.

Table 2.1: Multiple States of financial Distress Studies

Studies	Financial Distress States	Variables	Methods	Gaps in study
Lau (1987)	State 0 - Financially stable State 1 – Omitted/Reduced dividend State 2 - Loan default State 3 - Protection under Chapter X of Bankruptcy Act State 4 – Bankruptcy and Liquidation	Accrual-based ratios	Multinomial logit	• Non-financial factors not included • No cash flow-based ratios • No distress state comparison
Ward (1994)	State 0 - Healthy State 1 - 40% deduction in DPS State 2 - Loan or Interest default State 3 - Bankrupt	Accrual-based ratios and Cash flow-based ratios	Ordinal logit	• Non-financial factors not included • No market-based variables • No distress state comparison
Johnsen & Melicher (1994)	State 1- Non-bankrupt State 2 - Financially Weak State 3 - Bankrupt	Accrual-based ratios & Cash flow ratios	Binary vs Multinomial logit	• No non-financial factors • No distress state comparison
Jones & Hensher (2004)	State 1- Non-failed firms State 2 - Insolvency State 3- Liquidation/ Administration	Cash flow and Accrual-based ratios	Mixed logit	• No non-financial factors and market-based variables • No distress state comparison
Hensher et al. (2007)	State 1- Non-failed firms State 2 - Insolvency State 3 - Delisted State 4 - Bankruptcy	Accrual-based ratios	Multinomial logit	• No non-financial factors and cash flow ratios • No distress state comparison
Chancharat (2008)	State 1 - Non-failed State 2 - Financial distress State 3 - Reorganisation State 4 - Bankruptcy	Accrual-based ratios	Cox Proportional Hazard	• No non-financial factors and market-based variables • No distress state comparison
Yao (2009)	Three financial distress states	Accrual-based ratios and Cash flow-based ratios	Support Vector Machine vs Multinomial logit	• Determinants of each state not identified • No non-financial factors and market-based variables • No distress state comparison
Sormunen & Laitinen (2012)	State 1 - Early Stage State 2 - Late Stage State 3 - Financial Distress	N/A	Theoretical	• Theoretical
Tsai (2013)	State 1 - Financial distress State 2 - Reorganisation State 3 - Bankruptcy	Accrual-based ratios	Multinomial logit	• No non-financial factors and cash flow-based ratios • No distress state comparison
Farooq et al. (2018)	State 1 - Profit reduction State 2 - Mild liquidity State 3 - Severe liquidity	Accrual-based ratios	Multinomial logit	• No Non-financial factors and cash flow-based ratios
Tinoco et al. (2018)	State 1- Non-financially distressed State 2 - Financially distressed State 3 - Corporate failure	Accrual & Market ratios, macroeconomic	Multinomial logit	• No cash flow-based ratios • No distress state comparison
Yi (2019)	Two, Three and Five state financial distress models	Accrual-based ratios and Cash flow-based ratios	Machine learning	• Determinants of each state not identified • No non-financial factors and market-based variables • No distress state comparison

Source: Author's compilation

Figure 2.2: Multiple State Financial Distress process



Source: Author's compilation

Figure 2.3 presents the multiple state financial distress process hypothesized after the financial process in the Chinese equity market. The hypothetical financial distress process for this research consists of four financial distress states which are non-financially distressed (state 0), financial decline (state 1), financially weak (state 2) and financially distressed (state 3). The hypothesized four financial distress states are derived from the non-ST, ST and SST and SSTdelisted status of the Chinese equity market delisting system. In Figure 2.3, we refer to the point from when a firm is deemed financially healthy until it is declared insolvent/bankrupt by the court as a *pre-insolvency stage* (states 0, 1, 2 and 3) for the sake of this research. From when the court declares the firm insolvent/bankrupt until the firm ceases to exist is referred to as *post insolvency stage* (states 4, 5 and 6). According to the InsolvencyAct (1986), an insolvent firm may proceed into any of these four routes: Company Voluntary Arrangement (CVA), receivership, administration or liquidation. The post insolvency stage represented by states 4, 5 and 6 are referred to as *terminal distress states* in this research. This is because these states present diverse corporate options for firms to cease existence.

The focus of this research is on symptoms that manifest at early states of the financial distress process (depicted by the "pre-insolvency" stage in Figure 2.3). What happens to Chinese firms in the "post-insolvency" stages is outside the scope of this research and that because there is less available data of firms in insolvency stage in the Chinese equity market. The hypothetical financial distress process for this research focuses on the pre-insolvency period for two reasons. First, the hypothetical financial distress process is modelled after the financial distress process in the Chinese equity market that practical ends within the pre-insolvency period. Financial statements of delisted Chinese firms are no longer published thus, such companies cannot be researched beyond delisting. Further, the data of firms that traverse through the post-insolvency period such as liquidation are not readily available in China for reasons such as protecting the distressed firm (Li, 2014). Notably, the terminal state of *liquidation* in developed markets is analogous to the *delisted* state in the Chinese equity market. That is because from the perspective of investors in the Chinese market, a firm ceases to exist once delisted and what happens to firms after delisting is beyond the public eye (Cheng & Li, 2014). Second, stakeholders lose a significant portion of their investment in firms at terminal distress state in the post-insolvency states (Chancharat, 2008). Further, firms in the pre-insolvency period can recover but at different likelihood, because as a firm's financial health deteriorates, the firm's probability of recovery diminishes Otherwise, firms in terminal states have almost no chance of recovery (Johnsen & Melicher, 1994; Laitinen, 1991). In rare cases, a firm at Company Voluntary Arrangement (CVA) (state 5) could enable a recovery (May, 2013). Otherwise, firms in terminal states of liquidation, merger or acquisition, administration or receivership have almost no chance of recovery (Farooq et al., 2018).

Not only does this research hypothesize that the states in a multiple state financial distress model are statistically and significantly different, but we also believe that the explanatory variables driving these states are different. Other than profitability as a criterion by the CSRC delisting system to designate firms with poor financial health, this research believes that other determinant factors could describe different financial distress states. Therefore, we establish the following hypothesis:

Hypothesis H2.8: *Significant determinant financial ratios and corporate governance factors that explain the four financial distress states (NFDIS, FDECL, FWEAK and FDIST) are different for non-financial listed firms in the Chinese equity market.*

The study by Senbet & Wang (2012) show that *symptoms* that determine financial distress change with the firm's financial distress state over time. The traditional approach in financial distress literature has been to assume the effects of explanatory variables are the same across the multiple states of a financial distress process. To contribute to this body of knowledge and to investigate whether this is the case using the Chinese equity market as a sample, we establish the following hypothesis:

Hypothesis H2.9: *The effect of financial ratios and corporate governance factors differ at the four financial distress states (NFDIS, FDECL, FWEAK and FDIST) states for non-financial listed firms in the Chinese equity market.*

Further, we empirically compare the effects of financial ratios and corporate governance indicators in the multiple state distress approach and the binary state distress approaches to assess additional information provided by the multiple state approach. Therefore, we established the following hypothesis:

Hypothesis H2.10: *Financial ratios and corporate governance factors and their effect in a multiple state model and a binary state model are different for non-finance listed firms in the Chinese equity market.*

Although there is no consensus in the literature, drawing from most prior studies, we suspect that both accrual-based ratios, market-based ratios, cash flow-based ratios and corporate governance indicators have a significant effect on financial distress. Intuitively and from the literature, these ratios assess diverse aspects of firm performance. Nonetheless, we don't know how these ratios interact with each other when combined in a model to assess or predict financial distress given a multiple state approach. Following on from hypothesis H2.1 to H2.6 that establishes the effect of these ratios, we examine whether the effects and explanatory power of accrual-based ratios and market-based-ratios changes after accounting for the cash flow-based ratios in a multiple state financial distress analysis. Likewise, we examine whether the effects and explanatory power of accrual-based ratios and market-based-ratios changes after including the corporate governance indicators in a multiple state financial distress analysis. Further, we examine how the effects and explanatory power of accrual-based ratios and market-based-ratios changes after both cash flow-based ratios and corporate governance indicators (board structure and ownership structure) are included. Therefore, we established the following hypotheses:

Hypothesis H2.11: *Cash flow-based ratios and corporate governance factors influence the effect, explanatory, and predictive power of accrual-based and market-based ratios in the Chinese equity market.*

Hypothesis H2.12: *Combining cash flow-based ratios and corporate governance indicators influence the effect, explanatory, and predictive power accrual-based and market-based ratios in the form of a model in the Chinese equity market*

2.5 Methods of Estimating and Predicting Corporate Financial Distress

From the first financial distress prediction model by Beaver (1966), several statistical and non-statistical methods have been employed in the study of financial distress. The comparative study by Bellovary, Giacomino & Akers (2007) and Aziz & Dar (2006) suggest that methods used in financial distress study include the Discriminant Analysis (DA) and Logistic Regression (LR)/Probit Regression (PR) which stand out in terms of popularity and performance followed by Neural Network (NN) and Survival Analysis (SA). However, the complexity and number of methods used in predicting corporate financial distress have dramatically increased and evolved into non-statistical methods that make use of biological science, IT techniques and theories. Besides statistical methods, theoretical methods such as the Cash Management Theory, Balance Sheet Decomposition Measurement Theory, Credit Risk Theories and Gambler's Ruin Theory have also been used in recent times to predict financial distress (Aziz & Dar, 2006). However, theoretical methods have largely been criticized and less used by researchers due to the significant absence of statistical methods which makes them appear subjective and unreliable. This accounts for their poor usage in the literature for modelling financial distress prediction.

2.5.1 Discriminant Analysis (DA) Models

The DA predicts financial distress using simple regression analysis to directionally discriminate firms into usually two groups using one factor (univariate discriminant analysis) or more than one factor at a time (multivariate discriminant analysis). The univariate discriminant analysis (UDA) is one of the earliest statistical methods used in financial distress study that involves the use of a single explanatory variable to discriminate between firms in a financial distress state of 'failed' and 'non-failed states. Beaver (1966) compares the explanatory power of several explanatory variables in a univariate analysis and selects an optimal cut-off point that minimizes the misclassification error in discriminating between firms. Unlike the UDA method that advocates for a single regressor, the Multivariate Discriminant Analysis (MDA) employs a combination of regressors. Altman (1968) noted the inconsistency of using a single explanatory variable in a UDA and proposed the MDA. Although the MDA filled some of the shortcomings of the UDA, the use of the MDA is restricted by its assumption of normally distributed explanatory variables that are often violated by researchers resulting in bias results (Deakin, 1972). In addition, the UDA method is less objective and robust in terms of statistical analysis of studying multiple groups compared to the LR method (Rodgers, 2011).

2.5.2 Survival Analysis (SA) and Hazard Method

The survival analysis (SA) method estimates both the survival function and hazard functions. The survival function estimates the probability of a firm's survival from a given time to an event time *t* while the hazard function is derived from the survival function estimation (Chancharat, 2008). The SA method has gained popularity in financial distress due to its ability to analyse events a firm transverse through the financial distress continuum and the times of these events (Chancharat, 2008). Where the probability of financial distress is a function of time the SA methods offer a primary advantage over LR or PR in their ability to parsimoniously account for time to financial distress state (Harrell, 2001; Laitinen, 2005). This study is restricted to the study of the pre-insolvency period of firms rather than the whole financial distress process. Furthermore, this study focuses on explanatory factors that drive each state rather than the time to financial distress events therefore, the SA method may not be suitable to achieve our objectives.

2.5.3 Artificial Intelligence Systems Expert Systems (AIES)

Neural Network is the most used Artificial Intelligence Systems Expert Systems (AIES) method after machine learning (ML) in the study of financial distress (Bishop, 1995). The AIES methods were developed to address restrictive assumptions (such as Gaussian distribution) which may not be applicable in the real world according to Shah & Murtaza (2000). It is still under debate as to whether AIES like NN and Statistical methods like DA and LR produce a better prediction of financial distress. The underlying concept behind NN follows the thinking pattern of the human brain which makes it less statistical. Boritz & Kennedy (1995), Cybinski (2001) and Zhang, Hu & Patuwo (1999) are some of the studies that argue in favour of NN producing superior prediction accuracy compared to LRA and MDA. Machine learning Models has been used by recent financial distress studies by Kim and Kang (2012) and Yi (2019) in studying multiple state financial distress. Nonetheless, Cybinski (2001) also acknowledges the shortcomings of lack of transparency in the NN and ML process which inhibits its use in the literature. Although NN and ML methods are modern methods in financial distress studies, they are relatively complex and not extensively validated in the literature compared to LR and DA (Rodgers, 2011). Specifically, neither the NN nor ML has the flexibility of being used to control for endogeneity at the same time, handle statistical analysis such as predicted probabilities and marginal effects.

2.5.4 Logit Regression and Probit Regression Models

The LR or PR uses a logistic function to predict an outcome of one of two categories of a dichotomous dependent variable (Y) – corporate financial distress risk based on two or more independent variables (X) – determinant symptoms. Ohlson (1980) study extended by Harrison (2005) was amongst pioneer studies to use binary logistic regression (BLR) to address the weakness of the MDA, especially as they relate to statistical techniques. There are several extensions to the LR method that could be used in modelling financial distress depending on the data and desired outcome however, Yi (2019) observed that the multinomial logit regression (MLR) is the most used. First, early multiple state financial distress studies such as Lau (1987), Johnsen & Melicher (1994) and Tsai (2013) have to use the multinomial logit regression. Unlike the BLR that is not suitable for models with more than two outcome variables, the MLR can model more than two categorical outcome variables. In the light of these arguments, the MLR appears more suitable in this research where non-financial factors and multiple dependent variables are proposed. Further, the MLR allows facilitates empirical observation of explanatory variables at each categorical outcome as well as comparing the estimates at each categorical outcome. This makes the MLR stand out from other statistical methods such as machine learning and survival analysis that can also be used to model multiple state financial distress.

2.6 Chapter Summary

This research uses the term *financial distress* as opposed to failed, default, insolvent (UK) or bankrupt (US) to refer to a 'state' in the financial distress process. The term *financial distress process* is used in this research to refer to the entire journey of the firm from when the firm is financially healthy until the firm ceases to exist or exits the market. This research will focus on the pre-insolvency period of the financial distress process. Although causes of financial distress are outside the scope of this research, it is relied upon in developing the research framework of our current research. Financial ratios used in this research address key firm performance areas include asset management efficiency, profitability, liquidity, market valuation and cash flows. Corporate governance indicators employed are from board structure and ownership structure. Research hypotheses are developed to test the effects of financial ratios and corporate governance indicators on multiple state financial distress. This chapter also reviewed prior literature on multiple state financial distress and the gaps in these studies that are current research aim to bridge. Identified gaps majour around the weak choice of explanatory variables, control for endogeneity and missing comparative study of financial distress states. This chapter reviewed several key methods used in financial distress studies including Discriminant analysis, logit/Probit regression, AIES and Survival analysis. Each method has its short-coming and has been used in financial distress studies. Nonetheless, the logit regression (MLR) stands out compared to other methods, in terms of robustness of statistical analysis, flexibility and ease of use and facilitates achieving the research objectives for this research better than other methods.

CHAPTER THREE

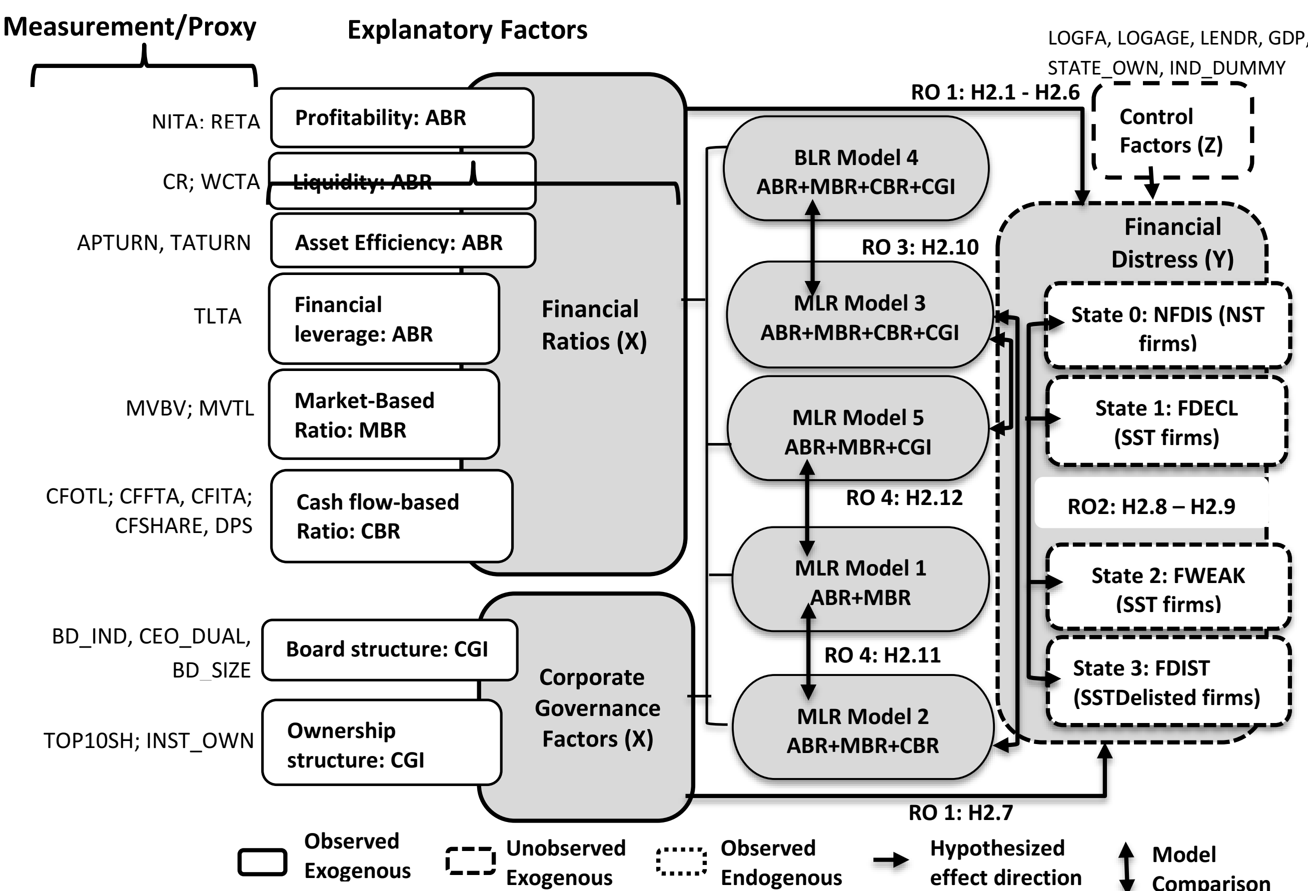
DATA AND METHODOLOGY

Chapter three describes the data and methodology used in this research. Section 3.1 presents the research design that pictorially describes the relationships between explanatory and outcome variables and how the hypotheses are tested. Section 3.2 discusses data collection methods and section 3.3 discusses sampling techniques. Section 3.4 specifies the variables used in this research. Section 3.5 discusses the endogeneity in the context of this research and the methods employed to account for it. Section 3.6 discusses methods and techniques employed in data analysis and testing hypotheses. Section 3.7 outlines the pre-estimation tests to be undertaken before testing the hypotheses and section 3.8 is the chapter summary.

3.1 Research Design

The research design in figure 3.1 captures observed explanatory variables "factors" (x), control variables (z) their "measurement" and their assumed relationship with financial distress (y).

Figure 3.1: Research design



Source: Author's compilation

3.2 Data Collection

Data are collected for listed A share of non-financial firms in the SSE and SZSE equity markets between 2009 and 2018. Data is not collected for B Share firms since these firms are listed in USD and report under IFRS which makes their data not directly comparable to A share firms that report under Chinese GAAP. In addition, data are not collected for H-shares firms since these firms operate in a different equity market (Hong Kong Stock Exchange) and are listed in HKD with significantly different listing and delisting rules different from those in the Chinese equity market (SSE and SZSE). The global credit crisis hit the Chinese economy in 2007 and the impact peaked of the crisis in 2008 the Chinese Government introduced the largest stimulus package(Wong, 2011). Wong (2011) also observed that China was also the first large economy in the world to recover from the crisis with economic growth of 8.7% in 2009 and 10.4% in 2010. Due to the possible impact of the global crisis on the outcome- financial distress as well as explanatory factors especially between 2007 and 2008, we set our sample period from 2009 to 2018. The CSRC delisting system was established in 1998 but became effective only in 2007 (Cheng, Yu, & Ke, 2007). Having a sample from 2009 (which is post 2007) also helps to sample firms according to their designation in the ST delisting system.

The outcome variable for this research is financial distress. The outcome variable made up of four financial distress states is specified in our hypothetical financial distress process are include non-financially distressed (NFDIS), financial decline (FDECL), financially weak (FWEAK) and financially distressed (FDIST). Data are collected on 1,415 non-financial listed firms in the four designation statuses of delisting system and they are NST, ST, SST and SSTDelisted designation status. The Schedule of firms' designation status contains firms listed on both the SSE and SZSE in the Chinese equity markets and operates across all CSRC industries except the financial service industry. The schedule shows listing changes during the financial year, the listing status of firms at the end of the financial year and reasons for a change in listing status, for each year from 2009 to 2018. The use of the Chinese equity market delisting system as a proxy for financial distress states is due to the lack of a robust database of firms in post-insolvency states in China. Several financial distress studies in the Chinese equity market that have used this approach include Zhang et al. (2010), Bhattacharjee & Han (2014), Yi (2012), Wang (2017) and Minhaz (2017).

Accrual accounting data is sourced from the income statement and balance sheet, cash flow accounting data from the cash flow statement, market data from equity market trading results and corporate governance data from published supplementary corporate reports. All data from published financial statements and supplementary reports are obtained from the China Stock Market & Accounting Research (hereafter CSMAR) database. The explanatory variables of interest are accrual-based ratios, cash flow-based ratios, market ratios and corporate governance factors. The accrual-based ratios are computed from accrual accounting data, cash flow-based ratios from cash flow accounting data, market-based ratios from market data and corporate governance indicators are derived from corporate governance data. Data are collected for macroeconomic variables used as control factors namely GDP, inflation rate and lending rate are sourced from the National Bureau of Statistics of China. Control variables – firm age and firm size are sourced from the firm's balance sheet and corporate governance data respectively.

3.3 Data Sampling

A few number of firms had randomly missing observation (1 or 2 observations in each firm case). It was not possible to collect such missing data for these firms since they are randomly missing in the CSMAR database in the data management process. These firms were included in the sample after missing observations were resolved with the mean imputation technique using the value of the arithmetic mean of available data from the same financial statement item from previous years. The mean imputation procedure treatment is consistent with Rubin (1987). In a few instances, missing or imputed financial statement items result in extreme financial ratios (outliers). Extreme ratios could skew the dataset that could affect the multinomial logit regression. In managing extreme financial ratios, an observation greater than the ninety-fifth percentile of a financial ratio is set to the value of the ninety-fifth percentile. Likewise, an observation less than the fifth percentile of a financial ratio is set to the value of the fifth percentile. The treatment of outliers for this research is consistent with Shumway (2001).

Firms newly listed or delisted within the sample period are included in the sample provided they have sufficient data for a panel data analysis (Himmelberg et al. (1999). Including newly listed and delisted firms helps avoid survivor bias in sampling (Brown, Goetzmann, Ibbotson & Ross, 1992;

Rein, Cannegieter, Rosendaal, Pieter H.Reitsma & Lijfering, 2014). Newly listed and delisted firms have missing financial statement items and market and corporate governance data during the study period from 2009 to 2018. For newly listed firms, missing data are not publicly available from the observation year 2009 until the year the firm is listed. For delisted firms, missing data are those from the observation year that the firm was delisted until 2018. Imputing missing data may truncate statistical results while excluding the available data from the sample would result in survivorship bias. Survivorship bias is a kind of sampling bias resulting when only data of firms that currently exist are observed with the exclusion of data of firms that have exited the system and no longer exist (Hosmer & Lemeshow, 2000). The impact of survivorship bias includes optimistic results that are far from real-life (Jennifer & Anthony, 1999). Likewise, having more observation years data for each firm facilitates the testing for second-order autocorrelation (Arellano & Bond, 1991). Including listed and delisted firms during the study period implies having unbalanced panel data for this research.

Firms in the financial service industry such as banking and insurance firms were excluded from the sample. Financial service firms typically hold relatively high financial leverage ratios and very liquid assets that might make their results incomparable with firms in the rest of the industries (Simpson & Gleason, 1999). Second, the reporting framework in terms of what constitutes assets and liabilities for financial services firms differs from a typical firm. As a result of these financial reporting and business operation differences, financial ratios for financial service firms may not be comparable to those of non-financial service firms in terms of interpretation and acceptable range. Including firms in the financial and banking industry would potentially skew the data and with such data potentially constitute outliers.

Collated data are structured into panel data after determining what firms to include in the sample. This research adopts a panel data sampling approach by Himmelberg et al. (1999). The use of Panel data sampling is employed since it facilitates addressing firm-level heterogeneity (Barros, Bergmann, Castro & Miceli da Silveira, 2020). Early studies in financial distress and bankruptcy such as Altman (1968) and Beaver (1966) notably used match-paring to provide an even 1:1 representation of failed and non-failed firms. Other studies such as Laitinen (1991)and Charitou et al. (2004), Lee & Yeh (2004) and Chen (2008) used arbitrary match-pairing ratios and /or firm-specific characteristics or industry similarity matching. Amongst the problems of the match-pairing sampling technique identified by Cram, Karan & Stuart (2009), is the failure to control for effects of samples that are imperfectly matched. Furthermore, the match-paring technique is criticised for not reflecting the actual financial distress ratio of the population which may adversely affect the estimated results (Cram et al., 2009). A more practical approach argued by Jones & Hensher (2004) is the use of the actual financial distress ratio. For this research, the financial distress ratio is the ratio of financial distress states- state 1(ST), state 2 (ST) and state 3 (SSTDelisted) to the default state 0 (NST). This research uses the prevailing financial distress ratio of firms in the SSE and SZSE and this reflects the actual financial distress rate in the market and at the same time help to curtail bias arising from the use of matched sample design (Casey & Bartczak, 1984; Jones & Hensher, 2004; Zmijewski, 1984).

Adopting the approach from Russell & Norvig (1995), the original sample dataset is split into two parts: 72% for model estimation and 28% for model validation. The estimation dataset is used to test the hypotheses and fit of the models while the validation dataset is used to evaluate empirical models and ensure the model results can be generalised. Table 3.1 shows the number of firms and corresponding observations in each estimation and validation dataset.

Table 3.1: Sample Dataset Spilt

	NST (NFDIS)	**ST (FDECL)**	**SST (FWEAK)**	**SSTDelisted (FDIST)**	**Total Obs per dataset**
Estimation	7,838	446	371	195	8,850
Validation	3,203	83	150	44	3,480
Total Obs per state	11,031	549	521	239	12,330

Source: Author’s compilation

The estimation sample consists of 1,415 firms and 8,850 observations sampled across 13 CSRC industries with exception of the financial services industry. Table 3.3 shows firm-year panel data of firms in the estimation dataset. Table 3.2 show firms’ samples across 13 industries including Agriculture, Forestry and Fishery, Construction, Education and Culture, Power, Energy and Utility, Healthcare, Hotels and Catering, IT and Software, Leasing and Business Services, Manufacturing, Mining, Scientific Research, Logistics, Storage and Retail and, Media and Publishing

Table 3.2: Industry Classification of the Estimation Sample

S/N	Industry	No. of Obs	Percentage
1	Agriculture, Forestry and Fishery	338	3.8%
2	Construction	470	5.3%
3	Education and Culture	105	1.1%
4	Power, Energy and Utility	1,527	17.4%
5	Healthcare	159	1.8%
6	Hotels and Catering	324	3.6%
7	IT and Software	340	3.8%
8	Leasing and Business Services	448	5.1%
9	Manufacturing	2,814	31.8%
10	Mining and Metals	958	10.8%
11	Scientific Research	125	1.4%
12	Logistics, Storage and Retail	910	10.3%
13	Media and Publishing	332	3.8%
	Total	**8,850**	**100.0%**

Source: CSMAR (2020)

3.4 Variable Selection and Specification

3.4.1 Outcome Variables Specification

For this research, the outcome variable – financial distress is defined in terms of a "multiple state" financial distress process and for comparison, as a "binary state" financial distress process. The hypothetical financial distress process for this research is specified in figure 2.3 and defined by the four-designation status delisting system of the Chinese equity. The delisting system has been widely used as a proxy for financial distress in the financial distress research in the Chinese equity market (Cheng, Xia & Wang, 2012; Du, Liu & Wong, 2007; Green, Czernkowski & Wang, 2009; Sun & Li, 2008; Zhang et al., 2010; Zhou, 2013; Zhou et al., 2012).

3.4.1.1 Multiple State Financial Distress Process

We refer to the multiple state financial distress process in figure 2.3. To define the mutually exclusive multiple state outcomes, State 0 is the non-financially distressed (NFDIS) state and is defined by firms on NST status. State 1 is the financial decline (FDECL) state and is defined by firms on ST status. State 2 is the financially weak (FWEAK) state and is defined by firms on SST status. State 3 is the financially distressed (FDIST) state and defined by firms on SSTDelisted status. The four mutually exclusive financial distress states in multiple state outcomes are discussed.

Non-Financially Distressed (NFDIS) State

The Non-Financially Distressed (NFDIS) state is the default state in a multiple state financial distress process. A financially healthy state is the first state of the financial distress process. For empirical research purposes, the financial performance of firms in this state is distinct from those in other financial distress states. The state has been referred to as the state 0 by studies such as Lau (1987) and Ward (1994) since this is the default state and firms in this state are regarded as *non-financially distressed*. This is the case in studies by Jones & Hensher (2004), Hensher et al. (2007), Chancharat (2008) and Tinoco et al. (2018) although these studies referred to this state as *state 1.* The proxy for the NFDIS state are firms on the NST designation on the Chinese equity market delisting system. The NST status is the default status that has no designation from the delisting system since they theoretically do not fulfil any of the criteria for designation as an ST, SST or SSTDelisted. As a result, these firms are considered *financially healthy* in the Chinese equity market thus are used as a proxy measurement for the 'Non-financially distressed' state and assigned 'State 0' on the financial distress process (see Figure 2.3). Most studies in the Chinese equity market such as those of Wang & Li (2007), Zhang et al. (2010) and Zhou et al. (2012) and Zhou (2013), have used the NST status as a proxy measure for financially healthy firms. For the multiple state outcome, there are 7838 observations for firms in the NFDIS state

Financial Decline (FDECL) State

From figure 2.3, the next on the financial distress process state after the non-*financially distressed* (NFDIS) state 0 is referred to as the *financial decline (FDECL) state 1*. This state is analogous to the 'decline' stage by Pozzoli & Paolone (2017) and referred to as the *early stage* by Laitinen (1991). ST firms are NST firms that experience two consecutive years of net loss which differentiates them from firms in default NFDIS state (Zhou et al., 2012). The proxy for the FDECL state is firms on the ST status on the Chinese equity market delisting system. In the case of the delisting system, ST firms have the highest potential for recovering and removing their designation compared to SST and SSTDelisted firms in the FWEAK and FDIST states respectively (Zhou et al., 2012). ST firms in this state are the closest to recovery and according to the delisting system, have only experienced profit decline which does not meet the definition of financial distress (InsolvencyAct, 1986). Therefore, we label this state *financial decline* (FDECL) state rather than *financially distressed* (FDIST). For the multiple state outcome, there are 446 observations for firms in the FDECL state.

Financially Weak (FWEAK) State

From figure 2.3, next on the financial distress process state after the *financially decline (FDECL) state* 1 is referred to as the *financially weak (FWEAK) state 2*. This state is analogous to the '*crisis* stage by Pozzoli & Paolone (2017) and referred to as the *late-stage* by Laitinen (1991). The delisting system designates firms in this state as "SST" based on mainly an additional consecutive year of declining profitability after the ST designation and for a few firms, negative equity and qualified audit opinion (Zhou et al., 2012). In the case of the delisting system, SST firms have better potential to recover and remove their designation compared to SSTDelisted firms (Zhou et al., 2012). The Chinese equity market requires firms in this state to recover and remove their designation usually by way of restructuring (Zhou et al., 2012). Zhou et al. (2012) also noted that a common practice for such restructuring is to lead to mergers or acquisitions. Where a firm cannot internally restructure and recover, an option is to source an external *liquidity lifeline* in the form of funding from shareholders or banks. Firms in this state have some recovery potential and exhibit (according to the delisting system) additional declining profitability or negative equity or a qualified audit opinion. Therefore, we label this state as a *financially weak* (FWEAK) state rather than *financially Distressed* (FDIST). For the multiple state outcome, there are 371 observations for firms in the FDECL state.

Financially Distressed (FDIST) State

From figure 2.3, the next on the financial distress process state after the *financially weak (FWEAK) state* 2 is referred to as the *financially distressed (FDIST) state 3.* This state is analogous to the *financial distress* stage by Pozzoli & Paolone (2017) and referred to as the *final stage* by Laitinen (1991). This state is referred to as 'financially distressed' since we regard it as the state a firm attains before being declared insolvent by the court or delisted from the Chinese equity market. The proxy for the FDIST state are firms on the SSTDelisted designated on the Chinese equity market delisting system. The delisting system designates firms into this state as "SSTDelisted" following a consecutive year of declining profitability after being suspended or designated with an SST or additional consecutive years of negative equity and qualified audit opinion (Zhou et al., 2012). Zhou et al. (2012) sighted other reasons for firms being designated into the SSTDelisted state such as, where the firm is declared insolvent by the court, the shareholders reach an agreement to delist or where the firm no longer meets or is not capable of meeting the listing criteria. It could be noted that any of these other reasons could be reached when the firm is in the FDECL or FWEAK states. This implies that firms could go from the FDECL state to the FDIST state without passing through the FWEAK state. Firms in this state are labelled as "financially distressed" (FDIST) as a result of three observed features that distinguish them from the three other financial distress states. First, firms in this state have sustained deteriorating financial health evidenced by their passage through different designated statuses from ST, SST and are subsequently delisted from the Exchange. Second, firms in this state have zero chance of recovery once delisted. Third, this state is the terminal state for firms in the Chinese equity market "in public eyes" since information and trading of firms post being delisted from the Stock Exchange (post-insolvency) are not available to the public (Zhou et al., 2012). For the multiple state outcome, there are 195 observations for firms in the FDIST state.

Table 3.3 reports financial distress states in a multiple state outcome, the proxy and identifier for each financial distress state, the measurement criteria, the financial distress ratio and the number of observations.

Table 3.3 Multiple Outcome Variable Specification

DISTRESS STATES	PROXY	IDENTIFIER	DELISTING SYSTEM CRITERIA	OBS	FD Ratio
Non-financially Distressed	• Non- Special Treatment firms (NST)	**NFDIS**	• Default category	7,838	-
Financial Decline	• Special Treatment (ST)	**FDECL**	• 2 consecutive years loss	446	5.6%
Financially Weak	• Star Special Treatment (SST)	**FWEAK**	• 1 consecutive year loss • Negative equity • Qualified audit opinion	371	4.7%
Financially Distressed	• Star Special Treatment Delisted (SSTDelisted)	**FDIST**	• 1 consecutive year loss – Suspension; 1 consecutive year loss - Delisting	195	2.6%
Total				8,850	12.9%

Source: Authors' compilation

3.4.1.2 Binary State Financial Distress Process

To define the mutually exclusive binary state outcome, State 0 is the non-financially distressed (NFDIS) state defined by firms on NST status. State 1 is the financially distressed (FDIST) state defined by firms on ST, SST and SSTDelisted status pooled together. The two mutually exclusive financial distress states in a binary state outcome are discussed.

Non-Financially Distressed (NFDIS) State

Likewise, in the multiple state financial distress process state, the Non-Financially Distressed state is the default state on the financially distressed process in the binary state outcome approach. The proxy for the NFDIS state are firms on the NST designation on the Chinese equity market delisting system. The NST status is the default status that has no designation from the delisting system since they theoretically do not fulfil any of the criteria for designation as an ST, SST or SSTDelisted. As a result, these firms are considered *financially healthy* in the Chinese equity market thus are used as a proxy measurement for the *non-financially distressed* state and assigned *State 0* on the financial distress process (see Figure 2.3). For the multiple state outcome, there are 7,838 observations for firms in the NFDIS state

Pooled Financially Distressed (FDIST) state

For the sake of defining the FDIST state in a binary state outcome, firms on ST, SST and SSTDelisted designation are pooled into a single *Pooled FDIST state*. Following a binary state outcome approach, the pooled FDIST state follows the NFDIS state in the financial distress process. Most firms are designated into the pooled FDIST state mainly on two consecutive years of net loss while a few firms are designated based on negative net assets or qualified audit opinion. For the binary state outcome, there are 1,012 observations for firms in the Pooled FDIST state.

Table 3.4 reports financial distress states in a binary state outcome, the proxy and identifier for each financial distress state, the measurement criteria, the financial distress ratio and the number of observations.

Table 3.4 Binary Outcome Model Specification

OUTCOME	MEASUREMENT	IDENTIFIER	DELISTING SYSTEM CRITERIA	OBS	FD Ratio
Non-Financially Distressed	• Non- Special Treatment firms (NST)	**NFDIS**	• Default category	7,838	
Pooled Financially Distressed	• Special Treatment (ST) • Star Special Treatment (SST) • Star Special Treatment SSTDelisted (SSTD)	**FDIST**	• 2 consecutive years loss • 1 consecutive year of loss, negative equity OR 1 consecutive year of qualified audit opinion • 1 consecutive year loss – Suspension; 1 consecutive year loss - Delisting	1,012	12.9%
				8,850	

Source: Authors' compilation

3.4.2 Explanatory Variables Specification

3.4.2.1 Selection of Model Regressors

The selected nineteen explanatory variables listed in Table 3.6 cover key firm performance areas including profitability, liquidity, asset management efficiency, financial leverage, market performance (market valuation), cash flow and corporate governance (board structure, ownership structure). Nineteen explanatory variables are selected based on the following criteria after a comprehensive review of financial distress literature:

i) Statistical significance and frequency of use in prior financial distress research; or
ii) Facilitates the diagnosis of cash-flow insolvency and balance sheet insolvency as defined by the InsolvencyAct (1986); or
iii) less susceptible to manipulation and creative accounting as recommended by Casey & Bartczak (1985); or

While not all factors mentioned in prior financial distress studies were selected, it is noted that selected factors were statistically significant in explaining financial distress over several studies. For instance, factors such as firm yield spread, annualized yield and corporate governance factors such as the ratio of female directors were amongst the initial 32 variables in this research. However, these factors did not make it to the 19 factors in Table 3.6 because of their weak significance in the prior financial distress studies or present study using likelihood ratio. Another reason for not including these variables is to avoid multicollinearity problems. While some explanatory variables such as corporate yield spread are highly associated with other covariates, their association with financial distress may be weak. For instance, using a quasi-natural experiment, Gao & Lin (2018) found a significant association between of market variables such as share prices, market returns and firm yield spread in China. In another study, Abudy & Raviv (2016) found that higher financial leverage is significantly associated with low yield spreads. Nonetheless, these studies did not find firm yield spread to significantly explain financial distress. These findings are supported by Zhang et al. (2010) that rather employed the market value of trading shares-to-total liabilities and book value of total share capital-to-market value of total shares instead corporate yield spread, in the Chinese equity market. In another instance, variables such as operating profit-to-total assets are highly correlated with return on assets (ROA) in the current research. While including both variables in the model results multicollinearity, the ROA was selected due to its strong significance in prior studies and current research.

Excluding weak variables that are weak and highly correlated with other covariates in the model is supported by Liu (2015).This study show that including explanatory variables that do insignificantly add to a model's explanatory power can reduce the prediction accuracy of the model. Second, excluding variables that are highly correlated and explain the same aspect of firm performance helps prevent the problem of multicollinearity. For instance, this research selects net income-to-total assets and not operating income-to-total assets since both variables measure the same aspect of firm profitability (Beaver et al., 2010). In addition, market value of trading shares-to-total Liabilities and book value-to-market value of total shares selected for this research were employed by studies such Zhang et al. (2010) and Männasoo, Maripuu & Hazak (2018). These variables measure aspects of market performance, market risk and default risk especially as it relates to financial distress risk compared to variables such as equity returns, annualized yield, firm yield spread that focus on overall market risk and investment risk as shown by Chen, Lesmond & Wei (2005) and Chen et al. (1986) and Campello, Chen & Zhang (2008)

We believe nineteen explanatory variables could be further reduced therefore we statistically select our final regressors using their likelihood ratio (LR) test according to Lui (2014). The LR test technique involves building a series of nested models with and without each explanatory variable and comparing the LR test chi^2 and significance for the full and restricted models to assess how much each explanatory variable contributes to the model. Following the LR test, eleven financial ratios and corporate governance indicators were selected for our MLR model (see Table 4.8). The variables include four accrual-based ratios; NITA, TATURN, WCTA, TLTA, three cash flow-based ratios; CFOTL, CFFTA and DPS, two market-based ratios; MVTL and MVBV and two corporate governance indicators; CEO_DUAL and INST_OWN.

3.4.2.2 Financial Ratios

Asset Management efficiency Ratios

In the study by Khunthong (1997) and Hossari & Rahman (2005) on the usage of financial ratios, the total assets turnover (TATURN) is the most statistically significant asset management efficiency ratio. Further, Altman (1968) and Ohlson (1980) found total turnover (TATURN) and working capital turnover (WCTURN) most significant in their financial distress discriminant models. Since firms use assets to make revenue, the TATURN ratio is expected to be a strong explanatory factor in assessing a firm's efficiency in asset utilization to generate revenue. Considering the definition of insolvency, accounts payable turnover (WCTURN) is a relevant explanatory factor since the ratio measures a firm's efficiency in utilizing working capital credit with the revenue. Therefore, the TATURN and WCTURN ratios are selected as a measure of efficiency in this study following their statistical significance and dominance in prior financial distress literature.

Profitability Ratios

In a comprehensive study of financial ratios by Hossari & Rahman (2005), the net income-to-total asset ratio (NITA) was found to dominate almost half of the studies that used accrual-based ratios seconded by retained earnings-to-total assets. Research on the Chinese equity market by Zhang et al. (2010) to develop the Z-China prediction model, the NITA is amongst the most significant amongst the thirty-two financial ratios used. In developed markets such as the U.S., Beaver et al. (2005) and Tinoco (2013) found NITA is most significant in explaining financial distress. NITA ratio measures a firm's efficiency in utilizing its assets to generate and its ability to retain profit from the revenue it generates. When assets are not efficiently utilised it could result in poor revenue and ultimately declining profitability. In addition to the ratio NITA, several financial distress research also found retained earnings-to-total assets (RETA) superior to other profitability ratios in determining financial distress (Altman, 1968; Beaver et al., 2010; Hossari & Rahman, 2005; Kenney et al., 2016; Ohlson, 1980); Ruibn et al. (2014); (Zhang et al., 2010). The retained earnings serve as the next source of funding after working capital. Therefore, the NITA and RETA ratios are selected measures of profitability in our study based on their statistical significance and dominance in prior financial distress literature.

Liquidity Ratios

The accrual-based liquidity aspect of firm performance is considered in this research due to its significance in the definition of cash flow insolvency by InsolvencyAct (1986). From a pioneer study in financial distress by Ohlson (1980) to a more recent study by Tinoco (2013), current assets-to-current liabilities (CR), quick ratio (QR) and working capital-to-total assets (WCTA) are the most used liquidity ratios. The QR ratio is often selected in place of the CR ratio in studies where inventory is a key factor otherwise, the two ratios measure the same aspect of liquidity. Notably, the CR and QR measure almost the same aspect of firm performance, so we select CR over QR because of its greater popularity in the literature. The comprehensive by Hossari & Rahman (2005) and Axel (2012) however found the WCTA ratio to dominant financial distress studies seconded by the CR and then the QR ratio. Iheanacho (2016) argue that the WCTA ratio is more effective than CR and QR in assessing working capital items. This is because the WCTA ratio compares current assets to total assets while CR and QR compare current assets to current assets. Consequently, the CR and WCTA ratios are selected measures of liquidity in our research based on their statistical significance and dominance in prior financial distress literature.

Financial Leverage Ratios

The financial leverage ratio most commonly used in the comprehensive review across 53 financial distress studies from 1996 to 2002 is the total liabilities (total debt)-to-total assets (TLTA) (Hossari & Rahman, 2005). The TLTA has been used as a financial leverage ratio by a host of key studies such as Altman (1968), Charitou et al. (2004), Charitou et al. (2004), Laitinen (2005), Beaver et al. (2010), Tinoco et al. (2018) and Tan (2019). The TLTA ratio appears to be the most dominant financial leverage ratio since it directly tests balance sheet insolvency and evaluates a firm's capital structure comparing debts to assets. Therefore, the TLTA ratio is selected as a measure of financial leverage in our study following their statistical significance, dominance in prior financial distress literature and significance in defining insolvency.

Cash Flow-Based Ratios

A financially distressed firm suffers declining cash flow from operations and increasing debt thus, the CFOTL ratio is expected to have a more significant impact than other explanatory variables. Stewart (2016) and Tin & Nga (2017) found cash flow from operation-to-total liabilities (debt) (CFOTL) the most used cash flow ratio in financial distress literature. Also, in a comparative study that used cash flow ratios, Fawzia, Kamaluddina & Sanusib (2015) and Sharma (2001) ranked the CFOTL as the most significant cash flow ratio. The cash flow from operations-to-outstanding shares (CFSHARE) ratio compares a firm's cash flow from operations to outstanding shares. The ratio is not common in financial distress studies, however, was popularized by Zhang et al (2010) on the Chinese equity market. This significance of the CFSHARE ratio in Zhang et al (2010) highlights the importance of the split-share structure in the Chinese equity market that is driving the ratio. Therefore, the CFOTL and CFSHARE ratios are selected as a measure of cash flow liquidity in our research following their statistical significance, dominance in prior financial distress literature and significance in defining insolvency. Lau (2014) found firms experiencing poor liquidity reduced their cash dividends (measured by cash dividend per share, DPS) as a matter of priority and this finding is consistent with Pecking Order. Cash flow from finance to total assets (CFFTA) and cash flow from investment to total assets (CFITA) are cash flow based ratios that assess other components of the cash flow statement and are significant in the study by Sharma (2001) and Stewart (2016). Therefore, we select CFFTA, CFITA, DPS in addition to CFOTL and CFSHARE.

Market-Based Ratios

In measuring market performance/valuation, Tinoco et al. (2018) used share prices, (Fama & Kenneth, 1992; Malik et al., 2013) used stock returns while (Agarwal & Taffler, 2008; Reisz & Perlich, 2007; Shumway, 2001) used market value which is computed as outstanding share multiplied by the share price. The book value of the equity-to-market value of equity (BVMV) is the conventional measure of market value in the literature and has been popularised by financial distress research such as Shumway (2001) and Agarwal & Taffler (2008). Further, BVMV was found to significantly discriminate between failed and non-failed firms in several other studies in such firms by Aharony et al. (1980), Hillegeist, Keating, Cram & Lundstedt (2004) and Reisz & Perlich (2007). Besides the BVMV, the market value of equity-to-total liabilities (MVTL) that compares market value (based on trading shares) to debt appears to be promising since the ratio is significant in the Z-China model by Zhang et al. (2010). Market valuation elsewhere may differ from the Chinese equity market considering that firms in the Chinese equity market have their outstanding total shares split into trading and non-trading (including state shares and legal representative shares). Since non-trading shares can go as high as 60%, it would be overvalued to use total outstanding shares to compute market ratios in the Chinese equity market (Zhang et al., 2010). As a result, market value is computed as share price multiplied by trading shares in our study. The MVTL ratio is selected alongside BVMV ratios as measures of market valuation in our research following their statistical significance, dominance in prior financial distress literature.

3.4.2.3 Corporate Governance Factors

Board Structure

Board structure as a key corporate governance mechanism has been measured with several proxies such as board size, board gender diversity, CEO/chairman duality, percentage of executive directors and percentage of NEDs (Männasoo et al., 2018). Among these measures, the board size, CEO/chairman duality and percentage of NEDs are the most frequently used (Adams & Ferreira, 2007) Studies in the Chinese equity market by Li (2014) and Rezaee et al. (2016) suggest that these measures hold significance in the Chinese equity market. Board size is measured (BD_SIZE) by the number of directors on the board of directors according to Adams & Ferreira (2007). The percentage of NEDs (BD_IND) is defined as the number of outside NED to the total number of directors on the board of directors. CEO/Chairman duality is defined as the separation of the positions of the CEO and the Chairman. A dummy variable of 1 is assigned if CEO and Chairman positions are held by separate persons and 0 if otherwise. Therefore, we employ BD_SIZE, CEO_DUAL and BD_IND as measures of board structure.

Ownership Structure

The ownership structure is another key corporate governance factor that is measured with several proxies such as the proportion of collective ownership and institutional ownership (Männasoo et al., 2018). These factors are significant in financial distress studies such as Adams & Ferreira (2007) and Md-Rus, Mohd, Latif & Alassan (2013). In addition to these measures, state ownership is a significant measure of ownership structure in the Chinese equity market (Li (2014), Hu & Zheng (2015) and Lai & Tam (2017)). In this study, we defined institutional ownership (INST_OWN) as the proportion of shares owned by an institutional entity to total outstanding shares. Block ownership is described as the number of shares owned by the top 10 shareholders to total outstanding shares (TOP10SH).

Table 3.5 reports the nineteen explanatory variables of interest in our research, their measurement, expected relationship sign, and key studies where the variables were used.

Table 3.5: Summary of Explanatory Variables

FACTOR	IDENTIFIER	MEASUREMENT	EXPECTED SIGN	KEY STUDIES
Profitability ratios	NITA	Net Income /Total Assets	-	Altman (1968), Ohlson (1980), Laitinen (1991), Sori & Jalil (2009), Hensher et al. (2007), Beaver et al. (2010), Axel (2012). Zhang et al. (2010), Zhou et al. (2012), Zhou (2013) Liang et al. (2016)
	RETA	Retained Earnings /Total Assets	-	Altman (1968), Ohlson (1980), Laitinen (1991), Sori & Jalil (2009), Axel (2012), Liang et al. (2016). Zhang et al. (2010), Zhou et al. (2012), Zhou (2013)
Liquidity ratios	CR	Current Assets/Current Liabilities	-	Altman (1968), Ohlson (1980), Laitinen (1991), Sori & Jalil (2009), Hensher et al. (2007), Beaver et al. (2010), Axel (2012), Liang et al. (2016). Zhang et al. (2010), Zhou et al. (2012), Zhou (2013)
	WCTA	Working Capital/Total Assets (WC = CA- CL)	-	Altman (1968), Ohlson (1980), Laitinen (1991), Sori & Jalil (2009), Zhang et al. (2010), Hensher et al. (2007), Axel (2012), Liang et al. (2016), Zhou et al. (2012), Zhou (2013) Liang et al. (2016)
Efficiency ratios	TATURN	Sales/Total Assets	-	Altman (1968), Ohlson (1980), Laitinen (1991), Sori & Jalil (2009), Zhang et al. (2010), Hensher et al. (2007), Beaver et al. (2010), Axel (2012), Liang et al. (2016)., Zhou et al. (2012), Zhou (2013)
	APTURN	Sales/Accounts Payables	-	Altman (1968), Ohlson (1980), Laitinen (1991), Hossari & Rahman (2005), Sori & Jalil (2009), Zhang et al. (2010), Axel (2012), Liang et al. (2016)
Financial Leverage	TLTA	Total liabilities /Total Assets	+	Altman (1968), Ohlson (1980), Laitinen (1991), Sori & Jalil (2009), Hensher et al. (2007), Beaver et al. (2010), Axel (2012). Zhang et al. (2010), Liang et al. (2016)

Table 3.5: Summary of Explanatory Variables (cont.)

FACTOR	IDENTIFIER	MEASUREMENT	EXPECTED SIGN	KEY STUDIES
Cash flow ratios	CFSHARE	Cash flow from operations/ Outstanding Shares	-	Zhang et al. (2010)
	CFOTL	Cash flow from operations/Total Liabilities	-	Tin & Nga (2017), Sayari & Mugan (2013), Ahmed (2014), Gombola et al. (1987), Stewart (2016), Rujoub, Cook & Hay (1995), Beaver (1966); Sharma (2001), Alostaz (2010), Almany et al. (2015),
	CFFTA	Cash flow from finance/Total Assets	+	Barua & Anup (2015); Bhandari & Rajesh (2013), Stewart (2016)
	CFITA	Cash flow from investment/Total Assets	-	Bhandari & Rajesh (2013) Barua & Anup (2015), Stewart (2016)
	DPS	Dividend/Total Assets	-	Zhang et al. (2010), Sharma (2001), Bhandari & Rajesh (2013)
Market valuation Ratios	MVTL	MV trading shares/Total Liabilities	-	Beaver et al. (1970), Clark & Weinstein (1983), Chan et al. (1985), Fama & Kenneth (1992), Lindsay & Campbell (1996), Shumway (2001), and Hillegeist et al. (2004), Reisz & Perlich (2007) Bharath & Shumway (2008). Zhang et al. (2010), Liang et al. (2016)
	BVMV	BV total shares/MV total shares	-	
Ownership structure	INST_OWN TOP10SH	Institutional share/Total outstanding shares Top 10 Shares/Total outstanding shares	- -	Rezaee et al. (2016), Mann (2005). Lee & Yeh (2004), Wu (2007), Cheung et al. (2008); Li & Naughton (2007), Lin et al. (2010), Wang & Yung (2011); Zhang et al. (2012), Hu & Zheng (2015),
Board structure	BD_SIZE BD_IND CEO_DUAL	No. Board Directors No. NED/No. Board Directors CEO & Chairman different 1, Otherwise 0	- - -	Brédart (2014), Rezaee et al. (2016), Mann (2005). Lee & Yeh (2004), Wu (2007), Cheung et al. (2008); Li & Naughton (2007), Lin et al. (2010), Zhang et al. (2012), Hu & Zheng (2015)

3.5 Endogeneity, Financial and Corporate Governance Factors and Financial Distress

3.5.1 Endogeneity, Financial and Corporate Governance Factors and Financial Distress

A key assumption of the Ordinary Least Square (OLS) is that the observed explanatory variable is uncorrelated with the error term. This assumption could be violated in the presence of endogeneity. Endogeneity describes a situation where an observed explanatory variable correlates with the error term in the model (Wooldridge, 2010). The consequences of endogeneity are that the performance of the empirical model is biased and estimates are inconsistent when validated with different sample sizes (Wooldridge, 2010). Peel (2018) and Barros et al. (2020) identified the three most common sources of endogeneity in corporate finance and accounting research. They have omitted variables, simultaneity and measurement error.

Measurement error occurs where a wrong parameter is used or a common error occurs in measuring an observed explanatory variable or outcome variable (Wooldridge, 2014). Measurement error could also occur where a proxy does not precisely capture the unobserved phenomenon that it is intended to measure (Wooldridge, 2014). In our study, the possible measurement errors, which may show up as outliers are adequately treated using mean imputation methods. Firm performance is measured using traditional financial ratios and corporate governance factors that were significant in prior financial distress studies.

Further, simultaneity occurs where the observed explanatory variable x, causes the outcome variable y but it is also possible that y causes x (Antonakis, Bendahan, Jacquart & Lalive, 2010). In the context of our research, this implies that financial ratios and corporate governance indicators influence financial distress but changes in financial distress states could also affect financial ratios. Cheng et al. (2012) studied the short-term impact of the *Special Treatment* designation on short-term share prices and found that Special Treatment of firms negatively affects their short-term share prices. Considering this finding, it is assumed that the market-based ratios such as the MVTL and MVBV used in this study might be endogenous – influenced by the ST designation of firms. The assumption around endogeneity of market-based ratio – MVTL and MVBV is tested.

Omitted variable bias may occur in various forms. Key sources of firm-level heterogeneity include the difference in firm size, age, business model and industry characteristics, etc. (Gippel, Smith & Zhu, 2015). Empirical studies such as Xu & Wang (1999), Chen, Firth & Xu (2008) and Wang & Yung (2011) found a significant relationship between state ownership and the probability of a firm accessing government grants, subsidies towards their uncovered expenses, relatively lower taxation and access to loans, especially from State banks. In the Chinese equity market, preferential treatment by the State Government creates further firm-level heterogeneity between SOE and non-SOE firms that may influence a firm's financial distress risk. Further, the equity market expectation of management of financially distressed firms (ST, SST firms) is to take urgent action towards remedying the reason the firm faces delisting (Zhou et al., 2012). In the course of restructuring, it is also a common practice for management to manage its earnings before a merger or acquisition (Lim & Chang, 2017). In this instance, management strategy is assumed as a confounding factor that influences earnings (NITA in our research) and at the same time may influence the probability of the firm designated as NST, ST, SST or SSTDelisted. The assumption around endogeneity of earnings-based explanatory variables - NITA is tested.

Accounting for Endogeneity

Where the source of the endogeneity problem is unobserved heterogeneity of firms, the fixed effect- panel data approach significantly reduces or eliminates the endogeneity problem by removing firm heterogeneity (Constantinides, Haris & Stulz, 2013). In this study, we believe that both the values of the omitted variables and their effect on explanatory variables are 'fixed' and time-invariant over the period, which concurs with the fixed effect estimator assumption. We do not believe unobserved time-variant covariates such as firm age and firm size vary enough over time to identify their effects. Where this is our case, Wooldridge (2014) still suggests the use of a fixed effect estimator compared to a random effect estimator. However, Wooldridge (2014) argues that removing individual heterogeneity alone would not suffice in the presence of additional endogeneity problems such as the correlation between an observed explanatory variable and the error term. Where unobserved heterogeneity exists in addition to other forms of endogeneity, then a fixed or random effect estimator may not be efficient, rather an instrumental variable or CFA estimator may be used (Wooldridge, 2014). Also, where there is more than one source of omitted variable bias, the use of a two-stage least square (2SLS) may require extensive modelling to isolate the effect of the unobserved omitted variable (Barros et al., 2020).

We account for possible omitted variable bias, possible confounding bias, unobserved firm-level and industry-level heterogeneity in our study using the two-stage control function approach (2SCFA) or two-stage residual inclusion (2SRI) described by Terza, Basu & Rathouz (2008) and Petrin & Train (2010). This 2SCFA method is an extension of the popular linear two-stage least square (2SLS) method that uses instrumental variables, to nonlinear models. For the 2SCFA method, the OLS is used in the first stage to regress the suspected endogenous variable on exogenous explanatory variables and control variables. The results from the first stage are used to generate predicted residuals of the endogenous variable from the first stage as predicted. The first-stage residual is included in the second-stage as an additional regressor alongside the endogenous variable (rather than replacing the endogenous variable) thereby accounting for the distribution of unobserved confounding factors (Guevara & Ben-Akiva, 2009; Terza et al., 2008). We employ the MLR at the second stage of 2SCFA to estimate our model parameters on the assumption that the MLR model holds conditional on the CFA estimator as argued by Wooldridge (2014). The control function approach (CFA) has been used in empirical studies by Hausman (1978), Heckman & Robb (1985), Guevara & Ben-Akiva (2009), Blundell & Powell (2004)and Petrin & Train (2010).

3.5.2 Control Variables Specification

In addition to explanatory variables of interest specified in section 3.4.2, this research employs control variables within a 2SCFA estimator to account for endogeneity. Two macroeconomic variables - Gross Domestic Product rate (GDPR) and lending rate are employed to control for unobserved confounding bias. Three firm-specific variables - firm size, firm age and percentage of state ownership are employed to control for firm-level heterogeneity. The industry dummy variable is used to control industry-level heterogeneity.

3.5.2.1 Macroeconomics Factors and Financial Distress

Hill, Perry & Andes (1996) and Evereth & Watson (1998) found lending rate and the unemployment rate as the most significant macroeconomic variables while Audretsch & Mahmood (1995) and Bhattacharjee, Higson, Holly & Kattuman (2007) found lending rate and economic growth (GDP) as most significant in their study. Changes in the business environment in terms of government policies, economic, technological and environmental factors are directly or indirectly captured in the economic growth (Tomas & Dimitrić, 2011). For instance, an economy in recession or an unfavourable Government policy could directly influence the probability of financial distress and at the same time negatively induce poor demand for goods and services that translates into poor sales and profitability.

Therefore, we use economic growth measured as Gross Domestic Product annual rate (GDPR) to control for external factors that may have a confounding influence on our model especially assets management and profitability ratios. Studies such as Audretsch & Mahmood (1995), Bhattacharjee et al. (2007), Tomas & Dimitrić (2011) and Bhattacharjee et al. (2007) also used GDPR as a proxy control variable for general external factors while Tinoco (2013) used it as a proxy for macroeconomic factors. Likewise, the lending rate influences the finance cost paid by firms as well as the decision to borrow (Tinoco, 2018). We see lending rate influencing both profitability ratios and financial leverage ratios as well as the probability of financial distress therefore, we employ the average lending rate as a control variable.

3.5.2.2 Firm-specific Variables and Financial Distress

Studies by Hensher et al. (2007), Chancharat (2008), Tinoco (2013) and Bhattacharjee & Han (2014) found a significant negative association between firm size and risk of financial distress. On the other hand, firm size and age could influence firm results such as the size of a firm's assets base as well as a reserve (retained earnings). For instance, increasing age and size enables the firm to establish themselves in their respective industries, gain experience and strategy, which increases firm resilience and as such, reduces the probability of the firm becoming financially distressed. On the other hand, firm differs by age and size. Therefore, we employ firm size and firm age to control for firm-level heterogeneity since these variables could influence financial distress in addition to our variables of interest. Firm size has been measured differently by researchers, however, most researchers have used the logarithm of fixed assets (Hensher et al., 2007; Zhang et al., 2010) and the number of employees (Chan et al., 1985) while others (Laitinen, 1991) used the logarithm of sales. This study measures firm size using the log of fixed assets (LOGFA) according to Zhang et al. (2010) and firm age as the log of the number of days (LOGAGE) from the establishment until 2018.

3.5.2.3 Industry-specific variable and Financial Distress

The relationship between the type of industry a firm operates and the probability of financial distress is based on the risk associated with the business line or industry a firm operates that influences firm performance. Lennox (1999) studied US firms and found that corporate financial distress was more prevalent in some industries than others and that some industries such as the hospitality industry and food service industry were more prone to financial distress than others. Hensler, Rutherford & Springer (1997) and Rommer (2005) found similar results of a positive effect of a company industry sector on the risk of corporate financial distress. This research uses industry dummy variables to control for possible industry-level heterogeneity in our model, business-specific risk and industry-specific risk. Thirteen industry dummies (designated as IND_DUMMY) are used to denote CSMAR industry sector classification in China namely (i) Agriculture, Forestry and Fishery (ii) Construction (iii) Education (iv) Power, Energy and Utility (v) Healthcare (vi) Hotels and Catering (vii) IT and Software (viii) Leasing and Business Services (ix) Manufacturing (x) Mining (xi) Scientific Research and Technology (xii) Transport, Storage and Postal (xiii) Wholesale and Retail

Table 3.7 summarises the control variables used in this research including their description and their proxy.

3.5.2.4 State Ownership and Financial Distress

State ownership is unique to the Chinese equity market. Empirical studies by Cheung et al. (2008), Faccio (2006) and Wang & Yung (2011) show the impact of state ownership on the performance of SOEs by way of providing subsidies, grants and other financial assistance not available to non-SOEs.

Findings from Wang & Deng (2006) and Li et al. (2008) suggest that the protection received by SOEs from the government from liquidated or delisted shows the influence of state ownership on the financial distress process for SOEs. Despite the importance of state ownership, the variable has a non-statistically significant and weak effect on financial distress thus was not included as a variable of interest. Nonetheless, the role state ownership plays in the Chinese equity market and its potential impact could raise Endogeneity concerns in the research. Therefore, we control for the influence of state ownership on our explanatory variables of interest since such influence is a potential source of firm-level heterogeneity. This study uses state ownership as a control variable which is measured as the percentage of state-owned shares to total outstanding shares (STATE_OWN).

Table 3.6: Control variables specification

FACTORS	PROXY/VARIABLE	IDENTIFIER	MEASUREMENT
Macroeconomic	Gross Domestic Product	GDPR	Annual GDP growth rate
	Lending Rate	LENDR	Annual Lending rate
Firm-specific	State ownership	STATE_OWN	Percentage of state-owned share to total outstanding shares
	Industry dummies	IND_DUMMY	The numbers 1 to 13 each for the thirteen industries
	Firm Size	LOGFA	Log of Fixed Assets
	Firm age	LOGAGE	Log of firm number of days

Source: Author's compilation

3.6 Methods of Estimating Financial Distress

3.6.1 Maximum Likelihood Estimation

The goal of the Generalized linear model (GLM) is similar to that of the ordinary least square (OLS) regression which is to model the outcome variable in terms of one or more explanatory variables. However, in our study, the outcome variable is categorical and not continuous as in the OLS regression, thus a GLM logistic regression is appropriate. In addition, GLMs offer more utility and flexibility with less restrictive assumptions which give them an advantage over other linear probability models (Johnsen & Melicher, 1994). The GLMs use the maximum likelihood estimation (MLE) rather than the OLS in estimating the parameters. The GLM does not assume normality of outcome and error term, linearity between outcome and explanatory variables and homoscedasticity (Lin, 2009). Also, both the outcome variable and the error term do not need to be normally distributed. GLMs are suitable where the outcome variable is binary (binary logit or probit model), ordinal (ordinal logit or probit model) or nominal (multinomial logit or probit model) (Burnham & Anderson, 2002). Theoretically, the outcome variable - financial distress in figure 2.3 is ordered. However, in practice, the process could be unordered when considering the possibility of a firm going from an FDECL to an FDIST without going through the FWEAK. As a result of the mix between the ordered and unordered processes, the multinomial logistic regression (MLR) method is adopted rather than the ordered logit regression. The MLR could be used for ordered or unordered categorical outcomes, however, it ignores the ordering of the outcome categories (Anderson & Rutkowski, 2007).

The objective of the MLE is to compute the maximum likelihood of parameters using the explanatory variables. The MLE is achieved by estimating model parameter values $\theta_1, \theta_{2, \ldots,} \theta_m$ that maximizes the likelihood function $L(\beta)$ and ensures the data being observed are probable. We consider a logit function of a four-category level outcome variable where one category level becomes the reference category can be written as below.

$$g_i(\mathrm{x}) = \ln\left(\frac{P(Y=1|x)}{P(Y=0|x)}\right) = \beta_{10} + \beta_{11}x_1 + \beta_{12}x_2$$

$$= \mathbf{x}'\boldsymbol{\beta}_1 \qquad (3.1)$$

$$g_i(\mathrm{x}) = \ln\left(\frac{P(Y=2|x)}{P(Y=0|x)}\right) = \beta_{20} + \beta_{21}x_1 + \beta_{22}x_2 = \mathbf{x}'\boldsymbol{\beta}_2$$

$$g_i(\mathrm{x}) = \ln\left(\frac{P(Y=3|x)}{P(Y=0|x)}\right) = \beta_{30} + \beta_{31}x_1 + \beta_{32}x_2 = \mathbf{x}'\boldsymbol{\beta}_3$$

Assuming a distribution with a random sample of $X_1, X_2, \ldots, X_n$ that relies on one or more parameters $(\theta_1, \theta_{2, \ldots,} \theta_m)$. Given the model parameters$(\theta_1, \theta_{2, \ldots,} \theta_m)$, the likelihood function of observing a data $X_1, X_2, \ldots, X_n$ can be written as:

$$\sum_{j=0}^{2} Y_j = 1\, L(\beta) = \prod_{i=1}^{n} [\pi_0\,(x_i)^{y0i}\, \pi_1\,(x_i)^{y1i}\;\; \pi_2\,(x_i)^{y2i}] \qquad (3.2)$$

For our research where outcome variable, financial distress Y_i has 4 states (category levels), then equation (3.1) could be extended with the log-likelihood in equation (3.3).

$$l(\beta) = \sum_{i=1}^{n} [y_{1i}g_1(x_i) + y_{2i}g_2(x_i) + y_{3i}g_3(x_i) + y_{4i}g_4(x_i) - 1n\, e^{g1(x_i)} + e^{g2(x_i)} + e^{g3(x_i)} + e^{g4(x_i)}] \qquad (3.3)$$

Since a log is used in association with the likelihood function, it is often referred to as the log-likelihood function. A negative of the log-likelihood function since the function is set to minimize and maximise the cost function. The MLE is the estimator used in empirical BLR and MLR models and in generating estimates for hypothesis testing.

3.6.2 Binomial logit regression

The BLR model with two outcome categories has a single logit link function that compares the base category to the binary category to compute the log-odds. Given category Y = 0 as the base category, the functions can be stated as follows:

Binomial Logit function for Y = 1 relative to the base logit function for Y = 0

The logit link function uses a linear combination of explanatory variables values and converts it to the probability of financial distress Y_{it} which takes the value of 0 or 1. In a BLR model where a logit function predicts an outcome of one of the binary outcome variables which are financial distress (y), based on k explanatory variables which are financial and corporate governance factors (x). The logit model probability is given in equation (3.4) below:

$$\mathrm{logit}(\pi) = \log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta ABR_{it} + \cdots + \beta MBR_{it} + \cdots + \beta CBR_{it} + \cdots + \beta CGI_{it} + .. + \beta X_{it} \quad (3.4)$$

Where *t* is the period which is 12 years in our study and *i* is the sample NST, ST, SST and SSTDelisted firms. Y_{it} is the outcome variable - financial distress which is binary for observed *i* NST, ST, SST and SSTDelisted firms at period t. The distribution of Y is assumed to be a binary dummy variable that takes the value of 0 if firm *i* is in an NFDIS state during the year *t* and, the value of 1 otherwise (if the firm *i* is in an FDIST state). β is the model estimated parameters of the explanatory variables, while β_0 in the model is constant. ABR, MBR, CBR and CGI are explanatory variables some of which are continuous and others binary and are linear in parameters. $ABR_{it}$are accrual-based ratios for observed *i* at period *t*, MBR_{it} are market-based ratios for observed *i* at period *t*, CBR_{it} are cash flow-based ratios for observed *i* at period *t* and CGI_{it} are the corporate governance indicators for observed *i* at period *t*.

3.6.3 Multinomial Logit Regression

The MLR model is part of the family of GLMs that use the MLE. GLMs perform the connection of a linear combination of explanatory variables and MLE estimated parameters (linear predictors) to the outcome variables using the link function. In the case of an MLR, the link function requires a non-linear transformation of the explanatory variables. The logit transformation $\text{logit}(\pi)$ is required to estimate the probability of a firm entering either of the four financial distress states. In essence, the MLR uses the function of one or more explanatory variables to explain the variation in three or more ordered or unordered categorical outcome variables using non-linear transformation (Hosmer & Lemeshow, 2000). In the literature, MLR has been vastly used in estimating multiple state financial distress by Lau (1987), Johnsen & Melicher (1994), Jones & Hensher (2004) and Farooq et al. (2018).

The MLR is an extension of the BLR that performs a comparison of binary combinations of the outcome categories with each binary combination comparing a particular category to the reference category to compute the logit (log-odds). The MLR model estimates the logit of an observation belonging to a given category relative to the reference category. Therefore, the odds ratio can be defined as the ratio of the probability of belonging in a given category to the probability of belonging to the reference category (Liu, 2015). This is written as in equation 3.5 below where *J* stands for multiple categories from 1 to *J-1* categories.

$$\text{Odds } (Y = j \text{ } vs. Y = J) = \frac{P(Y=j)}{P(Y=J)} \tag{3.5}$$

For this research, there are four nominal categories (states) for the outcome variable financial distress and these are NFDIS state 0, FDECL state 1, FWEAk state 2 and FDIST state 3. We estimate the three odds with NFDIS state 0 as the reference state: The odds of being in FDECL state 1 versus NFDIS state 0, the odds of being in FWEAK state 2 versus NFDIS state 0 and odds of being in FDIST state 3 versus NFDIS state 0. The odds ratio for three odds can be expressed as follows:

$$\text{Odds } (Y = 1 \text{ } vs. Y = 0) = \frac{P(Y=1)}{P(Y=0)} = \frac{P(1)}{P(0)} \tag{3.6}$$

$$\text{Odds } (Y = 2 \text{ } vs. Y = 0) = \frac{P(Y=2)}{P(Y=0)} = \frac{P(2)}{P(0)} \tag{3.7}$$

Odds $(Y = 3\ vs. Y = 0) = \frac{P(Y=3)}{P(Y=0)} = \frac{P(3)}{P(0)}$ (3.8)

Assuming all firms must enter one of J = four financial distress states and the state each firm will finally enter is predicted by k = explanatory variables defined as $ABR_1, CBR_1, MBR_1\ CGF_1, \dots, X_j$ regressors made up of accrual-based ratios, cash flow-based ratios, market-based ratios and corporate governance factors. If p_j is defined as the probability that a firm will eventually enter state J then the multinomial logit function for the full MLR model is given as follows;

$$p_j = \frac{\exp(\beta_0 + \beta_{j1}\ ABR_{j1} + \cdots + \beta_{jk}\, MBR_{jk} + \cdots + \beta_{jk}\, CBR_{jk} + \cdots + \beta_{jk} CGI_{jk} + \cdots + \beta_{jk}\ X_{jk})}{1 + \sum_{j-1}^{k-1} exp\ (\beta_0 + \beta_{j1}\, ABR_{j1} + \cdots + \beta_{jk}\, MBR_{jk} + \cdots + \beta_{jk}\, CBR_{jk} + \cdots + \beta_{jk} CGI_{jk} + \cdots + \beta_{jk}\ X_{jk}} \quad (3.9)$$

Where;

p_j is the probability of financial distress for firm i, exp is the exponential function, $\beta_{j1}, \beta_{j2}, \dots, \beta_{jk}$ are the slope coefficients, $ABR_{j1}, ABR_{j2}, \dots, ABR_{jk}$ are accrual-based ratios, $MBR_{j1}, MBR_{j2}, \dots, MBR_{jk}$ are market-based ratios, $CBR_{j1}, CBR_{j2}, \dots, CBR_{jk}$ are cash flow-based ratios and $CGI_{j1}, CGI_{j2}, \dots, CGI_{jk}$ are corporate governance factors.

The odds ratio of being in a particular category j relative to reference category J is computed as the exponential of the log coefficient β. In a MLR model, the odds ratio (or relative risk in a MLR model) is the change in odds for a one-unit change in the values of an explanatory variable while holding other explanatory variables constant (Anderson & Rutkowski (2007).

Four outputs of the MLR model which are the log coefficients (parameter estimates), odds ratios, predicted probabilities and marginal effects could be used (Anderson & Rutkowski, 2007). A key issue with interpreting the log coefficient output of the MLR model is that the relationship between explanatory variables and the outcome variable is nonlinear and the coefficient sign may change in the distribution of a given explanatory variable (Wulff, 2015, p.303). Consequently, interpreting the log coefficients of the MLR model as the coefficients from an OLS or a BLR model may not be appropriate (Anderson & Rutkowski, 2007). Interpreting a single log coefficient of a category relative to the reference category alone may be appropriate in a BLR model where there are binary categories. However, in the MLR model, doing this neglects the inevitable interrelationship that exists between other categories which increase the risk of misinterpretation (Wulff, 2015). The log coefficients and Wald z statistics are used to test the linear hypothesis of the effects of financial ratios and corporate governance indicators on the probability of financial distress. We employ non-linear means: odds ratios, predictive probabilities and marginal effects to further explain the relationship between financial ratios, corporate governance indicators and the probability of financial distress.

3.6.4 Research Methods

This section details the estimation methods and hypotheses testing techniques employed in this research to achieve set research objectives. Our research design outlined as follows is set to test hypotheses H2.1 to H2.18 and achieve the four research objectives for this research.

First research objective methods

The *first research objective* is to examine the effects of the explanatory variables on the probability of a firm entering any of the multiple states of financial distress and the research hypotheses are H2.1 to H2.12 in section 2.3. We employ the multinomial logit model that uses the maximum likelihood method to estimate the effect of explanatory variables on the outcome variable - financial distress. We achieve this objective in two steps, the first is through a test of the linear hypothesis and odds ratios. The second is through predicted probabilities and marginal effects.

Effects of explanatory variables – Linear hypothesis

With the linear hypothesis testing, individual log coefficients and odds ratios in the MLR model are tested with the Wald z statistic to assess the effect of explanatory variables on each of the four financial distress states. In the MLR model, testing that an explanatory does not affect the outcome variable requires a test that $J-1$ coefficients are simultaneously equal to zero (Long & Freese, 2014). From J categories of the outcome in equation (3.4), there are $J-1$ non-redundant number of coefficients for each explanatory variable x_k.The Wald test, tests the null hypothesis that the coefficient associated with the explanatory variable x_k has no effect on the probability of financial distress can be written as:

$$H_0: \beta_{k,1|b} = \cdots = \beta_{k,J|b} = 0 \qquad 3.10$$

Where b is the base category and β are the coefficients of explanatory variables.

The hypothesis places constraints on $J-1$ coefficients since $\beta_{k,b|b}$ is 0. The effect of each explanatory variable is assessed at the three distress states with each state relative to the reference state.

In the linear hypothesis testing, we observe the significance of the effects from the p-value of Wald z statistic at pv<0.05 level while the relationship direction is determined by the sign of the log coefficient. However, it should be noted that the sign of the log coefficient of an explanatory variable explains how the explanatory variable relates to the probability of choosing a particular category relative to the reference category in a binary combination (Anderson & Rutkowski, 2007). Wulff (2015) argues there is no guarantee that the sign of the marginal effect effects is the same as the sign of the log coefficient for an explanatory variable. Therefore, in interpreting the relationships in the linear hypothesis and sign of the log coefficients, we limit our analysis to comparing each distress state – FDECL, FWEAK and FDIST states to the reference state - NFDIS (MLR model) and comparing the FDIST state to the reference state - NFDIS state (BLR model).

The odds ratios are the nonlinear exponentials of log coefficients that measure the effect of a one-unit change in an explanatory variable value on the decrease or increase in the probability of a firm entering any one of the three financial distress states- FDECL, FWEAK and FDIST relative to reference state –NFDIS. In our case, the effect of X_i on the log odd $\Pr(Y=1)$ is represented by the coefficient β_1 while X_j is held constant. For instance, the effect on the log odds of one unit increase in X_j is represented by $\exp(\beta_1)$ while X_j is held constant. To find the relationship between k explanatory variables $X_1, X_2, X_3, \ldots, X_j$, and the probability of an observation falling into any of j^{th} category as represented by π_j, the multinomial logit is defined as:

$$\log\left(\pi_j(X_i)\right) = \frac{\exp(a_{0i} + \beta_{j1} X_{i1} + \beta_{j2} X_{i2} + \cdots + \beta_{jk} X_{ik}}{1 + \sum_{j-1}^{k-1} exp\left(a_{0i} + \beta_{j1} X_{i1} + \beta_{j2} X_{i2} + \cdots + \beta_{jk} X_{ik}\right)} \tag{3.11}$$

Where $Z_j = \beta_{j1} X_{i1} + \beta_{j2} X_{i2} + \cdots + \beta_{jk} X_{ik}$, for each financial distress state *j* = 0, 1, 2, 3. The effect of K^{th} explanatory variables on the probability of a firm entering into any of the financial distress states *j* are represented by the coefficient β_{jk}.

Effects of explanatory variables – Predicted probabilities and Marginal effects

In a linear model, the associated increase in the outcome variable could be directly associated with an increase in one unit of the explanatory variable which makes interpreting the coefficients relatively straightforward. However, in a non-linear model such as the multinomial logit, the directional association between a regressor and the probability of an outcome depends on all explanatory variables in the model and their log coefficients across different outcome levels (Wulff, 2015, p.312). Therefore, we cannot completely rely on the sign and value of log coefficients, as in several financial distress research, when evaluating the direction of the effects of financial ratios and corporate governance indicators on the probability of financial distress. Indeed, we cannot guarantee that the sign of the log coefficients in our model will be the same as those produced by predicted probabilities and marginal effects. Changes in the odds ratios may not be sufficiently reflected in the change in probabilities since there are instances where the odds ratio remains the same notwithstanding a huge change in probability (Long & Freese, 2014, p.234). Furthermore, Long & Freese (2014) argue that predicted probabilities may provide a better interpretation than the odds ratio. Therefore, we believe predicted probabilities give us a better understanding of the non-linear effects of an explanatory variable on financial distress when other explanatory variables are held at a certain value. We assess the probabilities of a firm belonging to any of the four financial distress states following the effect of each explanatory variable using predicted probabilities.

In our MLR model with four financial distress states, the predicted probabilities can be computed thus:

$$\mathrm{P_{ij}} = \Pr(y_i = \mathrm{j}\,|x_i) = \frac{\exp(\mathrm{x_i'\beta_j})}{\sum_{\mathrm{j=0}}^{3} \exp\,(\mathrm{x_i'\beta_j})} \qquad (3.12)$$

Equation 3.12 computes the probability that i^{th} the firm will be classified into one of the financial distress states j $(\mathrm{j} = 0{,}1{,}2{,}3)$, x_i are explanatory variables in the model that explain the financial distress states. β_j is the log coefficient which has the slope β_{kj} and intercept $\beta_{0\mathrm{j}}$. While setting the β_j for the reference financial distress state – NFDIS to zero, computing predicted probabilities for FDECL, FWEAK and FDIST states results in equation 3.13:

$$\mathrm{P_{ij}} = \Pr(y_i = \mathrm{j}\,|x_i) = \frac{\exp(\mathrm{x_i'\beta_j})}{1 + \sum_{\mathrm{j=1}}^{3} \exp(\mathrm{x_i'\beta_j})} \qquad (3.13)$$

For reference NFDIS states we have:

$$\mathrm{P_{ij}} = \Pr(y_i = \mathrm{j}\,|x_i) = \frac{1}{1 + \sum_{\mathrm{j=1}}^{3} \exp(\mathrm{x_i'\beta_j})} \qquad (3.14)$$

With equations 3.13 and 3.14, we can calculate the predicted probabilities and plot our results to show a graphical presentation of the relationship between financial ratios, corporate governance indicators and the probability of financial distress. Since predicted probabilities are point estimates, we account for variances in the sampling with confidence interval (CI)

Nonetheless, as informative as the predicted probability is, it is challenging to establish whether the effect of a change in an explanatory variable is significantly related to the change in predicted probability (Greene, 2003). Further, it may be difficult to ascertain whether a true relationship exists especially where the predictive plot is flat (Wulff, 2015). Therefore, to measure how much change in predicted probabilities is associated with a change in a regressor, we employ the marginal effects (Wulff, 2015). Marginal effects measure the expected instantaneous changes in the probability of financial distress for a given increase in one unit of a given explanatory variable while holding all the other explanatory variables at their means. For non-linear models, Cameron & Trivedi (2010), argue that marginal effects produce a better interpretation of the relationship between explanatory variables and the outcome variable than coefficients. Greene (2003), argue that the marginal effect must be computed and assessed to draw a valid conclusion as to the direction and magnitude of the relationship between explanatory variables and outcome variables in the MLR model. According to Cameron & Trivedi (2010), marginal means is employed to measure the effect on the conditional mean of financial distress (y) as a result of a change in one explanatory variable (x). The marginal effect is also a way to address possible "spurious" effects that might have been created by hidden mediation of other explanatory variables in the model (Cameron & Trivedi (2010). The value of the marginal effect of x_1 depends on the value of x_1, the probability of alternative outcome and the values of other regressors in the model (Liu, 2015). Therefore, to better understand the effect that x_1 is responsible for, we filter out the effect of other explanatory variables in the model by holding them at a given value. There are four ways we may compute marginal effects, by observation alone, computing average marginal effect (AME), marginal effects at mean (MEM) or marginal effect at a representative (MER). We employ the AME since it may present a better approach by computing the marginal effect of each observation using actual values of the explanatory variables and then averaging the marginal effects. In addition, unlike in MEM, AME are useful in producing a single quantity summary that reflects the full distribution of an explanatory variable rather than arbitrary values (Wulff, 2015). We express the AME as:

$$\mathrm{AME} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{P}_{\mathrm{ij}}\left(\beta_{\mathrm{kj}} - \overline{\beta_{\iota}}\right) \tag{3.15}$$

In addition, Cameron & Trivedi (2010) suggest that the AME is generally more appropriate since it explains how other covariates correlate with each other. Econometric literature such as Lui (2015) notes that the sign and even significance of the marginal effect of an explanatory variable may change across the distribution of a particular explanatory variable (Liu, 2015). This is a good reason to plot the results of a marginal effect since this facilitates observing the values and signs of marginal effect changes as the values of the explanatory variable change.

Second research objective methods

The *second research objective* is to determine whether explanatory factors and their effects on each of the four financial distress states of a multiple state financial distress model are different for non-financial listed firms in the Chinese equity market. First, we observe the differences in the median distribution in the four financial distress states using a non-parametric Kruskal-Wallis H test according to Mahachie, Van-Lishout, Gusareva & Van-Steen (2013). The null hypothesis in the KW test as adapted for our research is that individual states of multiple financial distress states are statistically the same in the distribution of explanatory variables (Kruskal & Wallis, 1952). Notably, the KW test is an omnibus test and can only determine whether at least two of the four financial distress states are different (Harrell, 2001). To investigate what financial distress states are different and how different they are, we compute the Dunn z test by test Dunn (1964) after the KW test, for each of the eleven explanatory variables. The null hypothesis in the Dunn test is that for each pairwise comparison, the probability of observing a random value in the first group that is larger than a random value in the second group equals one half (Dunn, 1964). We use the Bonferroni adjustment to address the probability of falsely rejecting the null hypothesis in the KW test and the Dunn test as suggested by Dinno (2015). Second, we establish the determinants of each of the three financial distress states (FDECL, FWEAK and FDIST state) relative to the reference NFDIS state. We observe the significance of the three coefficients for FDECL, FWEAK and FDIST state compared to the reference NFDIS state, associated with each financial ratio or corporate governance indicator. Three coefficients resulting from the three pair comparisons are $\beta_{2,FDECL|\,NFDIS}$ (FDECL relative to NFDIS), $\beta_{2,FWEAK|\,NFDIS,}$ (FWEAK relative to NFDIS) and $\beta_{2,FDECL|\,NFDIS,}$ (FDIST relative to NFDIS). A paired comparison is said to be indistinguishable regarding an explanatory variable x if x does not significantly affect the probability of outcome category m relative to outcome category n (Anderson & Rutkowski (2007), In our case, where a log coefficient (and Wald z) of a paired comparison is not significant at p<0.10 level, this would indicate that the explanatory variable for the respective pair of states is indistinguishable. The third step is to compute a second difference analysis, that is, a Wald test comparison of the effects of financial ratios and corporate governance indicators across six binary combinations from our four-state financial distress model.

Third research objective methods

The *third research objective* is to determine whether explanatory factors and their effects on financial distress in a binary state distress model and multiple state distress models are different for non-financial listed firms in the Chinese equity market. First, we compare the first difference analysis of a multinomial logit regression (MLR) model to the binomial logit regression (BLR) model where the financial distress states are pooled. This entails examining the significant financial ratios and corporate governance indicators across the two models. Next, we examine the magnitude of effects of financial ratios and corporate governance indicators across the two models using computed average marginal effects. Average marginal effects are computed and compared for explanatory variables across the binary state and multiple state models.

Fourth research objective methods

The *fourth research objective* is to examine what influence Cash flow-based ratios and corporate governance indicators have on the explanatory power of accrual-based and market-based ratios of non-financial listed firms in the Chinese equity market. First, we fit our multiple state nested models from the following equations:

- Equation (3.18) henceforth MLR *accrual* Model 1 consists of accrual-based and market-based ratios only.
- Equation (3.19) henceforth MLR *cash flow* Model 2 consists of accrual-based, market-driven and cash flow-based ratios.
- Equation (3.20) henceforth MLR *corporate governance* Model 5 consists of accrual-based ratios, market-based ratios and corporate governance indicators.
- Equation (3.9) earlier specified henceforth MLR "full" Model 3 which consists of accrual-based ratios, market-based ratios, cash flow-based ratios and corporate governance indicators.

Assuming all firms must enter one of J = four financial distress states and the state each firm will finally enter is predicted by k = explanatory variables defined as $ABR_1, CBR_1,\ MBR_1\ \ CGI_1, \dots,\ X_j$ regressors made up of accrual-based ratios, cash flow-based ratios, market-based ratios and corporate governance factors. If p_j is defined as the probability that a firm will eventually enter state J and the logit function for the restricted MLR model 1 and MLR model 2 is given as follows;

$$p_j = \frac{\exp(\beta_0 + \beta_{j1}\ ABR_{j1} + \cdots +\ \beta_{j2}\, MBR_{j2} + \cdots +\ \beta_{jk}\, X_{jk})}{1 + \sum_{j-1}^{k-1} exp\left(\beta_0 + \beta_{j1}\, AR_{j1} + \cdots +\ \beta_{j2}\, MBR_{j2} + \cdots +\ \beta_{jk}\, X_{jk}\right)} \tag{3.18}$$

$$p_j = \frac{\exp(\beta_0 + \beta_{j1}\ ABR_{j1} + \cdots +\ \beta_{jk}\, MBR_{jk} + \cdots +\ \beta_{jk}\, CBR_{jk} + \cdots + \beta_{jk}\, X_{jk})}{1 + \sum_{j-1}^{k-1} exp\left(\beta_0 + \beta_{j1}\, ABR_{j1} + \cdots +\ \beta_{jk}\, MBR_{jk} + \cdots +\ \beta_{jk}\, CBR_{jk} + \cdots + \beta_{jk}\, X_{jk}\right)} \tag{3.19}$$

$$p_j = \frac{\exp(\beta_0 + \beta_{j1}\ ABR_{j1} + \cdots +\ \beta_{jk}\, MBR_{jk} + \cdots +\ \beta_{jk}\, CGI_{jk} + \cdots + \beta_{jk}\, X_{jk})}{1 + \sum_{j-1}^{k-1} exp\left(\beta_0 + \beta_{j1}\, ABR_{j1} + \cdots +\ \beta_{jk}\, MBR_{jk} + \cdots +\ \beta_{jk}\, CGI_{jk} + \cdots + \beta_{jk}\, X_{jk}\right)} \tag{3.20}$$

Where;

p_j is the probability of financial distress for firm i, exp is the exponential function, $\beta_{j1}, \beta_{j2}, \dots, \beta_{jk}$ is the slope coefficients, $ABR_{j1}, ABR_{j2}, \dots, ABR_{jk}$ are accrual-based ratios,

$MBR_{j1}, MBR_{j2}, \ldots, MBR_{jk}$ are market-based ratios, $CBR_{j1}, CBR_{j2}, \ldots, CBR_{jk}$ are cash flow-based ratios and $CGI_{j1}, CGI_{j2}, \ldots, CGI_{jk}$ are Corporate governance factors.

The fourth research objective is achieved in three steps. The incremental information of cash flows and corporate governance is assessed in terms of changes in the explanatory power of accrual-based ratios in the models, improved model goodness-of-fit and improved classification/predictive power. The first step towards achieving this objective is to examine the changes in the effects of accrual-based and market-based ratios across the nested multiple state models as cash flow-based ratios and corporate governance indicators are introduced. In linear regression, this could be achieved by observing the significance of coefficient for accrual-based and market-based ratios across a series of nested multiple state models. However, this approach may not be appropriate in nonlinear models because the coefficients are only identified up to a scale factor (Karlson, Bernt & Breen, 2012). Therefore, we follow the framework by Mize, Doan & Long (2019) in comparing effects across models. To compare how accrual-based ratios are associated with financial distress across the four nested multiple state models, we begin by computing the marginal effects and Wald Chi-squared to quantify the effects of explanatory variables across the nested models. The seemingly unrelated estimation (SUEST) is employed to combine results from two nested multiple state models so that cross-model comparison tests could be performed (Weesie, 1999). We compare the effects of accrual-based ratios in base *accrual-based* model 1 with the *cash flow* model 2 after cash flow-based ratios are introduced. Next, we compare the effects of accrual-based ratios in the base *accrual-based* model 1 with the "corporate governance" model 5 after corporate governance indicators are introduced. Further, we compare the effects of accrual-based ratios in the base accrual-based model 1 with the "full" model 3 that includes both cash flow-based ratios and corporate governance indicators.

There is no consensus as to the best goodness of fit statistics to compare models. Nonetheless, for multinomial logit models, Long & Freese (2014, p.122) suggests Log-likelihood, Deviance, AIC and BIC. Allison (2009) recommends Cox and Snell's R-squared and McFadden R-squared as measures of predictive power. Therefore, we compute the goodness of fit and predictive power test across the four multiple states nested models 1, 2,3 and 5. According to Tabachnick & Fidell (2013) the closer the R^2 is to 1, the better the model. The smaller the value of the AIC, BIC, LR test and Deviance, the better the model goodness-of-fit Lee, Chen & Lee (2019) (Lee, Chen & Lee, 2019). In other words, the larger the difference between two nested models (restricted and full model), the better the improvement resulting from the inclusion of the set of the explanatory variable(s) in the full model. Since one of the outputs of this research is to estimates models that predict the probability of financial distress, it is imperative to evaluate the classification accuracy of the models. The last step to achieving the fourth objective is to compute and compare the classification/prediction accuracy of the four models using a cut-off of 0.5 according to Hosmer & Lemeshow (2000).

Since our fitted "full" model 3 could be used to predict the financial distress state of firms, it is important to perform an external validation of the model using a separate validation sample (Hosmer & Lemeshow, 2000).

3.7 Pre-Estimation Tests

For the sake of justifying our multiple state outcome approach and to satisfy the independence of irrelevant alternatives (IIA) test assumption, we test that the four states are mutually exclusive and independent of each other. The pre-estimation test also includes multicollinearity test diagnosis to ensure the endogenous variables are not highly correlated.

All regressors are tested for endogeneity using the Hausman-Wu test according to Roodman (2006). The null hypotheses under the Hausman-Wu test are that the endogenous variable(s) are exogenous. if the null hypothesis is rejected then it implies the variable(s) is exogenous. Otherwise, the regressor is endogenous and must be controlled or instrumented.

This study adopts the panel data approach of where observations are repeated for the same firm, we suspect the presence of autocorrelation and heteroscedasticity. Heteroscedasticity does not cause the coefficient estimates to be biased however, it may cause the standard errors and test statistics to be biased (Wooldridge, 2001). As a pre-estimation specification test, the Breusch-Pegan Test and White test are used to test for heteroscedasticity while the Breusch-Godfrey test is used to test for autocorrelation. The null hypothesis is that there is no presence of heteroscedasticity or no autocorrelation in the dataset. Cameron & Trivedi (2005) argue that White Huber standard error is robust to heteroscedasticity and autocorrelation. For all pre-estimation tests, the null hypothesis is rejected when the p-value is significant at a 0.05 significance level.

3.8 Chapter Summary

This research uses an unbalanced panel dataset of 8,850 firm-year observations from 1,415 non-financial listed firms in the SSE and SZSE of the Chinese equity market between 2009 and 2018. Data on the outcome variable includes the listing status of NST, ST, SST and SSTDelisted firms. Accrual-based ratios are sourced from the balance sheet and income statement, cash flow-based ratios are sourced from the cash flow statement and market data is sourced from market prices. Corporate governance indicators are sourced from corporate governance data. This research employs firm size, firm age and state ownership, GDP, lending rate and industry dummy as control variables. Control variables are employed to account for endogeneity with the 2SCFA MLR method suggested by Wooldridge (2014). Heteroscedastic and autocorrelation robust standard errors were used within the MLR and BLR models. The MLR and BLR model specification test of the IIA is undertaken to determine whether the outcome variable and the explanatory variables satisfy this assumption. Pre-estimation tests include the DHW test for endogeneity of regressors, the Breusch-Pagan Test and the White test for heteroscedasticity and the Breusch-Godfrey test for Autocorrelation.

The first research objective is achieved by post-2SCFMLR linear hypothesis testing and odds ratios followed by predicted probabilities and average marginal analysis. In achieving the second research objective, we perform the first and second different analyses is using the Kruskal-Wallis test and Dunn test of median distribution followed by post- post-2SCFMLR Wald test is employed in achieving the second research objective. The multiple and binary state approaches are compared by comparing the 2SCFMLR and 2SCFBLR models. Further, odds ratios, predicted probabilities and average marginal effects analysis results across both models are examined. The explanatory power performance comparison across the four multiple state nested models is achieved with average marginal effects, SUEST method and Wald test. Goodness-of-fit and predictive accuracy performance is assessed with AIC, BIC, Cox and Snell's R-squared and McFadden R-squared, Deviance and Log likelihood. Finally, classification accuracy performance is achieved with a classification table.

CHAPTER FOUR

EMPIRICAL RESULTS AND ANALYSIS

Chapter four presents and discusses the empirical results. Section 4.1 presents the Hausman-McFadden IIA specification test and pre-estimation test including the Breusch-Pagan / Cook-Weisberg heteroscedasticity test, the Wooldridge test for autocorrelation and the DWH test for endogeneity of regressors and multicollinearity diagnosis. Section 4.2 reports the key findings of this research while achieving the four research objectives and testing research hypotheses. Section 4.3 presents the validation of empirical full models and section 4.4 summarises the chapter.

4.1 Pre-Estimation and Specification Tests

In this section, all pre-estimation data tests are performed before testing the hypotheses and estimating the models. Pre-estimation tests include heteroscedasticity and autocorrelation tests. In addition, the explanatory variables are tested for endogeneity and the models are tested for the IIA.

4.1.1 Independence of Irrelevant Alternatives Specification Test

The test for IIA is an underlying assumption for the multinomial logit regression model. The IIA assumption states that the exclusion or inclusion of a category would not affect the relative risk of regressors in the other categories. Table 4.1 reports the results of the Hausman-McFadden tests for IIA. The p-value for each financial distress state (category) is insignificant, thus we fail to reject the null hypothesis that outcome-J versus outcome –K is independent of other alternatives. This suggests that the IIA assumption is not violated for each of the four financial distress states. Hausman & McFadden (1984) noted that where there are no p-values, a negative chi-square result (as is the case in the FDECL and FDIST states in Table 4.1) implies the IIA assumption is not violated. Notwithstanding the IIA results, there are concerns in the literature over the relevance of the IIA test. Fry & Harris (1998) and Cheng & Long (2007) used a simulation study to show that both the Small-Hsiao test and the Hausman-McFadden test for IIA perform poorly even with large dataset samples. Fry & Harris (1998) further argued that the IIA test is irrelevant for predictive modelling. The bottom line as pointed out by McFadden (1973) is that outcome categories of the MLR model are distinct and mutually exclusive and, that one category does not substitute for another category. In addition to rejecting the null hypothesis for the IIA test, our analysis will validate whether we are correct in treating the four financial distress states as discrete and mutually exclusive.

Table 4.1: Hausman-McFadden test for IIA

Financial Distress states	chi^2	df	P-value
Non-Financially Distressed (NFDIS)	15.183	9	0.086
Financial Decline (FDECL)	-3.330	8	-
Financially Weak (FWEAK)	6.210	8	0.624
Financially Distressed (FDIST)	-0.111	8	-

Ho: Odds (outcome J versus outcome - K) are independent of other alternatives

Source: Author's computation

4.1.2 Tests for Heteroscedasticity and Autocorrelation

A key assumption in regression is that the error term is constant when observed over a given period and this assumption is homoscedasticity (Arellano & Bond, 1991). Heteroscedasticity is present where the standard error of a variable differs across observations over a given period (Arellano & Bond, 1991). We used the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity in our panel dataset as suggested by Rehman, Wang & Mirza (2017). Table 4.2 presents the F-statistic and P-value results of the Breusch-Pagan / Cook-Weisberg test and Wooldridge test for each of the five models. The Breusch-Pagan / Cook-Weisberg test shows that the p-value of all the five models is significant at 0.001 level, therefore we reject the null hypothesis that the variance is constant and there is no joint significance. This result suggests the presence of heteroscedasticity in the models which is common in panel data analysis (Rehman et al. (2017).

Autocorrelation is often associated with time-series observations and results from the correlation between two-time series where one time series is in its original form and the other in its lagged form (Arellano & Bond, 1991). To ensure the validity of instruments and regressors to be used in model estimation, these need to be free from autocorrelation (Ha, 2018). In testing for the presence of autocorrelation according to Wooldridge (2010), the Wooldridge test was performed on the panel dataset that produced the models specified in section 3.6.3. The Wooldridge test in Table 4.2 shows a p-value< 0.01 which is small, thus we reject the null hypothesis at a 0.01

significance level that there is no autocorrelation and accept the alternative hypothesis which implies the presence of autocorrelation in the estimation panel dataset.

The presence of heteroscedasticity may not constitute a bias to OLS estimators for a variable however, the standard error of the estimates would be wrong since it is not consistent (Lee, Chen & Lee, 2019). To account for the presence of autocorrelation and heteroscedasticity in a dataset, we use heteroscedasticity-robust and autocorrelation-robust standard error suggested by Lee et al. (2019) in estimating all empirical models in this research,

Table 4.2: Breusch-Pagan/Cook-Weisberg test and Wooldridge test

Breusch-Pagan/Cook-Weisberg test for Heteroscedasticity

	MLR Model 1 ABR+MBR	**MLR Model 2 ABR+MBR+CBR**	**MLR Model 3 ABR+MBR+CBR+CGF**	**BLR Model 4 ABR+MBR+CBR+CGF**	**MLR Model 5 ABR+MBR+CGF**
F-Stat	F(6, 9090) = 553.71	F(9, 9087) = 245.82	F(11 , 9085) = 218.59	F(11 , 9085) = 218.59	F(8, 9088) = 326.71
PV	0.0000	0.0000	0.0000	0.0000	0.0000

Ho: Constant variance

Wooldridge test for Autocorrelation in panel data

	MLR Model 1 ABR+MBR+CBR	**MLR Model 2 ABR+MBR+CBR**	**MLR Model 3 ABR+MBR+CBR+CGI**	**BLR Model 4 ABR+MBR+CBR+CGI**	**Model 5 ABR+MBR+CGI**
F-Stat	F(1,764) = 195.23	F(1, 764) = 182.70 0.0000	F(1, 764) = 163.94	F(1 ,764) = 148.59 0.0000	F(1, 764) = 162.50
PV	0.0000		0.0000		0.0000

Ho: no first-order autocorrelation

Source: Author's compilation.

4.1.3 Test of Endogeneity of Regressors

We test our suspected regressor -NITA alongside other regressors suspected to be endogenous. We employ household consumption and Government spending as instruments. These instruments affect the probability of financial distress through their influence on firm performance such as profitability. We also test that the instruments are exogenous, valid and do not have a direct significant effect on financial distress except through the explanatory variables they control (exclusion restriction). Table 4.3 reports the robustified Durbin-Wu-Hausman (DWH) test for endogeneity of regressors and the Hansen J test for overidentification and validity of instrumental variables. The null hypothesis for the DWH test is that OLS estimates on the same equation are consistent that is, the variable being tested is exogenous. Table 4.3, shows the Chi-squared for the robustified DWH test is insignificant at a 0.05 level. Therefore, we fail to reject the null hypothesis that NITA in each model is exogenous which implies the regressor can be treated as exogenous in our models. In addition, the Hansen J test of Overidentification was computed for regressors in each of the five models. In Table 4.3, the Chi-squared for the Hansen J test on the instruments are insignificant at 0.05 significance level thus, we fail to reject the null hypothesis in each model instance which suggests that our instruments are valid and exogenous.

Table 4.3: Durbin-Wu-Hausman (DWH) test of Endogeneity of Regressors

	MLR "Accrual" Model 1 ABR+MBR		**MLR "Cash flow" Model 2 ABR+MBR+CBR**		**MLR "Full" Model 3 ABR+MBR+CBR+CGI**		**BLR "Full" Model 4 ABR+MBR+CBR+CGI**		**MLR "Corporate Governance" Model 5 ABR+MBR+CGI**	
	DWH test	**HansenJ test**	**DWH test**	**HansenJ test**	**DWH test**	**HansenJ test**	**DWH test**	**HansenJ test**	**DWH test**	**HansenJ test**
chi^2 **P-V**	0.0715 0.7891	0.4469 0.7997	1.1986 0.2736	0.5526 0.7586	1.7968 0.1801	1.0681 0.8993	0.8182 0.3657	1.0322 0.5532	1.2798 0.2579	1.6707 0.7960

DWH tests Ho: Regressors are Exogenous
Hansen J test (Overidentification test) Ho: Instruments are valid
Source: Author's computation

For brevity of comparison, we estimate other options for addressing endogeneity in our research. We estimate a fixed effect multinomial logit (FE-MLR) and random effect multinomial logit (RE-MLR) that control for time-variant and time-invariant firm-level heterogeneity respectively, as well as heteroscedasticity and autocorrelation. In addition, we estimate a 2SCFMLR that controls for firm-level and industry-level heterogeneity, heteroscedasticity, autocorrelation as well as possible confounding bias and simultaneity endogeneity. For this research, we employ the 2SCFMLR model that controls for endogeneity beyond firm-level heterogeneity and produces smaller standard errors. Firm heterogeneity is controlled with firm size (LOGFA), firm size (LOGAGE), state ownership (STATE_OWN) and industry dummy (IND_DUMMY) while confounding influence of external factors are controlled with gross domestic product rate (GDPR) and lending rate (LENDR)

4.1.4 Multicollinearity Test and Correlation Coefficient

Explanatory variables that belong to the same group and produce similar outcomes can often be strongly correlated. It is necessary to ensure such a strong correlation between the explanatory variables is not present as it is one of the assumptions of the GLMs models. A multicollinearity test is performed using Spearman correlation (instead of Pearson correlation) that is a non-parametric test suitable for our non-normally distributed dataset. Table 4.4 presents Spearman's correlation coefficient for the eleven explanatory variables (regressors) and five control variables used in this research and their significance levels. The correlation coefficient is below 0.8 which suggests an imperfect correlation between explanatory variables (Little & Rubin (1987).

In addition to the Spearman correlation coefficient, Table 4.5 reports the variance inflation factor (VIF) The VIF test measures and describes the intensity of multicollinearity in an OLS regression. Table 4.5 shows that the VIF for all regressors is below the threshold of 5.0 suggested by O'Brein (2007) and less than 10.0 recommended by Tabachnick & Fidell (2013) and O'Brein (2007), suggesting no presence of multicollinearity in our dataset

Table 4.4: Spearman correlation coefficient

	FINANCIAL DISTRESS	TATURN	NITA	WCTA	TLTA	MVTL	MVBV	CFOTL	CFFTA	DPS	INST_ OWN	CEO_ DUAL	LOGFA	STATE_ OWN	GDPR
FINANCIAL DISTRESS	1.00														
TATURN	-0.376***	1.00													
NITA	-0.132***	0.042***	1.00												
WCTA	-0.067***	0.037***	-0.001	1.00											
TLTA	0.096***	-0.032***	-0.002	-0.011	1.00										
MVTL	-0.192***	0.092***	0.072***	0.025	-0.020	1.00									
MVBV	-0.353***	0.141***	0.002	0.043***	-0.046***	-0.364***	1.00								
CFOTL	-0.147***	0.103***	-0.124***	0.013	-0.035***	-0.039***	0.213***	1.00							
CFFTA	0.117***	-0.036***	-0.107***	-0.002	0.001	-0.062***	0.000	0.225***	1.00						
DPS	-0.176***	0.045***	0.026	0.016	-0.015	0.055***	0.024***	-0.138***	-0.071***	1.00					
INST_OWN	-0.116***	0.044***	0.115***	0.003	-0.011	0.062***	0.025*	0.016	-0.114***	0.033***	1.00				
CEO_ DUAL	-0.661***	0.266***	0.085***	0.055***	-0.096***	0.180***	0.325***	0.143***	-0.085***	0.105***	0.094***	1.00			
LOGFA	-0.230***	0.083***	0.136***	0.022	-0.030***	0.085***	0.115***	0.055***	-0.089***	0.026***	0.179***	0.195***	1.00		
STATE_OWN	0.095***	-0.077***	0.058***	-0.008	0.015	-0.030***	-0.033***	-0.154***	-0.069***	0.005	-0.008	-0.070***	0.027**	1.00	
GDPR	0.038***	-0.025	-0.091***	0.002	-0.006	-0.017	0.044***	0.097***	0.078***	-0.047***	-0.215***	0.032***	-0.049***	0.151***	1.00
IND_ DUMMY	0.003	0.001	-0.002	0.006	-0.028**	-0.023**	0.011	0.038***	0.001	0.003	-0.059***	0.001	0.008	0.010	0.005

Legend: ** Significant at 10 percent level, ** Significant at 5 percent level, *** Significant at 1 percent level*

Source: Author's computation

Table 4.5: Variance Inflation Factor (VIF)

Variable	MVBV	CEO_ DUAL	MVTL	GDPR	LENDR	CFOTL	TATURN	CFFTA	LOGFA	INST_ OWN	WCTA	DPS	STATE_ OWN	TLTA	IND_ DUMMY	NITA	MEAN VIF
VIF	1.52	1.41	1.36	1.31	1.22	1.21	1.24	1.14	1.15	1.17	1.13	1.09	1.07	1.05	1.03	1.01	1.21
1/VIF	0.655	0.712	0.734	0.765	0.768	0.764	0.824	0.832	0.853	0.870	0.901	0.921	0.931	0.990	0.994	1.000	

Source: Author's compilation

4.2 Empirical Results

4.2.1 Effects of Financial Ratios and Corporate Governance Indicators

The following sub-sections achieve the *first research objective* that is to evaluate effects of financial ratios and corporate governance indicators on multiple states of financial distress and test *hypotheses* H2.1 to H2.7. Table 4.7 reports descriptive statistics for the multiple states of financial distress models; MLR "Accrual" Model 1, MLR "Cash flow" Model 2 and MLR "full" model 3. Table 4.6 reports the KW H test Chi-squared tests on whether there is a significant difference between the four financial distress states in terms of the median value distribution of eleven regressors. The Dunn test further shows how individual financial distress states- FDECL, FWEAK and FDIST differ from the NFDIS state. Table 4.8 reports the Odds ratio, robust standard errors, Wald z statistics, Wald test chi-squared, marginal effects (on a percentage basis), standard errors (using the Delta method) and significance statistics for individual explanatory variables in MLR "full" model 3. A meaningful way of interpreting the nonlinear relationship between explanatory variables and the outcome variable is by calculating and plotting the predicted probabilities, therefore we plot our results (Wulff, 2015).

Table 4.6: Multiple states - Kruskal-Wallis H test and Dunn $z - test$ Pairwise comparison

	TATURN	NITA	WCTA	TLTA	MVTL	MVBV	CFOTL	CFFTA	DPS	INST_ OWN	CEO_ DUAL
KW chi^2 (3) ***p-value***	1295.05 ***	66.73 ***	60.43 ***	119.84 ***	618.65 ***	1810.85 ***	268.49 ***	153.51 ***	275.93 ***	137.45 ***	1077.37 ***
FDECL vs NFDIS (State 1) Dunn $z - test$	**20.52 *** **	**9.15 *** **	1.29	-2.82	-0.69	1.55	1.71	**-2.53 ** **	**10.83 *** **	**4.77 *** **	**19.33 *** **
FWEAK vs NFDIS (State 2) Dunn $z - test$	**25.61 *** **	**8.38 *** **	**5.78 *** **	**-6.35 *** **	**20.30 *** **	**36.08 *** **	**13.36 *** **	**-9.65 *** **	**11.47 *** **	**8.53 *** **	**55.65 *** **
FDIST vs NFDIS (State 2) Dunn $z - test$	**18.31 *** **	**5.53 *** **	**5.48 *** **	**-8.83 *** **	**14.92 *** **	**23.86 *** **	**9.93 *** **	**-7.80 *** **	**7.28 *** **	**7.11 *** **	**41.01 *** **

Legend: ** Significant at 10 percent level, ** Significant at 5 percent level, *** Significant at 1 percent level*

Source: Author's compilation

Table 4.7: Multiple States MLR models Descriptive Statistics

	TATURN	NITA	WCTA	TLTA	MVTL	MVBV	CFOTL	CFFTA	DPS	INST_ OWN	CEO_ DUAL
Panel A: All firms											
Mean	1.132	0.101	0.313	0.333	1.283	3.751	0.155	0.154	0.45	0.386	0.914
Std. Dev.	0.551	0.104	0.122	0.127	0.611	1.752	0.169	0.082	0.245	0.172	0.273
Min	0.139	-0.172	-0.086	0.176	0.214	0.333	-0.124	0.034	0.00	0.012	0.000
Max	2.186	0.307	0.530	0.782	2.994	8.199	0.707	0.683	2.19	0.895	1.000
Obs	8,850	8,850	8,850	8,850	8,850	8,850	8,850	8,850	8,850	8,850	8,850
Panel B: Non-Financial Distress (NFDIS) firms											
Mean	1.213	0.110	0.323	0.330	1.335	3.978	0.164	0.133	0.47	0.397	0.987
Std. Dev.	0.540	0.113	0.122	0.121	0.612	1.641	0.161	0.072	0.251	0.175	0.102
Min	0.286	-0.065	0.106	0.174	0.467	0.433	-0.062	0.034	0.11	0.201	0.001
Max	2.181	0.307	0.532	0.617	2.994	8.192	0.707	0.346	2.19	0.895	1.000
Obs	7,838	7,838	7,838	7,838	7,838	7,838	7,838	7,838	7,838	7,838	7,838
Panel C: Financial Decline (FDECL) firms											
Mean	0.722	0.054	0.312	0.339	1.285	3.864	0.167	0.162	0.35	0.358	0.763
Std. Dev.	0.371	0.065	0.113	0.134	0.525	1.853	0.203	0.078	0.214	0.194	0.421
Min	0.203	-0.152	0.096	0.183	0.304	0.392	-0.070	0.055	0.00	0.032	0.000
Max	1.721	0.146	0.492	0.717	2.528	6.517	0.639	0.459	0.84	0.790	1.000
Obs	446	446	446	446	446	446	446	446	446	446	446
Panel D: Financial Weak (FWEAK) firms											
Mean	0.575	0.052	0.287	0.367	0.775	1.212	0.064	0.196	0.32	0.314	0.286
Std. Dev.	0.263	0.044	0.093	0.116	0.381	0.355	0.086	0.113	0.126	0.131	0.455
Min	0.176	-0.172	-0.081	0.206	0.214	0.351	-0.092	0.062	0.00	0.024	0.000
Max	1.273	0.137	0.456	0.762	1.477	1.685	0.283	0.620	0.76	0.583	1.000
Obs	371	371	371	371	371	371	371	371	371	371	371
Panel E: Financial Distress (FDIST) firms											
Mean	0.494	0.044	0.261	0.410	0.736	1.104	0.053	0.214	0.30	0.287	0.172
Std. Dev.	0.282	0.042	0.113	0.126	0.125	0.354	0.080	0.126	0.076	0.126	0.381
Min	0.133	-0.174	-0.092	0.211	0.328	0.335	-0.124	0.072	0.00	0.012	0.000
Max	1.122	0.076	0.420	0.783	0.992	1.587	0.270	0.683	0.49	0.577	1.000
Obs	195	195	195	195	195	195	195	195	195	195	195

MLR "Accrual" Model 1 consists of ABR (TATURN, NITA, WCTA, TLTA) and MBR (MVTL, MVBV)

MLR "Cash flow" Model 2 consists of: ABR (TATURN, NITA, WCTA, TLTA), MBR (MVTL, MVBV) and CBR (CFOTL, CFFTA, DPS)

MLR "Full" Model 3 consists of: ABR (TATURN, NITA, WCTA, TLTA), MBR (MVTL, MVBV), CBR (CFOTL, CFFTA, DPS) and CGI (CEO_DUAL, INST_OWN).

In addition to the marginal effects reported in Panel B Table 4.8, we report the graphical analysis of marginal effects and predicted probabilities of the eleven explanatory variables on the four financial distress states in Figures 4.1 to 4.8 with a 95% confidence interval (CI). The marginal effects computed are the average marginal effects (AME) on the probability of Y= j for individual explanatory variables with a 95% confidence interval. The predictive probabilities of financial distress (Y) =1 or average marginal effects are plotted on the y-axis against the explanatory variable values on the x-axis. The 95% confidence interval (CI) is captured as a shading around each curve and we focus our discussion on the portion of the curve with the smallest CI since those give a closer representation of the dataset and show less variation in means.

In the following sections 4.2.1.2 to 4.2.1.9, we test the hypotheses H2.1 to H2.8 relating to the effect of financial ratios and corporate governance indicators on the probability of financial distress.

4.2.1.1 Descriptive Statistics for Multiple States of Financial Distress Models

The KW test in Table 4.7 shows that the median distributions of all eleven regressors for firms in the four financial distress states are statistically different and the difference is significant at $p<0.01$ level. This also suggests that we are correct in treating the four financial distress states as mutually exclusive in this research as per the IIA assumption of the multinomial logit. From the Dunn test, we observe that the difference between FDECL and NFDIS firms regarding the median distributions of WCTA, MVTL, MVBV, TLTA and CFOTL is not significant at the 0.10 level. This indicates that the distribution of WCTA, MVTL, MVBV, TLTA and CFOTL for FDECL and NFDIS firms are statistically the same. On one hand, the difference between FWEAK and NFDIS firms and between FDIST and NFDIS firms regarding the median distribution of all explanatory variables are significant at 0.01 level. This suggests the distribution of explanatory variables for FWEAK compared to NFDIS firms and FDIST compared to NFDIS firms are significantly different. We observe the strongest difference in the distribution of explanatory variables is seen between FWEAK firms compared to NFDIS firms and not FDIST compared to NFDIS which is surprising, seeing that the FDIST state appears to be the most distant from the NFDIS state. On the other hand, the weakest difference is observed in the distribution for FDECL firms compared to NFDIS firms. While the FWEAK firms are closest to FDIST firms, FWEAK firms are the farthest from NFDIS. This provides some hints on the non-linear relationship that exists between financial distress states.

The asset management efficiency in Table 4.6 measured by TATURN (total asset turnover) reports the mean TATURN value for NFDIS firms as 1.213 which is higher compared to 0.722 for FDECL firms, 0.575 for FWEAK firms and 0.494 for FDIST firms. While NFDIS firms showed the greatest assets management efficiency, FDIST firms showed the least assets management efficiency. In addition, we notice that asset management efficiency declined through the four financial distress states from NFDIS through to FDIST state. Furthermore, asset management efficiency had the greatest median difference as indicated by a KW chi^2 of 1,295.05 that is significant at p<0.001. More emphasis from the Dunn test shows the difference in the distribution of TATURN for firms in the three financial distress states (FDECL, FWEAK and FDIST) as being statistically different from those of firms in the NFDIS state. Indeed, TATURN reporting the strongest median distribution suggest a wide difference in asset management efficiency levels at which firms across the four financial distress states operate.

Profitability measured with NITA (net income-to-total assets) from Table 4.6 shows that NITA mean value for NFDIS firms of 0.110 is higher than 0.054 for FDECL firms, 0.052 for FWEAK firms and 0.044 for FDIST firms. Similarly to TATURN, we notice the declining trend in the NITA mean value across the four financial distress states from NFDIS to FDIST state. The results further suggest that profitability declines as firms deteriorate through the financial distress states. The median distribution for NITA is the smallest in the model which is driven by firms in the NFDIS and FDECL reporting losses.

From Table 4.6, liquidity and short-term solvency measured by WCTA (working capital-to-total assets) show that the WCTA mean score for NFDIS firms is 0.323 but this declines to 0.312 for firms in the FDECL state, further to 0.287 for firms in the FWEAK state and then to 0.261 for firms in the FDIST state. In addition to poor asset management efficiency and profitability, we also observe that firms in the financial distress state experienced lower liquidity. Firms in the NFDIS state experience better liquidity and short-term solvency compared to firms in the FDECL, FWEAK and FDIST states. Furthermore, liquidity is observed to follow a declining trend through the financial distress states from the NFDIS state to the FDIST state. This suggests that an increasing inability to settle short-term obligations as they fall due is driving firms further down the financial distress process. The KW chi^2 and Dunn test in Table 4.7 suggests that the median distribution of WCTA for NFDIS firms is significantly different from FWEAK firms and FDIST firms but the same for FDECL firms.

Table 4.6 shows that NFDIS firms have the lowest financial leverage - TLTA (total liability-to-total assets) mean score of 0.330 however, the TLTA is high up to 0.339 for FDECL firms, even higher up to 0.367 for FWEAK firms, and finally higher to 0.410 for FDIST firms. The results suggest the firms tend to rely more on debt borrowing as they deteriorate on the financial distress process. The KW chi^2 and Dunn test in Table 4.7 suggests that the median distribution of TLTA for NFDIS firms is significantly different from FWEAK firms and FDIST firms but the same for FDECL firms, like the WCTA ratio.

Cash flow is measured by CFOTL (cash flow from operations to total liabilities), CFFTA (cash flow from finance-to-total assets) and DPS (dividend paid per share). From Table 4.6 we observed that NFDIS maintained the largest mean cash flow from operations compared to those for FDECL, FWEAK and FDIST firms. A similar result is observed for the DPS ratio, NFDIS firms paid the largest average cash dividend (DPS) of RMB 0.47 per share compared to RMB 0.35 per share paid by FDECL firms, RMB 0.32 per share by FWEAK firms and RMB 0.30 per share by FDIST firms. Conversely, FDIST firms sourced the largest external cash flow from finance as suggested by a CFFTA mean score of 0.214 compared to a CFFTA mean value of 0.196 for FWEAK firms, a mean CFFTA mean value of 0.162 for FDECL firms and a CFFTA mean value of 0.133 for NFDIS firms. From Table 4.7, the median distributions of CFOTL, DPS and CFFTA for firms in the NFDIS state are observed to be significantly different from those of firms in the other three financial distress states, FDECL, FWEAK and FDIST.

Market valuation measured by MVTL (market value-to-total liabilities) and MVBV (market-to-book value) shows that NFDIS firms have greater market valuation than firms in financial distress states. Table 4.7 results reveal that the median distribution of MVTL and MVBV ratios is significantly different for NFDIS firms compared to FWEAK and FDIST firms, however, significantly the same with that of firms FDECL firms. The largest median distribution of market valuation is observed between NFDIS and FWEAK firms and between NFDIS and FDIST firms which reflects a high level of market price volatility in the Chinese market (Cheng & Li, 2015a)

Compared to FDECL, FWEAK and FDIST firms, NFDIS firms have a higher percentage of shares held by institutional entities such as brokers and corporate entities and a greater instance of separation of CEO and Chairman positions. The CEO_DUAL mean score for NFDIS is 0.987 which implies an average NFDIS firm implemented corporate governance best practice of having different officers carry out the roles of the CEO and Chairman of the board. CEO_DUAL mean score declined to 0.763 for FDECL firms, 0.286 for FWEAK firms and further declined to 0.172 for FDIS firms. NFDIS firms had the highest percentage of institutional ownership as suggested by an INST_OWN mean score of 40%. Notably, the INST_OWN mean score declined to 36% for FDECL firms and further declined to 31% for FWEAK firms and then to 28% for FDIST firms. Further, Table 4.7 reports that significant differences in the median distributions of INST_OWN and CEO_DUAL for NFDIS firms compared to FDECL, FWEAK and FDIST firms.

Table 4.8: Multinomial Logit Regression "full" Model 3 results

The table reports the results of the MLR "full" model 3 results that include the Odds ratios, robust standard error, Wald z statistics, Wald test, marginal effects (on a percentage basis), standard errors (Delta method) and significance statistics of explanatory variables which enables us to test hypotheses H2.1 to H2.8.

	PANEL A: Odd ratios and Wald tests							**PANEL B: Average Marginal Effects**			
	FDECL vs NFDIS		FWEAK vs NFDIS		FDIST vs NFDIS		All Four States	NFDIS State 0	FDECL State 1	FWEAK State 2	FDIST State 3
	OR & SE	**Wald(Z)**	**OR & SE**	**Wald(Z)**	**OR & SE**	**Wald(Z)**	**Wald chi^2**	**Marginal Effects**	**Marginal Effects**	**Marginal Effects**	**Marginal Effects**
TATURN	**0.105*** (0.131)**	-17.59	**0.045*** (0.426)**	-7.29	**0.016*** (0.458)**	-7.72	**365.44*** **	0.117*** (0.006)	-0.067*** (0.003)	-0.024*** (0.001)	-0.025*** (0.005)
NITA	**0.003*** (0.422)**	-13.32	**0.000*** (1.898)**	-5.47	**0.000*** (2.134)**	-6.12	**212.46*** **	0.315*** (0.024)	-0.182*** (0.213)	-0.077*** (0.024)	-0.066*** (0.026)
WCTA	0.587 (0.383)	-1.43	**0.022*** (1.359)**	-2.83	**0.003*** (1.284)**	-3.86	**17.27*** **	0.063** (0.015)	-0.034*** (0.016)	-0.017*** (0.015)	-0.014*** (0.014)
TLTA	1.426 (0.382)	0.95	3.561 (1.041)	1.25	**69.599*** (1.147)**	3.59	**21.13*** **	-0.062*** (0.019)	0.037*** (0.014)	0.014*** (0.003)	0.012*** (0.014)
MVTL	0.876 (0.105)	-1.33	**0.009*** (0.432)**	-10.74	**0.006*** (0.389)**	-10.93	**130.62*** **	0.068*** (0.002)	-0.034*** (0.007)	-0.018*** (0.004)	-0.010*** (0.004)
MVBV	0.947 (0.045)	-1.27	**0.025*** (0.315)**	-11.60	**0.013*** (0.362)**	-11.27	**153.08*** **	0.037*** (0.004)	-0.014*** (0.002)	-0.004*** (0.003)	-0.003*** (0.006)
CFOTL	0.617 (0.356)	-1.39	**0.047*** (0.932)**	-3.24	**0.008*** (1.249)**	-3.69	**16.37*** **	0.077** (0.016)	-0.047*** (0.014)	-0.019*** (0.014)	-0.019*** (0.013)
CFFTA	**5.146*** (0.638)**	2.58	**38.420*** (1.089)**	3.33	**161.520*** (1.144)**	4.15	**19.97*** **	-0.145*** (0.029)	0.087*** 0.023)	0.033*** (0.010)	0.025*** (0.011)
DPS	**0.087*** (0.232)**	-10.29	**0.024*** (0.762)**	-4.97	**0.007*** (0.802)**	-5.32	**130.03*** **	0.133*** (0.011)	-0.074*** (0.011)	-0.031*** (0.008)	-0.025*** (0.007)
INST_OWN	**0.398*** (0.315)**	-2.95	**0.068*** (0.883)**	-3.03	**0.016*** (0.987)**	-3.91	**23.84*** **	0.069*** (0.014)	-0.040*** (0.014)	-0.016*** (0.008)	-0.013*** (0.007)
CEO_DUAL	**0.034*** (0.166)**	-19.68	**0.019*** (0.316)**	-12.53	**0.011** (0.344)**	-12.16	**433.82*** **	0.155*** (0.007)	-0.089*** (0.007)	-0.036*** (0.003)	-0.033*** (0.003)
Controls	STATE_OWN, LOGFA, LOGAGE, GDPR, LENDR, IND_DUMMY										

Legend: ** Significant at p<10% level, ** Significant at p<5% level, *** Significant at p<1% level SE= Standard Error, in parenthesis OR= Odds Ratio*
Wald test H2.1 to H2.12: All three coefficients associated with a given variable are equal to zero SE= Delta-method Standard Error, in parenthesis

Source: Author's compilation

4.2.1.2 Effects of Asset Management Efficiency on Financial Distress

Linear Hypothesis

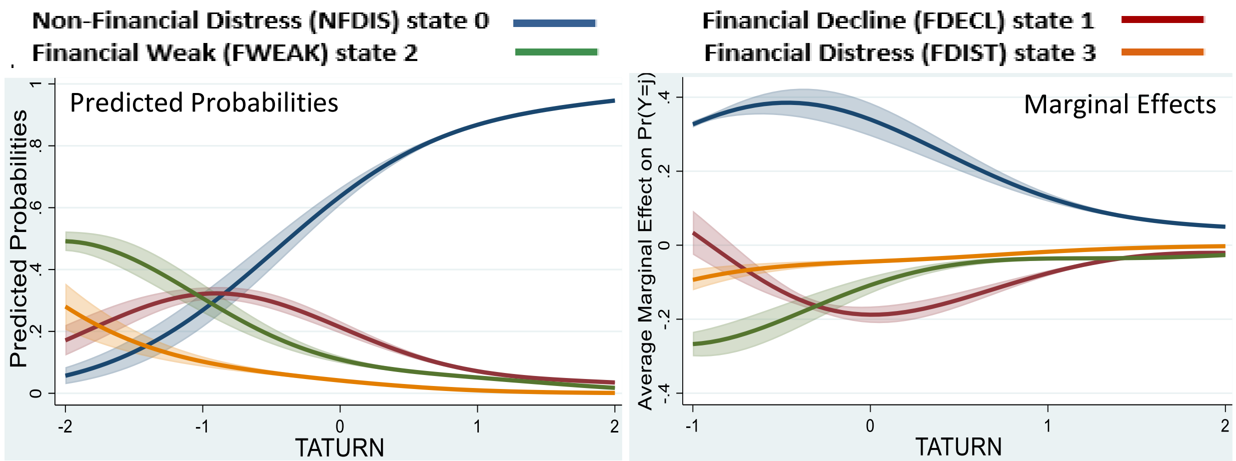
From Panel A, Table 4.8, we observe that across the four financial distress states, the effect of asset management efficiency (TATURN) on the probability of financial distress is statistically significant at p<0.01 level as indicated by the Wald chi^2 of 365.44. Therefore, we strongly reject the null hypothesis and accept the alternative *hypothesis H2.1* that asset management efficiency has a significant effect on the probability of financial distress of listed non-finance firms in the Chinese equity market. Panel A, Table 4.8 shows that for a unit increase in a firm's TATURN ratio, the odds of being in the FDECL state, FWEAK state and the FDIST states relative to the NFDIS state *decrease* by a factor of 0.105 (90%), 0.045 (95.5%) and 0.016 (98%) respectively, holding all other explanatory variables in the model constant. The results suggest a negative association between asset management efficiency and financial distress which is expected and consistent with Zhang et al. (2010), Hensher et al. (2007), Beaver et al. (2010), Axel (2012), Liang et al. (2016)., Zhou et al. (2012) and Zhou (2013). In essence, where a firm was to increase its asset management efficiency, the odds of the firm being in any of the three financial distress state decreases. It is interesting to observe that the asset management efficiency had the most effect amongst FRs in our MLR "full" model 3 as indicated by the largest Wald chi-squared of 365.45. The result is surprising when compared with findings from prior studies such as Beaver et al. (2005) and Tinoco (2013) that find the NITA (profitability) as having the most impact. However, this result is not surprising in the light of the TATURN ratio being influenced by the "profit-based" criteria of the delisting system in the Chinese equity market. Revenue draws from profit and where cost is controlled, revenue is expected to have a significant positive relationship with profit that implies that a declining revenue results in declining profit. By designating firms into the ST pool based on two consecutive years of net losses, the Chinese delisting practice seems to influence the effect of revenue-generating ability as well.

Predicted probabilities and Marginal effects

Graphically, figure 4.1 show the predicted probabilities of a firm being in the FDECL, FWEAK and FDIST states decline as firm asset management efficiency increases. Inversely, the predicted probability of a firm being in the *healthy* NFDIS state dramatically increases as firms improve on their asset management efficiency. Further, the gap between the curves in figure 4.1 widens with the increasing value of TATURN which implies, the more a firm improves on its asset management, the more the distinction between being *financially healthy* and being *financially distressed*. For instance, where a firm's TATURN value is 0.5 times, it is most likely (78% probability) the firm will be in a NFDIS state and the least likely (3% probability) in a FDIST state. However, where the firm TATURN value was to improve to 1.5 times, the probability of being in the NFDIS state increases to 94% and the probability of the firm being in the FDIST state is 0%. Figure 4.1 reveals that the curves for FDECL and FWEAK but not for that of FDIST state did initially increase (positive relationship with TATURN) and then start declining to adopt a negative relationship for the remaining values of TATURN. This suggests that, at lower but increasing levels of asset efficiency management, there are some chances of a firm belonging in the FDECL and FWEAK states. Nonetheless, as asset management efficiency advances, the probability of such firm remaining in financial distress diminishes. This situation is common where, as part of the reorganisation process, firms in FDECL or FWEAK state undertake asset restructuring that involves the disposal of fixed assets or part of the business line (Lee, 2011). Where such one-off non-revenue disposal is treated as revenue by way of creative accounting then a firm in a FDECL and FWEAK state may experience an increase in TATURN ratio without an actual increase in asset management efficiency. This explains the initial positive association exhibited by the FDECL and FWEAK curves. Where such asset disposal is not sustainable, we observe the curves for FDECL and FWEAK begin adopting a negative association. Our result highlights the shortcomings of the accrual-based ratios in the context of the Chinese equity market.

Panel B, Table 4.8 reports that the marginal effects of TATURN on the four financial distress states are significant at $p<0.01$ level which supports our afore rejection of the null hypothesis and accepts the alternative *hypothesis H2.1* that asset management efficiency has significant effects on the probability of financial distress. Figure 4.1 graphically present the nonlinear effect of asset management efficiency which is negative on the probability of financial distress and positive on the probability of being financially healthy. Figure 4.1 shows an instantaneous massive change in the marginal effect of TATURN on the probability of NFDIS, growing increasingly positive, slowing down, and beginning to decline for higher values of the TATURN. Notably, the decline does not imply a decline in the probability of NFDIS rather, it suggests that the rate at which the marginal effect of TATURN is increasing is slowing down. Similar to the NFDIS curve but with a negative association, we observe a steep decline and increase in the marginal effects of TATURN on the probability of FDECL and FWEAK. TATURN made the smallest and declining marginal effect at the FDIST state which implies that any improvement in TATURN by FDIST firms may not result in a significant change in the predicted probabilities of being in that (FDIST) state and this is indicated by a flat curve for the FDIST state. The flat predicted probabilities curve for the FDIST state provides some insight into what transpires in that state. When a firm approaches later or terminal financial distress states which in our study is the FDIST state, the flat curve suggests that simply improving on the firm asset management efficiency alone, while other aspects of firm performance remain unimproved, may not be sufficient to restore the firm to an earlier financial distress state. Indeed, improvement in asset management efficiency at a terminal distress state has minimal to zero marginal effect on the probabilities of being at the FDIST state and that is the slight increase that we see in the FDIST state curve. The relationship direction between TATURN and financial distress as suggested by the sign of the coefficients in Table 4.8 is consistent with the relationship direction in our predicted probabilities and marginal effect plot. As earlier pointed out, the two consecutive years net loss criteria for designation into the ST (FDECL) state significantly contributed to the strong effect of the TATURN ratio especially at the NFDIS and FDECL states. For instance, where a firm's TATURN ratio was to grow from 0.25 times to 1.5 times, this would result in a huge decrease in the predicted probability of FDECL from 18% to about 5% and a massive increase in the probability of belonging in the NFDIS state from 72% to 92%. However, this results in a very small decrease in the probability of FDIST from 5% to 0%.

Figure 4.1: Predicted probabilities & Marginal effects of Asset management efficiency with 95% CI



Source: Author's compilation

4.2.1.3 Effects of Profitability on Financial Distress

Linear Hypothesis

From Panel A, Table 4.8, we observe that across the four financial distress states, the effect of profitability (NITA) on the probability of financial distress is statistically significant at $p<0.01$ level as indicated by the Wald chi^2 of 212.46. Therefore, we strongly reject the null hypothesis and accept the alternative *hypothesis H2.2* that profitability has a significant effect on the probability of financial distress of listed non-finance firms in the Chinese equity market. From Panel A, table 4.8, for a unit increase in a firm's NITA ratio, the odds of belonging in the FDECL state, FWEAK state and the FDIST states relative to the NFDIS state *decrease* by a factor of 0.003 (99.7%), 0.0 (99.9%) and 0.0 (99.9%) respectively, holding all other explanatory variables in the model constant. Based on the Wald z statistics in Table 4.8, we observe the effect of NITA is strongest at the early FDECL state compared to other later financial distress states - FWEAK and FDIST. This finding, in addition to profitability making the second greatest contribution to our model after assets management efficiency, emphasizes the impact of the *profit-based* delisting system. Where most firms go through the delisting system based on consecutive net losses, the expectation is that declining firm profitability would increase the probability of firms being designated as ST, SST or SSTDelisted (delisted) from the Chinese equity market. Our finding that profitability has a significant negative effect on financial distress is consistent with the finding that increasing profitability performance of a firm reduces the probability of the firm becoming financially distressed or insolvent as shown in several studies including Beaver et al. (2005), Beaver et al. (2010), Axel (2012), Tinoco (2013), Zhou (2013) and Liang et al. (2016). The significance of the variable, NITA in our research is consistent with financial distress models by Zhang et al. (2010) and Zhou et al. (2012) in the Chinese market.

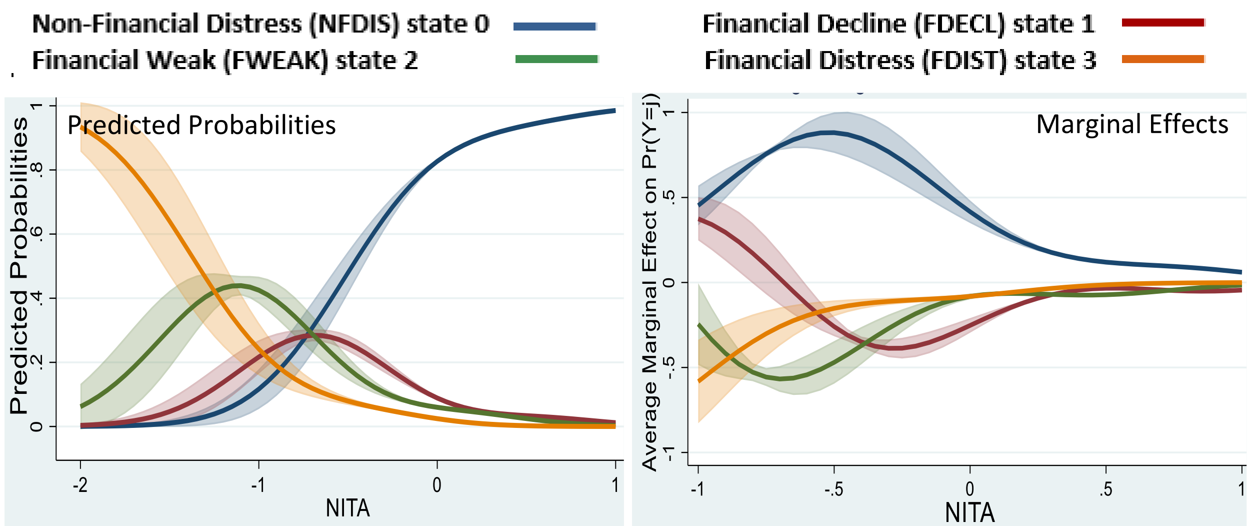
Predicted probabilities and marginal effects

Our results in figure 4.2 show the predicted probabilities of a firm belonging to the FDECL, FWEAK and FDIST states decline as firm NITA value increases. Inversely, the predicted probability of a firm belonging to the NFDIS state steeply increases as firm NITA improves. For instance, figure 4.2 shows that where a firm reports losses and NITA value is -0.5, it is most likely the firm would be in the FDIST state and less likely in the NFDIS or FDECL state. However, where firm NITA improves to 0.50 then, it is most likely to be in an NFDIS state and least likely to be in a FDIST state. Comparing figures 4.1 and 4.2, the similarities between the effects of the asset management efficiency and profitability reflect the relationship between revenue and income since the latter is based on the former. Further, we observe that the curves for the FDECL and the FWEAK states but not for the FDIST state initially increase as NITA increases which suggest a positive relationship with NITA which is similar to the NFDIS state. However, with increasing profitability, the FDECL and the FWEAK state curves begin to decline and take a negative relationship with increasing NITA. This suggests that, at lower but increasing levels of profitability, there is a probability of a firm belonging in the FDECL and the FWEAK states. Nonetheless, as a firm becomes continuously profitable, the probability of such firm remaining in any financial distress state diminishes. The result suggests there is a probability that a firm could be in either the FDECL or FWEAK state and make profits. Our results also show that such profits are occasional, which is the reason the firms are predicted to be in the FDECL or the FWEAK state. At a point where profits start increasing (NITA value of -1.25 for FWEAK firms and 0.75 for FDECL firms), the probability of the firms remaining in the financial distress states begins to decline (figure 4.2). In the case of the Chinese equity market, ST (FDECL) and SST (FWEAK) firms could post profits by way of one-off disposal of assets during the restructuring without an actual profit from normal business activity. Besides reorganisation, earnings management is another activity that firms on the ST and SST designations are mostly likely to engage in (Wang & Yung, 2011 and Lai & Tam, 2017). Nonetheless, the predicted probabilities for FDECL and FWEAK eventually decline with increasing profitability. Further, figure 4.2 reveals that not all net losses suggest a probability of FDECL or FWEAK seeing that some values of NITA, below zero, are predicted to be in the NFDIS state. This portion of the plot accounts for the sample of NFDIS firms that report first-year net loss yet are categorised as NST (NFDIS) by the delisting system.

Panel B, Table 4.8 reports that the marginal effects of NITA on the four financial distress states are significant at $p<0.01$ level which supports our afore rejection of the null hypothesis and accepts the alternative *hypothesis H2.2* that profitability has significant effects on the probability of financial distress. We observe from figure 4.2 that the curve for the marginal effect of NITA on the probability of NFDIS increase is dramatically positive, slows down, and begins declining steeply for higher values of the variable. The NFDIS curve in figure 4.2, suggests a clear positive effect of profitability on the probability of NFDIS. On the other hand, the curve for the marginal effects of NITA on the probability of FDECL and FWEAK decreases steeply, slows down, and begins increasing steeply for higher values of the variable. Figure 4.2 suggests a complicated but negative relationship between financial distress and the probability of FWEAK and FDECL as well as a flat but negative relationship between financial distress and the probability of FDIST.

Table 4.8 likewise shows that the largest marginal effects of profitability are at the NFDIS and FDECL states while the marginal effects at the FWEAK and FDIST states are weak. While the marginal effect curve for the NFDIS state (figure 4.2) is remarkably steep, that of the FDIST state is revealed to be almost flat suggesting a very small effect of profitability on the probability of FDIST state which is like the case of the TATURN ratio in figure 4.1. Likewise, asset management efficiency, the two-year net loss criteria by the Chinese delisting system significantly contributed to the strong effect of the NITA ratio at the NFDIS and FDECL states as confirmed by the steep probability curves for these states. For instance, where a firm's NITA ratio was to grow from -0.25 to 0.25, this would result in a small decrease in the predicted probability of FDIST from 5% to about 0% and a massive increase in the probability of belonging in the NFDIS state from 70% to 90% (figure 4.2). This is because of the low effect of profitability at the FDIST state as noted in the almost flat marginal effect curve for FDIST which suggests a very low chance of a firm in the FDIST state to make a profit. The direction of the association between profitability and individual financial distress states is expected. Further, the sign of the coefficients in Table 4.8 is consistent with the direction of our predicted probabilities and marginal effect plot.

Figure 4.2: Predicted probabilities and Marginal effects of Profitability with 95% CI



Source: Author's compilation

4.2.1.4 Effects of Liquidity and Short-Term Solvency on Financial Distress

Linear Hypothesis

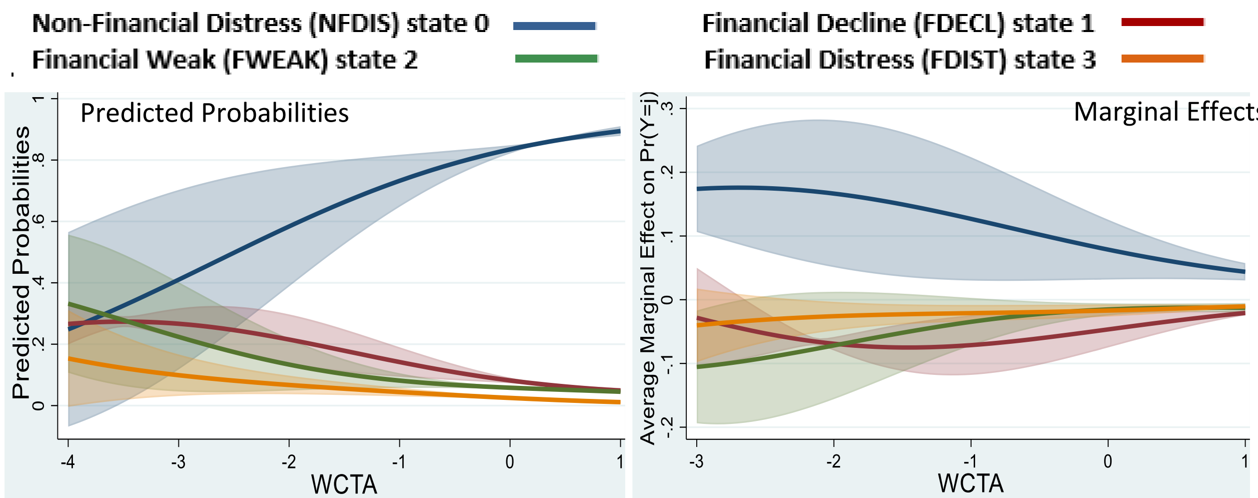
Panel A, Table 4.8 reports that the effect of short-term solvency (WCTA) on the probability of financial distress across the four financial distress states is statistically significant at $p<0.01$ level as indicated by the Wald Chi-squared of 17.27. Therefore, we strongly reject the null hypothesis and accept the alternative *hypothesis H2.3* that liquidity and short-term solvency has a significant effect on the probability of financial distress of listed non-finance firms in the Chinese equity market. Panel A, Table 4.8 shows that for a unit increase in a firm's WCTA ratio, the odds of being in the FDECL state, FWEAK state and the FDIST state relative to the NFDIS state would be expected to *decrease* by a factor of 0.587 (41.5%), 0.022 (97.8%) and 0.003 (99.7%) respectively, holding all other explanatory variables in the model constant. The odds decrease by the greatest factor at the FDIST state relative to the NFDIS state compared to the FWEAK and FDECL states relative to the NFDIS state. This goes on to show that there are few chances that a firm with increasing liquidity would belong in the FDIST state. Our results indicate that the more liquid a firm is, the less probable it would enter any of the financial distress states- FDECL, FWEAK or FDIST. This is because liquidity enables a firm to settle its obligations when due and finance its working capital, thus poor liquidity impairs a firm's ability to operate efficiently and profitably. Our result suggests that the less liquidity a firm holds, perhaps because of poor revenue and inability to pay trade creditors, the more probable the firm would enter any of the distressed states – the FDECL, FWEAK or FDIST state. The WCTA ratio is a key ratio in Altman (1968) model however, its contribution to our model (going by Wald test) ranks surprisingly second lowest next to the CFOTL ratio and this is noteworthy. We recall that it is only the WCTA and CFOTL ratio that has the closest definition of "cash flow insolvency" by the Insolvency Act (1986). For instance, the more firm working capital would shrink, the more it is unable to settle its short-term obligations that include current tax, short-term loan and trade payables and the WCTA ratio declines. Thus, it is expected that their contribution would be sparing but strong and significant. The direction of the association between liquidity and financial distress results is expected and consistent with prior studies including Altman (1968) Laitinen (1991), Sori & Jalil (2009) and Beaver et al. (2010).

Predicted probabilities and marginal effects

Figure 4.3 shows that the predicted probability of a firm belonging to the NFDIS state steeply increases as firm liquidity improves, indicating a positive relationship. Inversely, the predicted probability of a firm belonging to the FDECL, FWEAK and FDIST state declines as the firm's WCTA value increases which suggest a clear negative association. The fitted curve is slightly raised and fluctuated for the probabilities of belonging in the FDECL and FWEAK states respectively when the WCTA ratio increased.

Panel B, Table 4.8 reports that the marginal effects of WCTA on the four financial distress states are significant at $p<0.01$ level which supports our afore rejection of the null hypothesis and accept the alternative *hypothesis H2.3* that liquidity has significant effects on the probability of financial distress. Figure 4.3 reveals that the marginal effect of WCTA on the probability of NFDIS declines steeply as firm liquidity increases and that suggests a clear positive effect of NITA on the probability of NFDIS. On the other hand, the marginal effects curve of WCTA for FDECL and FWEAK initially declines and then maintains a gradual increase for higher values of the variable. Like other regressors, the largest marginal effect of liquidity is observed at the NFDIS state seconded by FDECL and FWEAK states. The marginal effects of liquidity on the probabilities of the FDIST are minimal thus the flat curve. The direction of the association between liquidity and individual financial distress states is expected and consistent with the sign of the coefficients for WCTA in Table 4.8 the direction of our predicted probabilities and marginal effect plots.

Figure 4.3: Predicted Probabilities and Marginal effects of Liquidity with 95% CI



Source: Author's compilation

4.2.1.5 Effects of Financial Leverage on the Probability of Financial Distress

Linear Hypothesis

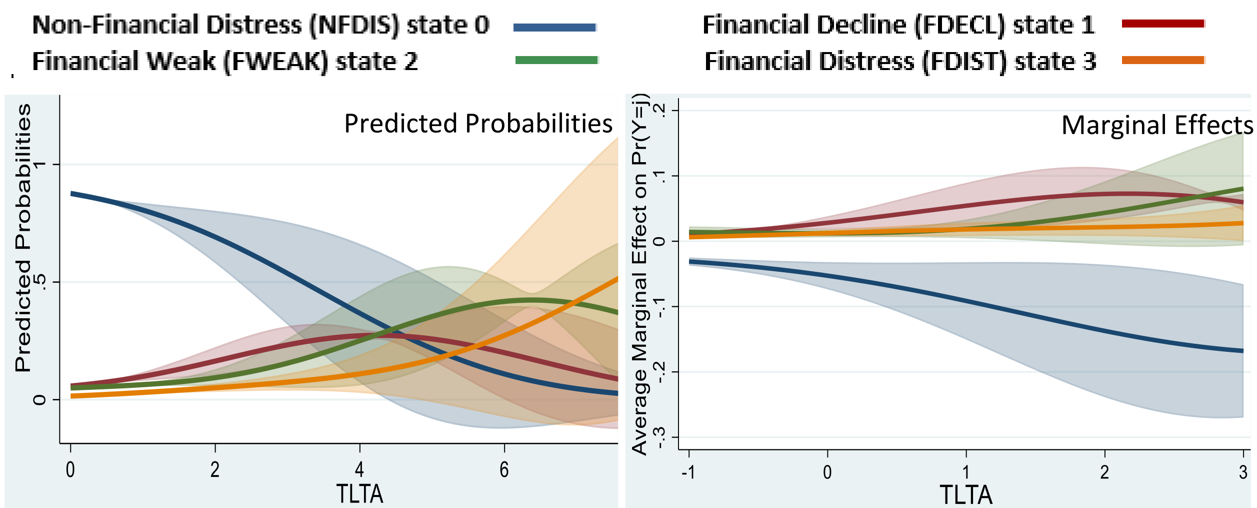
Panel A, Table 4.8 reports the effect of financial leverage (TLTA) across the four financial distress states is statistically significant at p<0.001 level as indicated by the Wald chi^2 of 21.13. Therefore, we strongly reject the null hypothesis and accept the alternative *hypothesis H2.4* that financial leverage has a significant effect on the probability of financial distress of listed non-finance firms in the Chinese equity market. Where a firm's TLTA were to increase by one unit the odds of the firm being in the FDECL state relative to the NFDIS state is expected to *increase* by a factor of 1.426, holding all other explanatory variables in the model constant, however, this is insignificant at the 0.10 level. The odds of being in the FWEAK state relative to the NFDIS state is also expected to *increase* by a factor of 3.561 but like the FDECL state, this is also insignificant at a 0.10 level. The odds of being in the FDIST state relative to the NFDIS state is expected to *increase* by a factor of 69.599 and only this effect is significant at p<0.001 level. Our result suggests that the higher a firm's financial leverage (perhaps from increased external borrowing or reduced revenue reserve or capital base), the more probable the firm would enter any of the distressed states- FDECL, FWEAK or FDIST state.

Predicted probabilities and marginal effects

Figure 4.4 shows that the predicted probability for belonging in the NFDIS state dramatically declines from left to right as the firm's TLTA ratio increases which suggest a negative relationship. Inversely, the predicted probability for the financial distress states – the FDECL, FWEAK and FDIST states increase from left to right as the firm's TLTA ratio increases which suggest a positive association. The curve steepness reflects the magnitude of changes in the predicted probabilities, and we see that the greatest magnitude of change takes place at the NFDIS state, seconded by the FDECL state and then the FWEAK and FDIST states. Our results show that although firms that are regarded as *financially healthy* do borrow it does not make them financially distressed and this point is captured on the fitted NFDIS curve for NITA value up to 4.20 with a larger range of CI. The declining NFDIS curve suggests that even though a *financially healthy* firm may source external borrowing, each additional borrowing that increases the TLTA ratio reduces the probability of belonging in the "financially healthy" NFDIS state while at the same time increasing the probability of belonging in any of the three other financial distress states. The TLTA value of 4.50 in figure 4.4 is where the switch in predicted probabilities for a firm takes place. Our predicted probabilities results indicate that the more a firm increase its financial leverage the more likely it will belong in any of the financial distress states and the less likely in the NFDIS state. For instance, where a firm's TLTA is as high as say 5.0, it would be most likely to be classified in the FWEAK state than in any other financial distress state. However, where the firm's financial leverage goes higher up to 7.0 then it will most likely fall into the FDIST state. It should be noted that from the TLTA value of 1.0, the CI starts increasing which implies there are fewer data supporting predictions beyond that point.

Panel B, Table 4.8 reports that the marginal effects of TLTA on the four financial distress states are significant at $p<0.01$ level which supports our afore rejection of the null hypothesis and accept the alternative *hypothesis H2.4* that financial leverage has significant effects on the probability of financial distress. Figure 4.4 show that as a firm's financial leverage increased, the change in probabilities (marginal effects) for firms at the NFDIS state decreased, those for firms at the FDIST state remain almost unchanged while those for firms at the FDECL and FWEAK states slightly declined and then increased. The relationship direction between financial leverage and financial distress is as expected and consistent with financial distress studies such as Chancharat (2008) Yi (2019) who also found the TLTA ratio positively related to financial distress risk.

Figure 4.4: Predicted Probabilities and Marginal Effects of Financial Leverage with 95% CI



Source: Author's compilation

4.2.1.6 Effects of Market Valuation on Financial Distress

Linear Hypothesis

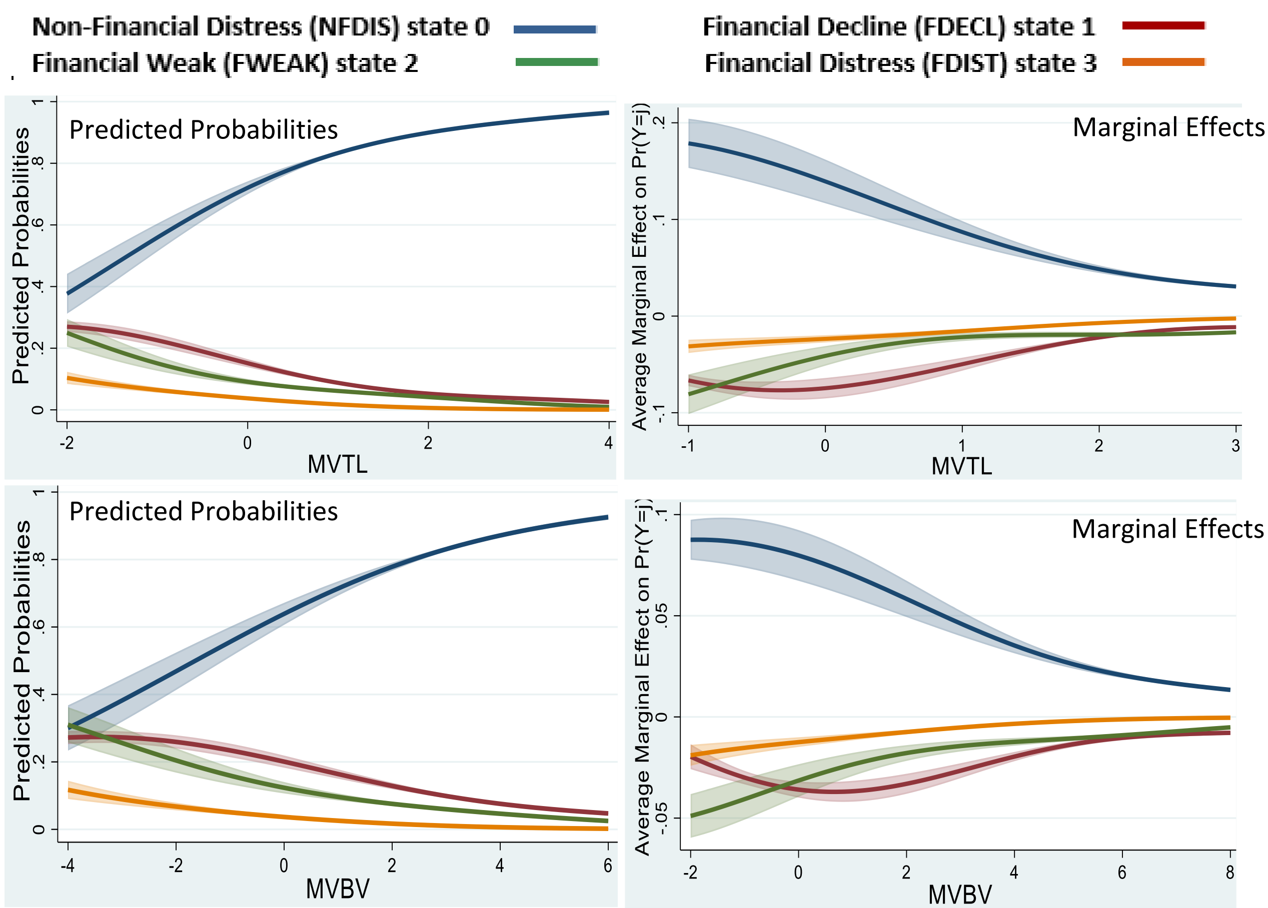
Panel A, Table 4.8 shows that the effect of market valuation, proxy by MVTL and MVBV, across the four financial distress states is statistically significant at p<0.01 level as indicated by a Wald chi^2 of 130.62 and 153.08 respectively. Therefore, we strongly reject the null hypothesis and accept the alternative *hypothesis H2.5* that market valuation has a significant effect on the probability of financial distress of listed non-finance firms in the Chinese equity market. Behind asset management efficiency and profitability, market valuation had the most effect on the probability of financial distress in our model. Where a firm's MVTL and MVBV were to increase by one unit, the odds of the firm being in the FDECL state relative to the NFDIS state is expected to *decrease* by a factor of 0.876 (12.6%) and 0.947 (5.3%) respectively, holding all other explanatory variables in constant. However, market valuation effects at the FDECL state are statistically insignificant at the 0.10 level. Where the MVTL and MVBV increase by one unit, the odds of being in the FWEAK state relative to the NFDIS state is expected to *decrease* by a factor of 0.009 (99.1%) and 0.025 (97.5%) respectively. Unlike the FDECL state, the effect at the FWEAK state is statistically significant at the $p<0.01$ level. Lastly, where the MVTL and MVBV increase by one unit, the odds of being in the FDIST state relative to the NFDIS state are expected to *decrease* by a factor of 0.006 (99.3%) and 0.013 (98.7%) respectively and these are statistically significant at $p<0.01$ level. The relationship direction between market valuation and financial distress is as expected and consistent with empirical studies like Shumway (2001), Reisz & Perlich (2007), Agarwal & Taffler (2008) and Tinoco et al. (2018) that explore market-based ratios' impact on financial distress. Our result suggests that the higher a firm's market valuation the less probable the firm would enter any of the financial distress states- FDECL, FWEAK or FDIST state.

Predicted probabilities and marginal effects

The predicted probability plots for MVTL and MVBV in figure 4.5 shows similar probabilities. Figure 4.5 shows that the predicted probability for the NFDIS state dramatically increases from left to right as the firm's MVTL or MVBV ratio increases which suggest a positive relationship. Inversely, the predicted probability for the financial distress state – FDECL, FWEAK and FDIST states decreases from left to right as the firm's MVTL or MVBV ratio increases which suggest a negative relationship. Our results suggest that an increasing firm market valuation (MVTL and MVBV) decreases the probability of the firm ending in any of the financial distress states. The effect of market-based ratios that measure market value is driven by market prices of the firm's stock which in turn are driven by demand and supply of the firm's stock by investors. In our research, the institutional background of the Chinese equity market may influence the effect of market-based ratios. For instance, estimating market value that includes total shares overvalues firms (especially SOEs) with a high percentage of non-trading shares. State enterprises have been found to constitute a significant portion of financially distressed firms in the Chinese equity market informally referred to as "zombie" stocks (Bai et al, 2000). We have used the market value of trading shares rather than the conventional total shares that include tradeable shares and non-tradeable shares (state-shares) to capture the true market valuation of firms especially *zombie* SOEs with a high portion of non-trading shares. This approach is consistent with Zhang et al (2010) and ensures we achieve a similar high magnitude of effects for market-based ratios used in studies in the US and UK. From the Wald test result in Table 4.8, MVTL and MVBV ratios made the third and fourth highest impacts respectively from FRs in our MLR "full" model, after profitability. Our result is close to the finding by Zhang et al (2010) that ranked the MVBV as having the second-highest effect in the *Z China model*. The magnitude of the effects of MVTL and MVBV on the four financial distress states is captured in the steepness of the curves for each financial distress state with the NFDIS curve the steepest and the FDIST curve the least steep.

Panel B, Table 4.8 reports that the marginal effects of MVTL and MVBV on the four financial distress states are significant at p<0.01 level which supports our afore rejection of the null hypothesis and accept the alternative *hypothesis H2.5* that market valuation has significant effects on the probability of financial distress. The relationship direction between market valuation and financial distress indicated in our marginal effects plots in figure 4.5 is consistent with our predicted probabilities and our linear hypothesis.

Figure 4.5: Predicted Probabilities & Marginal effects of Market Valuation with 95% CI



Source: Author's compilation

4.2.1.7 Effects of Cash Flows on Financial Distress

Linear Hypothesis

Panel A, Table 4.8 reports the effect of CFOTL, CFFTA and DPS across the four financial distress states are statistically significant at $p<0.001$ level as indicated by a Wald chi^2 of 16.37, 19.97 and 130.03 respectively. Therefore, we strongly reject the null hypothesis and accept the alternative *hypothesis H2.6* that cash flow has a significant effect on the probability of financial distress of listed non-finance firms in the Chinese equity market. Where a firm's CFOTL and DPS were to increase by one unit, the odds of the firm being in the FDECL state relative to the NFDIS state is expected to *decrease* by a factor of 0.615 (12.6%) and 0.089 (5.3%) respectively, holding all other explanatory variables in the model constant. However, this effect at the FDECL state is statistically insignificant at the 0.10 level for the CFOTL ratio. Further, where firm CFOTL and DPS increase by one unit, the odds of being in the FWEAK state relative to the NFDIS state are expected to *decrease* by a factor of 0.047 (95.3%) and 0.024(97.6%) respectively. Unlike the FDECL state, the effect at the FWEAK state is statistically significant at the $p<0.01$ level. Lastly, where the firm's CFOTL and DPS increase by one unit, the odds of being in the FDIST state relative to the NFDIS state is expected to *decrease* by a factor of 0.008 (99.2%) and 0.007 (98.3%) respectively and these are statistically significant at $p<0.001$ level. We observe that for a unit increase in a firm's CFFTA ratio, the odds of being in the FDECL state, FWEAK state and the FDIST state relative to the NFDIS state would be expected to *increase* by a factor of 5.144, 38.420 and 161.520 respectively, holding all other explanatory variables in the model constant.

Predicted probabilities and marginal effects

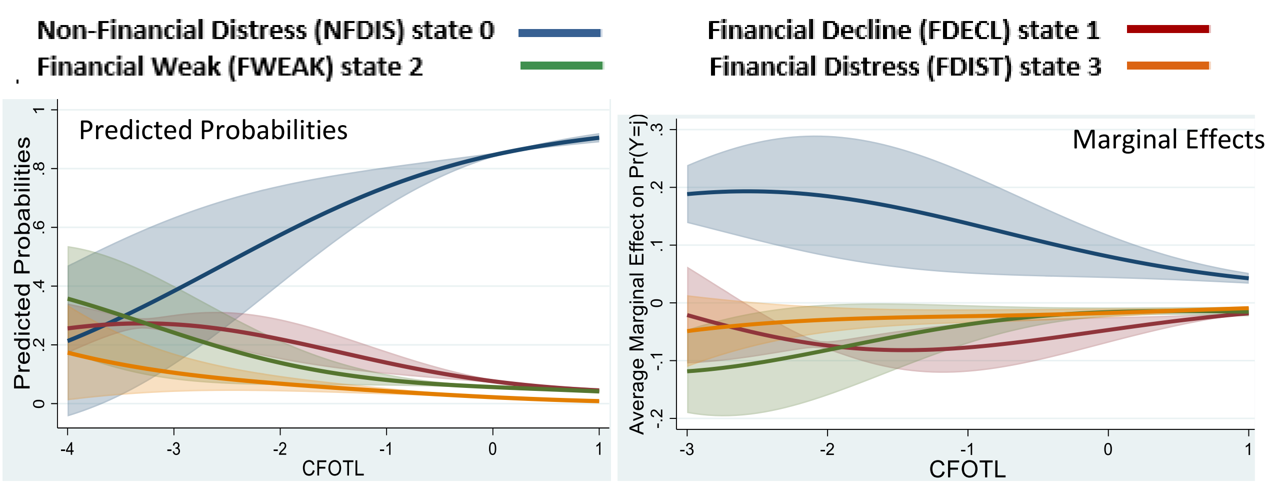
Figure 4.6 shows the fitted curve for the probabilities for NFDIS steeply increases from left to right as the CFOTL ratio increases which suggest a positive relationship. On the other hand, the curves for the probabilities of FDECL, FWEAK and FDIST states decline from left to right as the CFOTL ratio increases which suggest a *negative* relationship. A similar relationship direction is shared by the predicted probabilities of the DPS ratio. In contrast, for the CFFTA ratio, the curve for the probabilities for NFDIS steeply declines from left to right as the CFFTA ratio increases which suggest a negative relationship. On the other hand, the curves for the probabilities of FDECL, FWEAK and FDIST states increase from left to right as the CFFTA ratio increase which suggests a *positive* relationship.

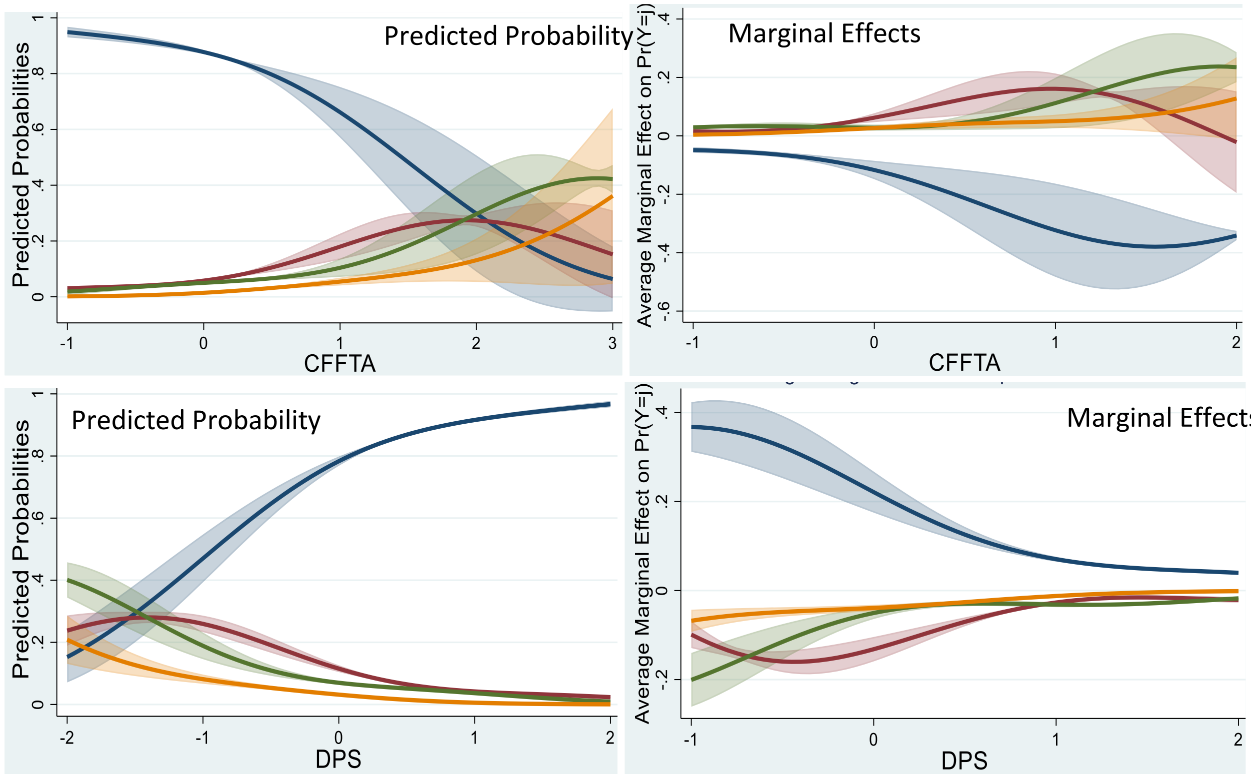
Panel B, Table 4.8 reports that the marginal effects of CFOTL, CFFTA and DPS on the four financial distress states are significant at $p<0.01$ level which supports our afore rejection of the null hypothesis and accept the alternative *hypothesis H2.6* that cash flow has significant effects on the probability of financial distress. Likewise, the other FRs, the CFOTL, CFFTA and DPS ratios had the greatest marginal effect at the NFDIS state followed by the FDECL state and lastly, the FWEAK and FDIST states and these are reflected in the steepness on their respective curves in figure 4.6. Our result suggests that the higher a firm's cash flow from operations, the less probable the firm would enter any of the distressed states- FDECL, FWEAK or FDIST state. The CFOTL ratio had the least effect in our full model. At the surface, this is surprising considering the ratio is the only variable in the Beaver (1966) univariate model and since then has been found to have a huge impact in detecting financial distress by several empirical studies such as Fawzia et al. (2015) and Sayari & Mugan (2013). It appears the dichotomous approach of these prior studies to financial distress study has masked the dynamic nature of the CFOTL. For instance, our results suggest that the CFOTL is insignificant at early FDECL state but significant at later financial distress states which influenced the poor contribution of the ratio in our model. A financially healthy' firm could make net losses (negative NITA) without being considered financially distressed. However, a firm with a close to zero or negative CFOTL must have suffered one or both net losses and increasing borrowing. Thus, a poor CFOTL is not only an indication of a strong indication of an existing financial distress condition but a prolonged one (Beaver, 1966). In other words, a *little* effect of CFOTL is considered of *great* significance, on the other hand, a net loss may not be a cause for concern unless it is sustained over a period.

Cash dividend payment is a key cash outflow for firms thus, a key source of cash flow for firms experiencing cash flow problems. Where a firm could delay payments to trade creditors, they could as well plough back cash dividend payments to shareholders although the latter seems easier. This is shown in our results that show that a delay in payment to trade suppliers that would reduce the WCTA ratio is insignificant at the early financial distress state nonetheless, the DPS is significant. Notably, all three coefficients associated with DPS are statistically different from zero and significant at p<0.001 level. This indicates that firms at the three financial distress states do plough back significant cash dividends by paying little or no cash dividend to shareholders to deal with their cash flow squeeze. Firms in financial distress cutting down on cash dividends (a key cash outflow component) contribute to the effect of the CFFTA ratio in our model. Like the DPS ratio, all three coefficients associated with CFFTA are statistically different from zero and significant at p<0.001 level. Notably, the negative association between CFOTL, DPS and financial distress contrasts with the positive association between cash flow from finance and financial distress. The significance of CFFTA in the Chinese equity market sheds light on the source of financing for firms in financial distress, especially for SOEs. Our results indicate reduced cash dividend payments and reduced loan repayment appears to be driving the increase in the CFFTA ratio especially at the FDECL and FWEAK states. Drawing from the TLTA ratio that is insignificant at the FDECL and FWEAK states, we argue that acquired loans are not amongst the factors driving CFFTA at the FDECL and FWEAK states.

The relationship direction between cash flow from operations, cash flow from finance and DPS financial distress are as expected and consistent with empirical studies such as those of Sayari & Mugan (2013), Stewart (2016) that found a strong relationship between cash flow components and financial distress. The relationship direction between cash flow components and individual financial distress states in our linear hypothesis is consistent with our marginal effects and predicted probabilities plots.

Figure 4.6: Predicted Probabilities and Marginal effects of Cash flows with 95% CI





Source: Author's compilation

4.2.1.8 Effects of Ownership Structure on Financial Distress

Linear Hypothesis

From Table 4.8, we observe the three coefficients associated with INST_OWN at the FDECL, FWEAK and FDIST states relative to the NFDIS state are significantly different from zero and statistically significant at p<0.01 level. Over the four financial distress states, the effect of ownership structure on the probability of financial distress is statistically significant as indicated by the Wald chi^2 of 23.84 that is significant at the $p< 0.01$ level. Therefore, we strongly reject the null hypothesis and accept the alternative *hypothesis H2.7* that ownership structure has a significant effect on the probability of financial distress of listed non-finance firms in the Chinese equity market. Our results suggest that for a unit increase in a firm's INST_OWN indicator, the odds of being in the FDECL state, FWEAK state and the FDIST state relative to the NFDIS state would be expected to *decrease* by a factor of 0.398 (60.3%), 0.068 (93.2%) and 0.016 (98.4%) respectively, holding all other explanatory variables in the model constant. Our results suggest that firms in financial distress states are most likely owned by individual investors rather than institutional investors such as brokerage houses, pension managers and financial institutions.

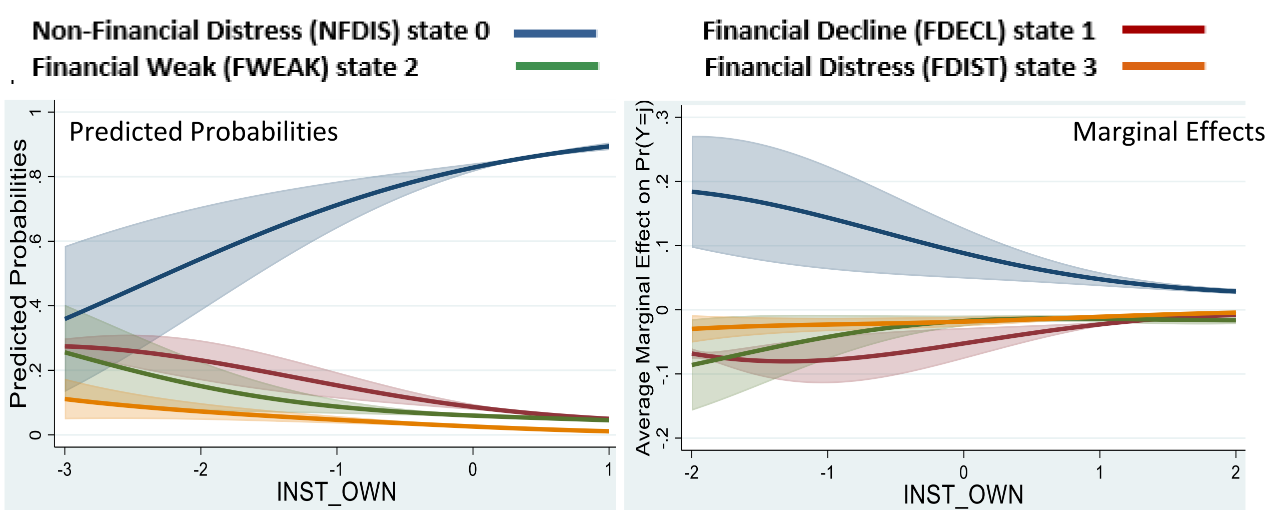
Predicted probabilities and marginal effects

Figure 4.7 provides a clearer picture of the relationship between ownership structure and financial distress. The fitted curve steeply increases from left to right for the predicted probabilities of NFDIS while a slight decrease from left to right is reported for the rest of the financial distress states- FDECL, FWEAK and FDIST as the INST_OWN indicator increases. On one hand, the INST_OWN displays a positive relationship with the predicted probability of NFDIS and on the other hand displays a negative relationship with the rest of the financial distress states. The relationship directions are as expected consistent with empirical studies including Charitou et al. (2004), Li (2014) Lai & Tam (2017), Chenchehene (2019) where ownership structure is found to have a significant effect on financial distress. Chen et al. (2001) and Cheng et al. (2012) both found that institutional investors have more access to insider and privileged equity market information compared to individual investors that rely on public information. This implies they are in an advantaged position and can envisage early poor firm performance and act promptly ahead of the market. Figure 4.7 reveals where institutional investors are most likely to channel their investments: increasing institutional ownership increasingly predicts that a firm will belong in the “financially healthy” NFDIS state and decreasingly predicts that it will belong in the “financially distressed” FDECL, FWEAK and FDIST states. This suggests a shift in the ownership structure of firms in financial distress from institutional investor ownership to individual investor ownership. The strong significance of the INST_OWN indicator likewise suggests that institutional shareholders are less likely, compared to individual shareholders, to engage in the speculative purchase of low price distressed SOE stocks. Our finding sheds more light on the study by Bai et al. (2004), who found that more than half of the sample ST designated firms experienced changes in the shareholding structure while about 36% made a significant change to their core business.

Amongst 91 predictors, Hensher et al. (2007) found ownership structure and CEO compensation amongst the strongest predictors of financial distress in a U.S. study of 1,115 bankrupt firms. Our results concur with the results of this study about the explanatory power of ownership structure; however, CEO compensation was not strong enough to make it to our final model. We earlier noted how the institutional background and poor dissemination of information have aided ownership structure in the Chinese equity market and our study. Regarding CEO remuneration which was also a strong predictor in Mann (2005) and Bredart (2013), Mann (2005) cited the lack of transparency in reporting the compensation of the CEO (General Manager) in China. In developed markets with relatively high transparency of reporting, sensitive information such as published CEO remuneration is more reliable than in an emerging market like China. This suggests a high risk of misstatement of the value of remuneration received by the CEO in China. Besides, there are several other channels explored by China's senior management to mask their remuneration and these include share options and diversion of income to related parties. This explains the weak effect of the CEO remuneration indicator in our research and shows how the equity market context could influence the explanatory powers of an explanatory variable.

Panel B, Table 4.8 reports that the marginal effects of INST_OWN on the four financial distress states are significant at p<0.01 level which supports our afore rejection of the null hypothesis and accept the alternative *hypothesis H2.7* that ownership structure has significant effects on the probability of financial distress. Figure 4.7 reveals that where a higher percentage of a firm's equity is held by institutional shareholders, the marginal effects of belonging in the NFDIS initially increase positively but gradually stabilize with more institutional equity holding. Inversely, the marginal effects of belonging in the FDECL, FWEAK or FDIST states decline slightly but steadily with more institutional ownership.

Figure 4.7: Predicted Probabilities and Marginal effects of Ownership structure with 95% CI



Source: Author's compilation

4.2.1.9 Effects of Board Structure on Financial Distress

Linear Hypothesis

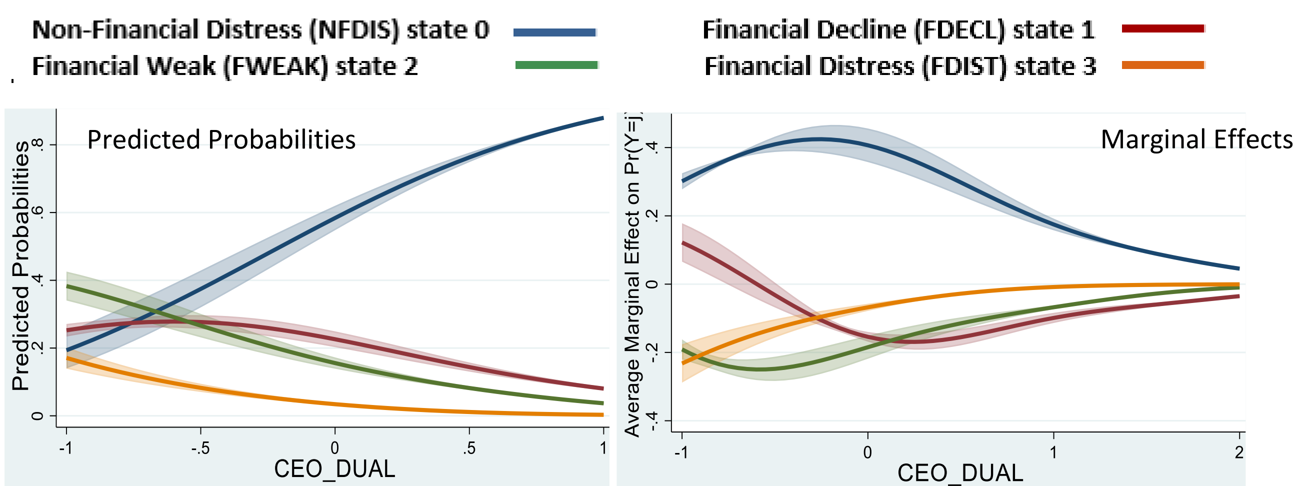
Panel A table 4.8, shows that the three coefficients associated with CEO_DUAL at the FDECL, FWEAK and FDIST states relative to the NFDIS state are significantly different from zero and statistically significant at $p<0.01$ level. Across the four financial distress states, the effect of board structure, proxy by CEO_DUAL, on the probability of financial distress is statistically significant as indicated by the Wald chi^2 of 433.82 that is significant at the $p< 0.01$ level. Therefore, we strongly reject the null hypothesis and accept the alternative *hypothesis H2.7* that board structure has a significant effect on the probability of financial distress of listed non-finance firms in the Chinese equity market. The checks and balances resulting from having different persons manage the positions of the CEO and board chairman help curtail possible CEO management decisions that may be too risky for the firms and capable of resulting in financial distress in the mid-term and long-term (Li, 2014). Where a firm does separate the positions of the CEO and board chairman, the odds of being in the FDECL state, FWEAK state and the FDIST state relative to the NFDIS state would be expected to *decrease* by a factor of 0.034 (96.4%), 0.019 (98.1%) and 0.011 (98.9%) respectively, holding all other explanatory variables in the model constant. We observe that the coefficients and effect of CEO_DUAL are significant at all four financial distress states and indeed, CEO_DUAL made the greatest impact in our full model from Table 4.8. Likewise, the INST_OWN indicator, the impact of CEO_DUAL on early FDECL state confirms that corporate governance indicators can diagnose and explain early-stage financial distress. Our results contribute to the finding by Santen & Soppe (2009a) that amongst corporate governance indicators, board structure has the greatest effect.

Predicted probabilities and marginal effects

Figure 4.8 reports the predicted probability curve slightly increases from left to right for NFDIS firms and decreases from left to right for the rest of the financial distress states- FDECL as the CEO_DUAL indicator increases. In addition, we observe that CEO_DUAL displays a positive relationship with the probability of NFDIS while displaying a negative relationship with the probability of financial distress- FDECL, FWEAK or FDIST. The massive effect of CEO_DUAL at the NFDIS, FDECL and FWEAK is reflected in the steepness of their curves while the low effects at the

FDIST state are reflected on the flat curve for this state in figure 4.8. CEO_DUAL made the second greatest effect in our model that emphasizes the importance of board composition corporate governance practice in the Chinese equity market. This finding shades more light on the concerns expressed by Cheng et al. (2007) over the general corporate governance practice of SOEs. Our finding suggests board composition as a strong factor driving inefficiency in the management of SOE that has been cited by several studies including Wang & Yung (2011) and Yu (2013). The results from figure 4.8 suggest that firms in financial distress make further changes to their board structure such as merging the positions of the CEO and board chairman perhaps to reduce cost as part of a reorganisation process. Non-adherence to such corporate governance codes further results in inefficiencies in the management board and possible unchecked management excesses such as earnings management (Lai & Tam, 2017). The relationship direction between board structure and individual financial distress states in our linear hypothesis is consistent with our marginal effects and predicted probabilities plots.

Figure 4.8: Predicted Probabilities and Marginal Effects of Board structure with 95% CI



Source: Author’s compilation

Table 4.9: Pairwise comparison of the effects of FRs and CGIs across multiple distress states

	FDECL vs NFDIS (State 1)	**FWEAK vs NFDIS (State 2)**	**FDIST vs NFDIS (State 3)**	**FDECL vs FWEAK**	**FDIST vs FDECL**	**FWEAK vs FDIST**
	Wald chi^2	**Wald chi^2**	**Wald chi^2**	**Wald chi^2**	**Wald chi^2**	**Wald chi^2**
TATURN	**308.53*** **	**52.83*** **	**59.55*** **	**3.53***	**11.45*** **	**8.35*** **
NITA	**177.05*** **	**29.64*** **	**37.69*** **	**6.03** **	**13.03*** **	**5.77** **
WCTA	1.98	**7.88*** **	**14.56*** **	**5.44** **	**11.39*** **	**6.26** **
TLTA	0.84	1.46	**12.63*** **	0.72*	**9.73*** **	**17.44*** **
MVTL	1.74	**115.79*** **	**119.23*** **	**97.64*** **	**102.57*** **	**5.23** **
MVBV	1.56	**136.03*** **	**126.26*** **	**124.31*** **	**118.03*** **	**10.25*** **
CFOTL	1.82	**10.66*** **	**13.45*** **	**6.73*** **	**10.24*** **	**3.13***
CFFTA	**6.42*** **	**11.25*** **	**17.03*** **	**3.26***	**7.56*** **	**3.86** **
DPS	**105.53*** **	**24.06*** **	**28.39*** **	**2.84***	**7.08*** **	**3.84***
INST_OWN	**8.79*** **	**9.22*** **	**15.64*** **	**3.64***	**8.75*** **	**5.42** **
CEO_DUAL	**386.92*** **	**156.61*** **	**148.08*** **	**4.58** **	**10.84*** **	**5.51** **

Legend: ** Significant at p<10% level, ** Significant at p<5% level, *** Significant at p<1% level*
H2.9 Ho: *Effect of a regressor at (J-1) state – Effect of regressor at NFDIS state = 0*
Source: Author's compilation

4.2.2 Comparison of Explanatory Factors and Effects in a Multiple State Financial Distress

In section 4.2.1 we tested the linear hypotheses and examined the effects of financial ratios and corporate governance indicators on each of the four financial distress states. However, from our empirical results so far we cannot say if the effects of financial ratios and corporate governance indicators on each of the four financial distress states are the same. For instance, the three coefficients associated with NITA suggest that profitability has a significant effect on the probability of a firm being in either the FDECL, FWEAK or the FDIST state relative to the NFDIS state. Nonetheless, we like to know whether the effects of profitability at the FDECL relative to the NFDIS is different from the effects of profitability on the FWEAK state relative to the NFDIS and so on. In Panel A of Table 4.8, we achieved the *first difference* analysis of the effects of financial ratios and corporate governance indicators on financial distress states (FDECL, FWEAK and FDIST) to the reference state- NFDIS. Table 4.9 reports the *second difference* analysis, that is, a Wald test comparison of the effects of financial ratios and corporate governance factors across six pairwise combinations from our four-state financial distress model. In this section, we set out to achieve the *second research objective* and test hypotheses H2.8 and H2.9.

4.2.2.1 Comparison of the Explanatory Factors in Multiple Financial Distress States

Explanatory factors in the Financial Decline (FDECL) State

From the results in Panel A of Table 4.8, only six of the eleven explanatory variables in the full MLR model 3 are significant a $p<0.01$ in explaining the FDECL state relative to the NFDIS state. Significant explanatory variables at the FDECL state are profitability (NITA), asset management efficiency (TATURN), cash flow from finance (CFFTA), cash dividend (DPS) and corporate governance (INST_OWN and CEO_DUAL). However, liquidity (WCTA), market valuation (MVTL, MVBV), cash flow from operations (CFOTL) and financial leverage (TLTA) are insignificant in discriminating between firms at the FDECL and NFDIS states. This suggests that in terms of liquidity, market valuation, cash flow from operations and financial leverage (TLTA), there is no significant difference between firms at the FDECL state and those at the NFDIS state.

We earlier discussed how the *profit-based* Chinese delisting system has influenced the effects of NITA and TATURN making these the only two accrual-based ratios statistically significant at the FDECL state. Besides TATURN and NITA, the other significant variables are CFFTA, DPS, CEO_DUAL and INST_OWN that are cash flow-based ratios and corporate governance indicators. This result suggests that, compared to cash flow-based ratios and corporate governance indicators, accrual-based ratios are not able to detect early financial distress. This finding does not conclude that accrual-based ratios have lesser explanatory powers than cash flow-based ratios or corporate governance indicators. Rather, our findings highlight the possibilities of firm management manipulating accrual-based information (not just earnings information) to cover up early financial distress *symptoms*. This results in accrual-based ratios being inadequate in assessing early financial distress and highlights their limitation in financial distress studies. This finding also emphasizes the importance of including cash flows and non-financial information such as corporate governance indicators in our research. In other words, an equivalent study outside the Chinese equity market that does not include either cash flow-based ratios or corporate governance indicators would most likely not differentiate between firms in the FDECL state and NFDIS state. Indeed, such a study would categorise firms in early financial distress states as *financially healthy*. Further, we observe that a cash flow-based ratio – CFOTL is insignificant at the early FDECL state. The effect of this variable has been undermined by another strong factor –

borrowing, which is the denominator of the CFOTL ratio and from our study is statistically insignificant at the early FDECL state. Our study finds decreasing asset management efficiency, declining profitability, increasing cash flow from finance, reduced dividend payment, weak board structure and ownership structure as factors that explain the FDECL state.

Declining Assets Management Efficiency

From Panel A table 4.8, the three coefficients associated with TATURN which are at the FDECL, FWEAK and FDIST states relative to the NFDIS state are significantly different from zero and statistically significant at $p<0.01$ level. This suggests that alongside results from the Wald test (Panel A, Table 4.8) and Dunn test (table 4.7) asset management efficiency is significantly different for firms in NFDIS state compared to a firm in FDECL, FWEAK and FDIST state. The results suggest that asset management efficiency decline for firms as they deteriorate through the financial distress process. This result is consistent with Pozzoli & Paolone (2017) who characterized this state with declining revenue. Pozzoli & Paolone (2017) further argue that one of the initial symptoms of a declining distress state is the inability to grow revenue or control operating expenses over a period. Declining revenue might result from loss of volume or price cut. We believe that the large magnitude of effect by the TATURN ratio further depicts the sustained inability of firms in financial distress to grow revenue. A sustained inability to grow revenue differentiates occasional revenue decline that firms in the NFDIS state could also experience. Our result is also consistent with Beaver (2016) who studied a sample of firms that failed between 2008 and 2012 in emerging markets and found the cause of failure to be linked to consistent operational inefficiency followed by increasing financial leverage and finally poor liquidity.

Declining Profitability

From Panel A table 4.8, the three coefficients associated with NITA which are at the FDECL, FWEAK and FDIST states relative to the NFDIS state are significantly different from zero and statistically significant at $p<0.01$ level. The Wald test (Panel A, Table 4.8) and Dunn test (table 4.7) results show that profitability is significantly different for firms in NFDIS state compared to a firm in FDECL, FWEAK and FDIST state. The results suggest that profitability decline for firms as they deteriorate through the financial distress process. This finding is consistent with Sormunen &

Laitinen (2012), Farooq et al. (2018) that characterized this state with declining profitability. Drawing from accounting theory, declining revenue and increasing expense result in declining profitability, with all other factors constant. Laitinen (1991) characterised this state using declining profitability compared to Pozzoli & Paolone (2017) that used declining revenue and increasing expense. However, this is not always the case since there are cases where a firm may suffer declining profits despite an increase in revenue. Since profitability is the *bottom line*, it reflects a clearer picture than revenue. As in the case of declining revenue, the emphasis is on sustained losses since a firm might experience one-off profit boosts occasioned by the sale of assets or loss from a one-off event. Revenue and profitability factors are reflected a good extent in the Chinese equity market delisting system "two year consecutive net loss" criteria for a ST status (FDECL state) designation. It is therefore not surprising to see both TATURN and NITA have the highest and second highest effects in the FDECL state.

Increasing cash flow from finance

The Wald test (Panel A, Table 4.8) and Dunn test (Table 4.7) shows that cash flow from finance is significantly different for firms in NFDIS state compared to a firm in FDECL, FWEAK and FDIST state and that, cash flow from finance increase as firms deteriorate through the financial distress process. Most studies in the financial distress process including Pozzoli & Paolone (2017) and Farooq et al. (2018) did not factor in cash flow from finance in their study. We observe the significance of cash flow from finance is boosted by institutional influences and the relationship between listed SOEs and the Government in the Chinese equity market. A major motivation for a "financially distressed" firm in the Chinese equity market to remain listed is to source equity funds from investors in the equity market (Cheng et al., 2007). When firms in financial distress are unable to source equity from the equity market, a good number of them that are owned by the State government rely on funding in the form of grants and subsidies from the Government and loans from mainly State banks (Wang & Yung, 2011). Desperate sourcing for external funding including loans from the state bank appears to strongly drive the increase in the CFFTA ratio. This is because equity and loans are key cash inflow components of the cash flow from finance. "Financially healthy" firms in the NFDIS state may also source equity funds and although this is another commonly shared performance, there appears to be more need for these funds by "financially distressed" firms.

Declining dividend payment

The results from the Wald test (Panel A, Table 4.8) and Dunn test (table 4.7) show that cash DPS is significantly different for firms in NFDIS state compared to a firm in FDECL, FWEAK and FDIST state and that, firms reduce their cash dividend as they deteriorate down the financial distress process. In support of our finding on cash flow from finance, we also observed in Table 4.8 that the DPS ratio had a significant negative effect on the financial distress state (Wald chi^2 = 58.11, pv <0.001). Our results also suggest cutting down on dividend payment in response to liquidity problems that occur at an early (FDECL) financial distress state. This is consistent with the findings by Lau (1987) and Ward (1994) who characterized the early distress state with a declining dividend payment. In the case of declining dividends, we assume firms prioritize payment to suppliers over shareholders, thus declining dividend payment precedes declining working capital. This is the case in our study such that working capital liquidity (WCTA) is insignificant at the FDECL state. So far, we had assumed the issue of equity shares and loan securing was driving the cash flow from finance. If securing a loan or issuing equity shares were driving cash flow from finance for FDECL firms, then it would be expected that the financial leverage would be significant. However, the financial leverage (TLTA) ratio is insignificant at the FDECL state and that suggests that firms in the FDECL state do not rely heavily on loans as a source of cash inflow. This leaves the drivers of cash flow from finance to reduced or zero dividend payment or issue of equity share.

Weak board structure and low institutional ownership

From the results in Table 4.8, board structure (CEO_DUAL) had the largest contribution and second strongest marginal effect at the FDECL state which is better compared to the contribution and marginal effect by INST_OWN. The integration of corporate governance indicators alongside financial ratios have been largely neglected in several studies of the financial distress process and multiple financial distress states. Key financial distress process studies including Laitinen (1991), Yao (2009), Pozzoli & Paolone (2017) and Yi (2019) did not factor in corporate governance indicators in their studies explaining determinant factors of financial distress states. An efficient board structure is required to effectively direct the daily affairs of a company (Santen & Soppe, 2009a). Our results suggest that whether the positions of the CEO are handled by the same or different persons significantly determines how effective a firm's management is in managing the affairs of a firm so that the probability of financial distress is significantly reduced. Our results found that both board structure and ownership structure factors explain early financial distress where the conventional accrual-based ratios such as WCTA, TLTA, MVBV, MVTL could not. The finding on corporate governance indicators explaining early financial distress is consistent with Argenti (1976) business failure process model that identifies "management weakness" as a key driver of "defects" that precede "symptoms of failure". Non-financial defects such as corporate governance weakness preceded financial weakness such as declining revenue and profitability.

Firms in the FDECL state share with firms in the NFDIS state, performance aspects of liquidity, financial leverage, market valuation and cash flow operations. This suggests that we are correct in not labelling this state as financially distressed (FDIST). Further, neither a declining revenue, profitability nor declining dividend payment satisfies the definitions of "insolvency" by the InsolvencyAct (1986). Consequently, we believe that the event of "inability to settle obligations as they fall due" is insignificantly evident amongst firms at the FDECL state.

Explanatory factors in the Financially Weak (FWEAK) State

From the results in Panel A, Table 4.8, ten of the eleven explanatory variables in the full MLR model 3 are significant at $p<0.01$ in explaining the FWEAK state relative to the NFDIS state. Significant determinant factors at the FWEAK state are profitability (NITA), asset management efficiency (TATURN), liquidity (WCTA), market valuation (MVTL, MVBV), cash flow from operations (CFOTL), cash flow from finance (CFFTA), dividend payment (DPS) and corporate governance (INST_OWN and CEO_DUAL). Nonetheless, financial leverage (TLTA) is insignificant in discriminating between firms at the FWEAK and NFDIS states. This suggests that in terms of financial leverage, there is no significant difference between firms at the FWEAK state and those at the NFDIS state.

The findings show that the same weak asset management efficiency, declining profitability, increasing cash flow from finance, reduced dividend payment, weak board structure and ownership structure that determine the FDECL state are also significant at the FWEAK state. This confirms the continual decline we earlier observed on the curves for the FDECL and FWEAK in Figures 4.1 to 4.8. However, at the FWEAK state, four additional explanatory variables are significant – WCTA, MVTL, MVBV and CFOTL. Thus, we could say that the FDECL state precedes the FWEAK state and we are correct in labelling the states as "state 1" and "state 2" respectively. Where the declining revenue and profitability "symptom" in the FDECL is not addressed promptly then a firms' financial health deteriorates into the FWEAK state. Declining asset management efficiency, declining profitability, increasing cash flow from finance, reduced dividend payment, weak board structure and ownership structure have been found to characterise the FDECL state. In addition to these factors, decreasing liquidity, decreasing cash flow from operations and decreasing market valuation are found to explain the FWEAK state:

Declining Liquidity and Working Capital

A firm incurring recurring net loss would experience a shrinking working capital relative to its total assets (Altman, 1968). The implications for a firm experiencing a sustained period of declining revenue and profitability is that these have a direct impact on the firm's cash inflow and accounts receivable which in turn results in a decline in liquidity (WCTA). In our preceding discussion, we observed that firms in the FDECL state sourced liquidity mainly by reducing or no dividend payment. In the face of a sustained period of declining revenue and profitability firms in the FWEAK state are most likely to extend internal funding from reducing and eliminating dividend payments to relying on working capital credit. This result is consistent with the Pecking Order of firms exhausting internal funding opportunities before seeking external funding. A period of sustained net losses is a precursor to poor working capital since the firm loses both cash and accounts receivable in this situation. The declining working capital situation could further deteriorate as the firm is pressured to source liquidity from increasing accounts payable as well as a possible increase in short-term borrowing driven by loan repayment defaulting or perhaps, additional borrowing. Paying attention to the trend in deteriorating financial health, we observe that at the FDECL state, asset management efficiency and profitability are significant but not liquidity. Nonetheless, all three coefficients of asset management efficiency, profitability and liquidity become statistically significant at $p<0.01$ at a later FWEAK state. This suggests the inability to generate revenue and profits precedes liquidity or working capital problems and our finding is consistent with Maness & Zietlow (2005). Working capital credit is the least risky and least expensive source of internal funding, thus the most viable source of funding operations for firms experiencing a liquidity squeeze (Atieh, 2014).

Our finding on liquidity is consistent with Pozzoli & Paolone (2017) and Farooq et al. (2018) who characterize this state with additional declining liquidity and working capital. However, Laitinen (1991) placed liquidity as the last factor in state 3 while placing financial leverage in state 2. Going by Pecking ranking theory, a firm in need of immediate liquidity would not at first instance source long term borrowing or issue equity shares that would affect their capital structure (Stewart & Nicholas, 1984). Theoretically, the poor liquidity and shrinking working capital of a firm receives the impact of declining revenue and profitability before the long-term borrowing that drives financial leverage, going by the Pecking Order. We find the reverse to be the case from our results where liquidity and working capital (significant at the FDECL state) precede financial leverage (significant at the FWEAK state). Beaver (2016) found that increasing financial leverage and poor liquidity almost always occurs at the same time for failed films. A firm with declining liquidity and working capital would struggle to pay suppliers and perhaps, loan creditors and this situation meet the definition of insolvency (financial distress) by the Insolvency Act (1986). In this research, liquidity (WCTA) is significant in the FWEAK while financial leverage is not. When a firm is experiencing short term insolvency (for instance, in the case of negative working capital), there is pressure to raise additional capital either from equity or debt or both according to and Pecking order (Alzomaia, 2014). Where additional equity is not available, the firm is under pressure to raise debt thereby increasing its financial leverage.

Further, the findings of this research are consistent with the Pecking Order which implies declining liquidity precedes increasing borrowing and financial leverage but is not consistent with Beaver (2016) that suggests the reverse. Although firms at the FWEAK state experience an inability to pay their trade creditors, we believe this situation is not sustained. In addition, there is no evidence of defaulting or increasing long-term borrowing (financial leverage is insignificant at the FWEAK state) which makes them not a perfect definition of “insolvent” or financially distressed. Nonetheless, we believe that firms at this state are beginning to show signs of "cash flow insolvency" since there is evidence of problems in paying trade suppliers.

Declining cash flow from operations

Cash flow is often ignored in financial distress process studies including those of Laitinen (1991), Pozzoli & Paolone (2017), Chancharat (2008) and Farooq et al. (2018). Theoretically, cash flow from operations is amongst elements of the financial statement that become directly impaired because of a prolonged period of losses. We observed that CFOTL was insignificant at the early FDECL state) but not at the FWEAK state. The importance of asset management efficiency and profitability at both the FDECL and FWEAK states suggests a prolonged period of losses that is long enough for a negative impact to show up in the cash flow from operations and revenue reserve. The significance of the CFOTL ratio in the financial distress studies as explored by Beaver (1966), Sayari & Mugan (2013) and Stewart (2016) is two-fold. First, it highlights both difficulties in generating cash flow from operations and increasing borrowing or difficulty in repaying existing borrowing. Since financial leverage is insignificant at the FWEAK state it points to the difficulty in generating cash flow from operations as driving the CFOTL ratio.

Declining market valuation

Notably, the market valuation that was statistically insignificant at the early FDECL state, however, became statistically significant at the FWEAK and FDIST states. This suggests that market valuation becomes a significant explanatory factor at a later financial distress state. Our finding is consistent with Su (2002) who found that investors in the Chinese equity market do not correctly predict changes in firm performance thus, fail to react quickly to early information contained in the firm's earnings release. On the other hand, Cheng et al. (2012) studied information transmission to investors in the Chinese equity market and found a correlation between the release of the auditor's report and the market prices of stocks. Listed Chinese firms have until the end of April to report their December previous year full results, while the audited financial statements come much later (Yang, 2017). Findings from Yang (2017) and Cheng et al. (2012) suggest that although investors and market prices react late to firm performance as a result of the timing of published firm results, investors do rely on published results in making investment decisions. Indeed, where it takes a firm one or more financial year periods to restate previous earnings then such earnings information gets to reach investors much later. The situation partly explains why both market valuation (MVTL and MVBV) is significant at the FWEAK state but not at an earlier FDECL state. Beyond delayed transmission of market information to individual investors and late market reaction, the DPS variable seems to play a key role in the effect of market-based ratios in our model. We recall DPS as one of the determinant factors of the early financial distress state- FDECL state. We observed earlier, the high likelihood of firms experiencing liquidity problems to rely on cash dividend payout so that little or no cash dividend is paid. The resultant decrease in dividend payment seems to signal to investors, who may already be feeling dissatisfied, impending financial problems with the firm. Table 4.8 shows the significance of MVTL and MVBV ratios at the FWEAK and FDIST states suggests that market valuation assess late and terminal financial distress but not early financial distress. The results indicate how indifferent investors in the Chinese equity market are towards the early financial distress state of FDECL. At such an early FDECL state, market prices seem not to reflect the financial health of the firm. The market reaction appears to significantly drive the market-based ratios to make not just a statistically significant but strong impact at the FWEAK and FDIST states relative to the NFDIS state as shown by the odds ratio in Table 4.8.

Explanatory factors in the Financially Distressed (FDIST) State

We observe from the marginal effects in figures 4.1 to 4.8 that the effect of financial ratios and corporate governance indicators on the FDIST state is very little, thus the flat FDIST curves. The Chinese market expects SST firms to complete a restructuring that entails improvement in several aspects of firm performance (Cheng, 2015). Although reorganisation is common amongst SST firms (FWEAK firms), there are low chances they can overhaul the overall financial health of the distressed firm as argued by Li & He (2006). The slim chances of success after the restructuring are reflected in the small marginal effect, we observed for FDIST firms in Table 4.8 and the almost flat slope for NFDIS firms in figures 4.1 to 4.8. This finding is consistent with studies such as Chancharat (2008) that found late restructuring as less effective. A firm in the FWEAK (State 2) that could not improve on the determinant factors we have identified would most likely deteriorate to the FDIST (State 3) over time. From the results in Table 4.8, the coefficient associated with each of the eleven explanatory variables in the full MLR model 3 is significant at p<0.001 level in explaining the FDIST state compared to the NFDIS state. Further, the five determinant factors or "symptoms" identified at the FDECL state (state 1) deteriorate to include three additional determinant factors around liquidity, market valuation, cash flow from operations at the FWEAK state (state 2). At the FDIST state (state 3) which is the terminal distress state in our study, we observe an additional financial leverage determinant factor. All eleven explanatory variables in our full model 3 are significant and these include financial leverage that was insignificant at the FDECL and FWEAK states. Argenti (1976) made a similar observation in his business failure process and referred to factors at the terminal state as 'terminal signs' which he said are obvious to a casual observer. Amongst the determinant factors significant at the FDIST state is the firms' inability to pay their obligations as they fall due (as indicated by WCTA and TLTA ratios) which the court mainly relies on as evidence in deciding a firm's insolvency/bankruptcy status (Palinko & Savoob, 2016). A sustained inability to pay suppliers (WCTA) is considered the situation that satisfies the definition of both "cash flow insolvency" while prolonged financial leverage may result in negative equity which satisfies the definition of "balance sheet insolvency". Firms at the FDIST state in our research satisfy both definitions and therefore are labelled "financially distressed". We believe the inability to pay suppliers is sustained since the WCTA ratio is significant at the FWEAK state as well as the FDIST state and at least a couple of years lapse between these states. Notably, Laitinen (1991), Pozzoli & Paolone (2017), Farooq et al. (2018) characterize this state with severe liquidity. Other studies on multiple financial distress states labelled firms in this state as 'bankrupt' (insolvent) (Chancharat, 2008; Jones & Hensher, 2004; Lau, 1987; Liang et al., 2016; Ward, 1994). In addition to declining asset management efficiency, declining profitability, declining liquidity, increasing cash flow from finance, declining cash flow from operations, reduced dividend payment, declining market valuation and weak board structure and ownership structure, increasing financial leverage is another factor that explains the FDIST state:

Increasing Financial Leverage

A poor liquidity level as identified at the FWEAK state may result in increasing the debt burden resulting from increasing financial cost and may further impair the ability to settle short-term and long-term obligations when they fall due. Indeed, a firm experiencing prolonged declining profitability and struggling to finance its daily operations with internal supplier credit would be under pressure to rely next upon external financing going by Pecking ranking theory (Stewart & Nicholas, 1984). Theoretically, such firms go for short term borrowing which further increases current liability and impairs liquidity and working capital ratios. Such a firm significantly alters its capital structure by first sourcing external long-term debt and then issuing equity as a last resort according to Pecking Order theory. Accessing additional debt would increase financial leverage however, accessing additional equity would reduce financial leverage. Although it could be argued that accessing additional equity would diminish this determinant factor, Laitinen (1991) noted that firms in this state must have acquired most of their debt while in earlier distress states which is the FDECL state in our case. At this state, the debt burden becomes heavier as the firm's cash flow position grows weak and interest charges grow larger coupled with other existing 'symptoms' such as poor profitability (Laitinen, 1991).

4.2.2.2 Comparison of the Effects of Explanatory Factors on Multiple Financial Distress States

Effects of explanatory variables on the FDECL state versus the NFDIS state

Table 4.9 shows that the Wald Chi-squared explanatory variables for the FDECL state relative to the NFDIS state are statistically significant at $p<0.001$ level. The results suggest that the effect of financial ratios and corporate governance indicators on the FDECL state compared to the NFDIS state is not the same except regarding liquidity, cash flow from operations, market valuation and financial leverage. Therefore, we strongly reject the null hypothesis *H2.9* that the effect of financial ratios and corporate governance indicators in the FDECL state is the same as the effect of financial ratios and corporate governance indicators in the NFDIS state for non-financial listed firms in the Chinese equity market. This implies that although this explanatory variable is significant in discriminating between firms in the FDECL state and the NFDIS state, their effects vary at different magnitudes at each state. In essence, our results further suggest that the magnitude at which firms in the FDECL state suffer from declining revenue, profitability and increasing cash flow from finance, declining dividends and weak corporate governance practice differs from that of firms in the NFDIS state. Further, the curves for the FDECL state in figures 1 to 8 are significantly different from the curve for firms in the NFDIS state which supports the rejection of null *hypothesis H2.9*.

Effects of explanatory variables on the FWEAK state versus the NFDIS state

Table 4.9 shows that the Wald Chi-squared explanatory variables for the FWEAK state relative to the NFDIS state are statistically significant at the $p<0.001$ level. The results suggest that the effect of financial ratios and corporate governance indicators on the FWEAK state compared to the NFDIS state is not the same except regarding financial leverage. Therefore, we strongly reject the null hypothesis *H2.9* that the effect of financial ratios and corporate governance indicators at the FDECL state is the same as the effect of financial ratios and corporate governance indicators at the NFDIS state for non-financial listed firms in the Chinese equity market. This implies that although these explanatory variables are significant in discriminating between firms in the FWEAK and NFDIS states, the magnitude at which firms in the FWEAK state suffer from declining asset management efficiency, profitability, liquidity, dividend payment, market valuation and, poor cash flows, and weak corporate governance practice differs from those of firms at the NFDIS state. This result contradicts the assumption in several financial distress studies such as Bharath & Shumway (2008), Chenchehene (2019), Tan (2019) and Barbuta-Misu & Madaleno (2020) that the effects of explanatory variables are constant all through the financial distress process.

Effects of explanatory variables on the FDIST state versus the NFDIS state

Table 4.9 shows that the Wald Chi-squared explanatory variables for the FDIST state relative to the NFDIS state are statistically significant at $p<0.001$ level. This suggests that the effects of these explanatory variables on the FDIST state compared to the NFDIS state are not the same. Therefore, we strongly reject the null hypothesis *H2.9* that the effect of financial ratios and corporate governance indicators on the financially distressed (FDIST) state is the same as the effect of financial ratios and corporate governance indicators on the non-financially distressed (NFDIS) state for non-financial listed firms in the Chinese equity market. This implies that although the same explanatory variables that were significant at earlier FDECL and FWEAK states are also significant at the FDIST state, the effects of these explanatory variables vary at different financial distress states. This is likewise true of the marginal effects of these explanatory variables at different financial distress states in Table 4.8.

Table 4.9 presents a three pairwise comparison of the effects of explanatory variables on the three financial distress states and the reference NFDIS state. In addition, we present results of the other three pairwise comparisons of the FDECL state relative to the FWEAK state, the FDIST state relative to the FDECL state and of the FWEAK state relative to the FDIST state. The Chi-squared for these pair comparisons is statistically significant at p<0.10. This indicates that the effects of financial ratios and corporate governance indicators between financial distress states in these pairs are not the same.

4.2.3 Binary State Financial Distress, Financial Ratios and Corporate Governance Indicator

The following sub-sections 4.2.2.1 to 4.2.2.3 achieve the *second research objective* of this research and include empirical analysis and discussion that follow the testing of *hypothesis* 2.1.

4.2.3.1 Descriptive statistics for the Binary states financial distress model

Table 4.11 presents summary statistics for the binary state BLR "full" models 4. Panel A presents summary statistics for the entire dataset, panel B presents summary statistics for the non-financially distressed (NFDIS) state dataset and panel C presents summary statistics for the financially distressed state (FDIST) dataset. Summary statistics are the mean, standard deviation, minimum and maximum. Explanatory variables include four accrual-based ratios (NITA, WCTA, TATURN, TLTA), three cash flow-based ratios (CFOTL, CFFTA and DPS), two market-based ratios (MVTL and MVBV) ratios and two corporate governance indicators (CEO_DUAL and INST_OWN). Table 4.10 reports comparison of the equality of distribution of explanatory variables between the NFDIS state and the pooled FDIST state.

Table 4.10: Binary states - Kruskal-Wallis H test and Dunn $z-test$ Pairwise comparison

	TATURN	**NITA**	**WCTA**	**TLTA**	**MVTL**	**MVBV**	**CFOTL**	**CFFTA**	**DPS**	**INST_ OWN**	**CEO_ DUAL**
KW chi^2 (3) ***p-value***	1,255.39 ***	166.77 ***	38.44 ***	80.05 ***	297.14 ***	984.33 ***	163.52 ***	107.52 ***	274.76 ***	120.73 ***	831.25 ***
FDIST vs NFDIS (State 2) Dunn $z-test$	**35.43 *** **	**12.91 *** **	**6.20 *** **	**-8.94 *** **	**17.23 *** **	**31.36 *** **	**12.74 *** **	**-10.43 *** **	**16.55 *** **	**10.93 *** **	**61.92 *** **

***Legend**: * Significant at 10 percent level, ** Significant at 5 percent level, *** Significant at 1 percent level*

Source: Author's compilation

Table 4.11: Descriptive Statistics for Binary-State (BLR) "Full" Model 4

This table presents descriptive statistics for BLR "full" Model 4 for explanatory variables: Total Assets Turnover (TATURN), Net Income to Total Assets (NITA), Working Capital to Total Assets (WCTA), Total Liabilities to Total Assets (TLTA), Market Value to Total Liabilities (MVTL), Market Value to Book Value (MVBV), Cash Flow from Operations to Total Liabilities (CFOTL), Cash Flow from Finance to Total Assets (CFFTA) and Dividend per Share (DPS), CEO duality (CEO_DUAL) and Institutional Ownership (INST_OWN). Descriptive statistics reported are the Mean, standard deviation, maximum and minimum values. Panel A reports descriptive statistics for the entire dataset, Panel B for non-financially distress (NFDIS) firms, and Panel C for financial distress (FDIST) firms

	TATURN	NITA	WCTA	TLTA	MVTL	MVBV	CFOTL	CFFTA	DPS	INST_OWN	CEO_DUAL
Panel A: All firms											
Mean	1.135	0.104	0.318	0.336	1.284	3.753	0.153	0.151	0.452	0.386	0.916
Std. Dev.	0.552	0.107	0.122	0.127	0.613	1.752	0.162	0.084	0.242	0.177	0.277
Min	0.136	-0.173	-0.090	0.172	0.213	0.336	-0.124	0.034	0.001	0.014	0.002
Max	2.184	0.306	0.536	0.781	2.992	8.198	0.705	0.683	2.194	0.894	1.003
Obs	8,850	8,850	8,850	8,850	8,850	8,850	8,850	8,850	9,097	8,850	8,850
Panel B: Non-Financial Distress (NFDIS) firms											
Mean	1.215	0.115	0.322	0.331	1.337	3.974	0.165	0.146	0.472	0.394	0.987
Std. Dev.	0.541	0.113	0.124	0.126	0.618	1.631	0.164	0.078	0.251	0.176	0.107
Min	0.289	-0.063	0.107	0.174	0.463	0.416	-0.068	0.034	0.115	0.203	0.000
Max	2.182	0.306	0.536	0.619	2.993	8.194	0.705	0.343	2.193	0.893	1.000
Obs	7,838	7,838	7,838	7,838	7,838	7,838	7,838	7,838	7,838	7,832	7,838
Panel C: Financial Distress (FDIST) firms											
Mean	0.632	0.054	0.292	0.364	1.002	2.404	0.103	0.181	0.336	0.323	0.483
Std. Dev.	0.334	0.057	0.103	0.123	0.505	1.853	0.161	0.109	0.174	0.167	0.502
Min	0.131	-0.179	-0.094	0.189	0.203	0.336	-0.126	0.051	0.000	0.012	0.001
Max	1.722	0.142	0.499	0.786	2.522	6.512	0.633	0.683	0.843	0.790	1.001
Obs	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012	1,012

In terms of asset management efficiency, the values of the TATURN ratio from Table 4.11 suggest that NFDIS firms are more efficient in utilizing their total assets to generate revenue. We further observed the mean NITA for NFDIS firms is almost twice the mean NITA for firms in FDIST. This suggests a much superior ability of firms in the NFDIS state to generate profit compared to those in the FDIST state. However, the mean WCTA of NFDIS firms is slightly higher than those for FDIST firms which shows that NFDIS firms have a slightly better ability to settle their short-term obligations when they fall due. In terms of cash flow from operations, we observe that the mean CFOTL for NFDIS is better than those of NFDIS firms and that draws from NFDIS having better asset management efficiency and better profitability. The relatively weak ability to settle short-term obligations appears to contribute to higher long-term borrowing and larger debt burden as indicated by the TLTA. Table 4.11 reports the mean TLTA ratio for FDIST firms is higher than those of NFDIS firms. The higher borrowing by FDIST firms appears to be connected to their revenue-generating and profit-generating ability which is observed to be inferior to that of NFDIS firms. On average, NFDIS firms pay a higher dividend, DPS of RMB 0.47 per share compared to FDIST firms that pay, on average RMB 0.33 per share. On average, firms in the FDIST state tend to source more cash flow from finance (CFFTA) than firms in the NFDIS state and this appears to be connected to their relatively poor cash flow from operations and liquidity. We observe, on average, NFDIS firms have a higher market value than FDIST firms as suggested by higher mean MVTL and mean MVBV. In regards to corporate governance, NFDIS firms adhere to best practice corporate governance practices more than FDIS firms. Almost all NFDIS firms have the positions of CEO and board chairman managed by different persons (CEO_DUAL) and this is higher compared to just half of FDIST firms that do so. Furthermore, NFDIST firms have a higher percentage of institutional owners (INST_OWN) than FDIST firms.

Table 4.10 reports binary state Kruskal-Wallis H test Chi-square results with 95% confidence interval, for all eleven financial ratios and corporate governance indicators for the BLR “full” model 4 are statistically significant at p<0.01. The largest differences are observed for TATURN, MVBV and CEO_DUAL variables while the smallest difference is observed for the TLTA and WCTA ratios. The information on the differences between firms in the NFDIS and FDIST states is expected to add value to our regression analysis around the BLR “full” model 4.

4.2.3.2 Determinants of the Financially Distressed (FDIST) State in a Binary State Model

Table 4.12 reports the Odds ratio, robust standard errors and marginal effects of individual financial ratios and corporate governance indicators for binary state “full” model 4 and multiple state “full” model 3. Results from Panel A table 4.12, all eleven financial ratios and corporate governance indicators in our binary state “full” model 4 are significant at p<0.05 in explaining the FDIST state relative to the NFDIS state. Panel A table 4.12 reports that, for a unit increase in a firm’s TATURN, NITA, WCTA, MVTL, MVBV, CFOTL, DPS, CEO_DUAL or INST_OWN ratio, the odds of the firm going into the FDIST state relative to the NFDIS state *decrease* by a factor of 0.081 (91.2%), 0.003 (99.8%), 0.448 (55.2%), 0.405 (59.3%), 0.667 (33.3%), 0.350(65%), 0.066(93.4%), 0.293 (70.9%) and 0.026 (97.4%) respectively, holding all other explanatory variables in the model constant. In addition, table 4.12 reports that for a unit increase in a firm’s TLTA or CFFTA ratio, the odds of the firm going into the FDIST state relative to the NFDIS state *increase* by a factor of 1.981 and 15.412 respectively, holding all other explanatory variables in the model constant.

Table 4.12: Binary State and Multiple State Financial Distress Model Results

This table directly relates to sections 4.2.3.2 to 4.2.3.3 below. The table compares the results of the MLR "full" model 3 and BLR "full" model 4 that include the Odds ratios, robust standard error, marginal effects (on a percentage basis) and significance statistics of individual explanatory variables which enable us to test hypotheses H2.14 to H2.15

	PANEL A: 2SCFBLR "Full" Model 4			**PANEL B: 2SCFMLR "Full" Model 3**							
Explanatory Variable	**FDIST VS NFDIS**	**FDIST**	**Rank**	**FDECL vs NFDIS**	**FWEAK vs NFDIS**	**FDIST vs NFDIS**	**NFDIS State0**	**FDECL State1**	**FWEAK State2**	**FDIST State3**	**Rank**
	OR & SE	**ME**		**OR & SE**	**OR & SE**	**OR & SE**	**ME**	**ME**	**ME**	**ME**	
TATURN	**0.081*** (0.121)**	-0.124 ***	**5th**	**0.105*** (0.126)**	**0.047*** (0.423)**	**0.018*** (0.455)**	0.117 ***	-0.062 ***	-0.027 ***	-0.028 ***	**5th**
NITA	**0.003*** (0.407)**	-0.317 ***	**1st**	**0.003*** (0.417)**	**0.000*** (1.896)**	**0.000*** (2.132)**	0.314 ***	-0.181 ***	-0.075 ***	-0.062 ***	**1st**
WCTA	**0.448** (0.356)**	-0.045 **	**9th**	0.586 (0.383)	**0.021*** (1.357)**	**0.002*** (1.282)**	0.063 **	-0.036 ***	-0.013 ***	-0.012 ***	**9th**
TLTA	**1.981** (0.343)**	0.039 **	**10th**	1.426 (0.381)	3.564 (1.045)	**69.596*** (1.146)**	-0.062 ***	0.033 ***	0.012 ***	0.015 ***	**10th**
MVTL	**0.405*** (0.082)**	-0.045 ***	**8th**	0.877 (0.103)	**0.009*** (0.432)**	**0.005*** (0.388)**	0.061 ***	-0.037 ***	-0.016 ***	-0.012 ***	**8th**
MVBV	**0.667*** (0.037)**	-0.023 ***	**11th**	0.949 (0.042)	**0.029*** (0.316)**	**0.016*** (0.363)**	0.031 ***	-0.016 ***	-0.005 ***	-0.005 ***	**11th**
CFOTL	**0.350*** (0.346)**	-0.057 ***	**7th**	0.610 (0.352)	**0.048*** (0.932)**	**0.005*** (1.247)**	0.078 **	-0.04 ***	-0.014 ***	-0.015 ***	**6th**
CFFTA	**15.412*** (0.557)**	0.142 ***	**3rd**	**5.146*** (0.633)**	**38.422*** (1.087)**	**161.522** (1.147)**	-0.143 ***	0.082 ***	0.033 ***	0.023 ***	**3rd**
DPS	**0.066*** (0.221)**	-0.145 ***	**4th**	**0.088*** (0.234)**	**0.022*** (0.761)**	**0.005*** (0.800)**	0.136 ***	-0.075 ***	-0.038 ***	-0.025 ***	**4th**
INST_ OWN	**0.293*** (0.295)**	0.060 ***	**6th**	**0.393*** (0.315)**	**0.066*** (0.882)**	**0.017*** (0.983)**	0.064 ***	-0.041 ***	-0.014 ***	-0.012 ***	**7th**
CEO_ DUAL	**0.026*** (0.153)**	-0.192 ***	**2nd**	**0.038*** (0.163)**	**0.017*** (0.315)**	**0.014** (0.342)**	0.154 ***	-0.087 ***	-0.037 ***	-0.031 ***	**2nd**
Control variables	STATE_OWN, LOGFA, LOGAGE, GDPR, LENDR, IND_DUMMY				STATE_OWN, LOGFA, LOGAGE, GDPR, LENDR, IND_DUMMY						
Obs	9,097				9,097						

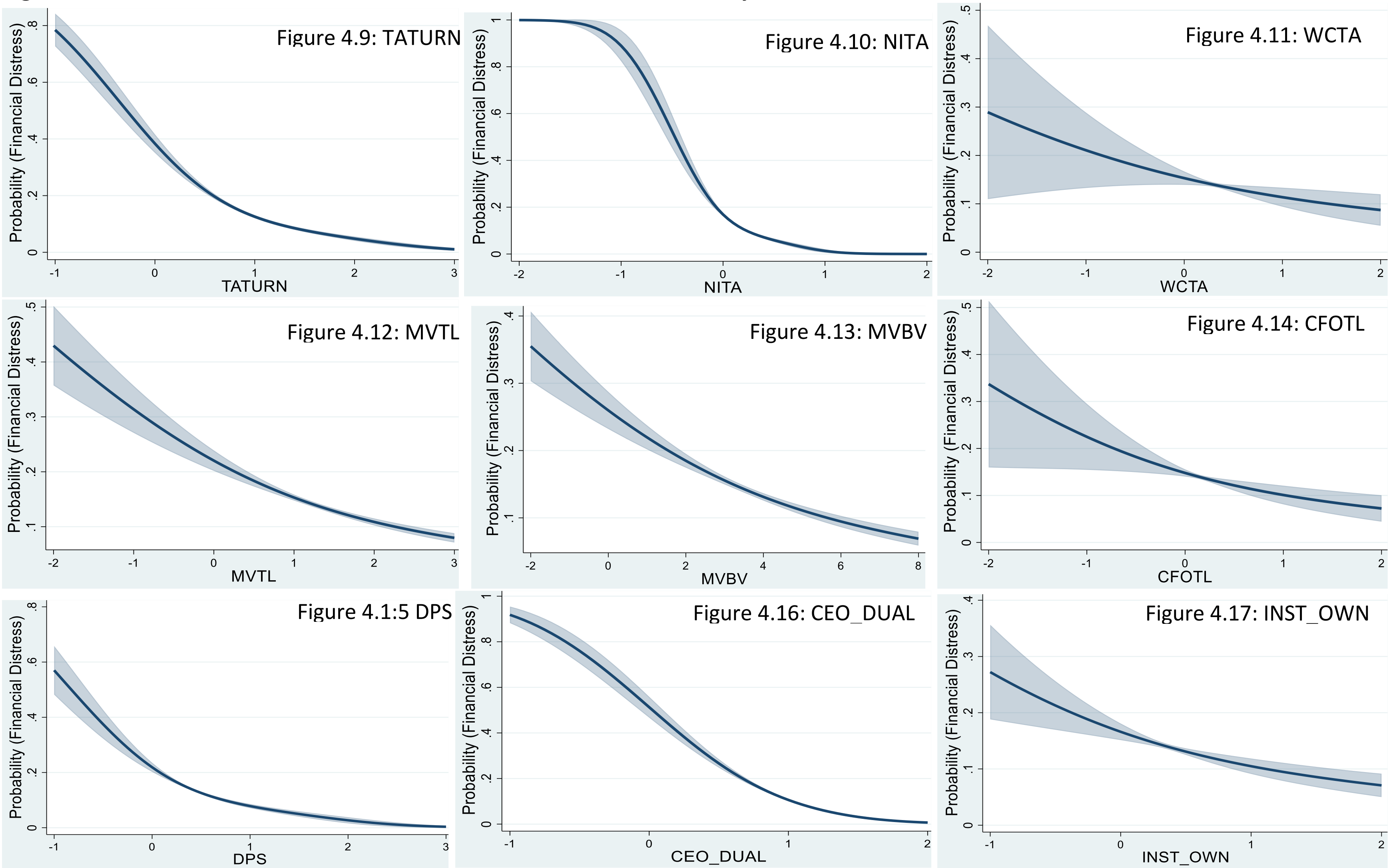
Legend: ** Significant at 10 percent level, ** Significant at 5 percent level, *** Significant at 1 percent level*
SE= Standard Error, in parenthesis OR= Odds Ratio ME = Marginal effects

BLR Model 4 chi-square is in 1 d.f. while MLR Model 3 chi-squared is 3 d.f.

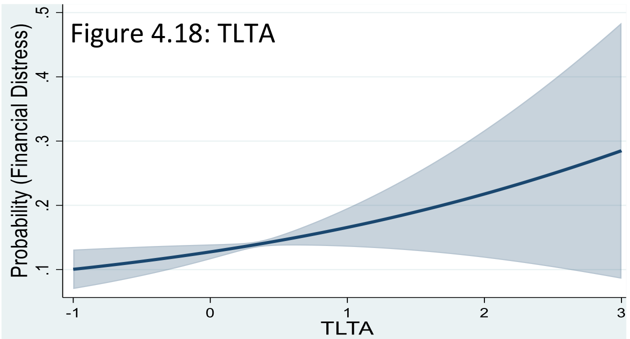
MLR Model 3 Wald test Ho: All three coefficients associated with a given variable are equal to zero

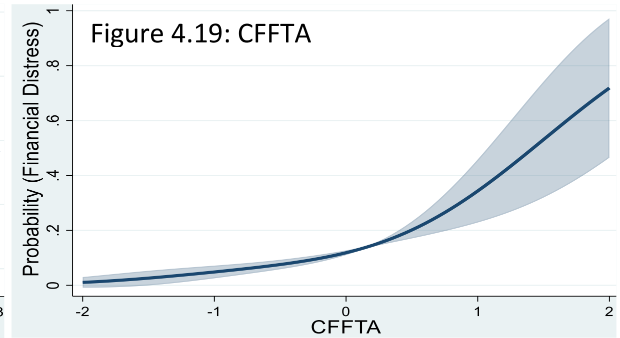
Source: Author's compilation

Figures 4.9- 4.17: Predicted Probabilities of financial distress for Binary states with 95% CI



Figures 4.18- 4.19: Predicted Probabilities of financial distress for Binary states with 95% CI





Source: Author's compilation

The direction of association reported by the Odds ratios is consistent with the curve of the predicted probabilities in Figures 4.9 to 4.19. Specifically, figures 4.9 to 4.17 show that the predicted probability of a firm entering the FDIST state *declines* from left to right as the value of profitability (NITA), liquidity (WCTA), market valuation (MVTL, MVBV), cash flow from operations (CFOTL), cash dividend paid (DPS), board structure (CEO_DUAL) and ownership structure (INST_OWN increase. The results suggest a *negative* association between these explanatory variables and financial distress. Figures 4.17 and 4.19 show that, on the inverse, the predicted probability of a firm entering the FDIST state *increase* from right to left as the value of financial leverage (TLTA) and cash flow from finance (CFFTA) increase. The results suggest a *positive* association between these explanatory variables and financial distress. The steepness of the predicted probability curves in figures 4.9 to 4.19 and the marginal effects reported on Panel A of Table 4.12 suggests that the effects of explanatory variables are at diverse magnitudes. In our binary state "full" model 3, profitability has the strongest marginal effect that is almost twice that of the board structure with the second strongest effect. Cash flow from finance, cash dividend and asset management efficiency likewise reported strong marginal effects and odds ratios ranking third, fourth and fifth respectively in our binary state model. Liquidity (WCTA), financial leverage (TLTA) and market valuation (MVTL and MVBV) achieved the least marginal effects and odds ratio in our binary state model.

It was earlier observed that liquidity assess cash flow insolvency while financial leverage assesses balance sheet insolvency. Market valuation ratios partly assess balance sheet insolvency.

Insolvency (both cash flow and balance insolvency) occur at a later stage of the financial distress process (figure 2.3). Thus, liquidity, financial leverage and market valuation assessing late financial distress appear to have reduced their effect but are not significant in our model. We observe that early explanatory variables such as profitability, asset management, cash flow from finance and cash dividend all made a strong effect on our model.

4.2.3.3 Comparison of the Binary State and Multiple State Financial Distress

The results of the multiple state "full" model 3 and the binary state "full" model 4 are reported in Table 4.12. In our multiple state "full" model, the explanatory factors at the early FDECL state were asset management efficiency, profitability, cash flow from finance, dividend payment and corporate governance. At the FWEAK state, significant explanatory factors grew to include liquidity, market valuation and cash flow from operations. And finally, at the terminal FDIST state, all the explanatory factors are significant and include financial leverage. In contrast, all the explanatory factors are significant at the FDIST state in a binary state "full" model 3. From Table 4.12, we observe the significant explanatory factors driving the FDECL and FWEAK in model 3 are different from those driving the FDIST state in the "full" model 4. Therefore, we reject the null *hypothesis H2.10* and conclude that significant financial ratios and corporate governance factors in multiple states and a binary state model are different for non-finance listed firms in the Chinese equity market. However, we note that significant explanatory factors at the FDIST state in a multiple state "full" model 3 and the FDIST state in a binary state "full" model 4 are the same. This is because both states are terminal distress states in both models where all explanatory variables are observed to be significant. Our finding is consistent with Lau (1987) who found that distress "symptoms" are present at every performance area of firms in terminal distress states and Argenti (1976) added that such "symptoms" are evident to a casual observer.

From Table 4.12, the marginal effects of financial ratios and corporate governance indicators are significantly stronger in the binary state model FDIST state compared to any distress state – FDECL, FWEAK and FDIST in the multiple state model. This result is as expected on the premise that the magnitude of the marginal effects is increased when three financial distress states are pooled into a single state. Nonetheless, our results are different for the effects of individual financial ratios and corporate governance indicators. For a unit increase in the individual financial ratios and corporate governance indicators, the odds of a firm entering any of the distress states have the greatest prediction at the FDIST and the FWEAK states in the multiple state model. The FDIST state in the binary state model ranks third in the predicted probabilities and the least ranked is the FDECL state in the multiple state model. First, our result indicates which financial distress state harbours the greatest and weakest effects of the financial ratios and corporate governance indicators. Second, our result shows that the effects of financial ratios and corporate governance indicators at the individual distress states in a multiple distress model differ from their effects in the individual distress state in a binary state model. Our empirical results suggest that the statistical approach employed does influence the explanatory power of the regressors. The relationship direction between individual financial ratios and corporate governance indicators and the probability of financial distress is the same irrespective of the binary state or multiple state model approaches.

4.2.4 Incremental Performance with Cash Flow Ratios and Corporate Governance Factors

4.2.4.1 Explanatory Power Performance and Goodness-Of-Fit

Table 4.13 presents the Wald pairwise comparison test of equality of the marginal effect of accrual-based ratios in “accrual” model 1 compared to the “cash flow” model 2, the “corporate governance” model 5 and the “full” model 3. Table 4.14 reports likelihood ratio, Wald chi-squared and Goodness-of-fit statistics for the “accrual” model 1, “cash flow” model 2, “full” Model 4 and the “corporate governance” model 5. The binary state “full” model 4 is excluded in this section since it has been dealt with in section 4.2.3 and we are interested in evaluating cash flow and corporate governance influence in our multiple state models 1, 2, 3 and 5.

Table 4.13: Comparison of equality of marginal effects across multiple state models.

	"Accrual" Model 1 *versus* "Cashflow" Model 2		"Accrual" Model 1 *versus* "Corporate governance" Model 5		"Accrual" Model 1 *versus* "Full" Model 3	
	Wald chi^2	**DF**	**Wald chi^2**	**DF**	**Wald chi^2**	**DF**
NITA	0.74	1	8.07***	1	4.92**	1
TATURN	2.26	1	20.38***	1	22.07***	1
WCTA	0.64	1	0.19*	1	0.26*	1
TLTA	0.95	1	8.06***	1	4.96**	1
MVTL	12.13***	1	88.41***	1	81.77***	1
MVBV	56.92***	1	180.43***	1	193.84***	1

***Legend:* * Significant at 10 percent level, ** Significant at 5 percent level, *** Significant at 1 percent**

Source: Author's computation

Table 4.14: Model explanatory power and Goodness-of-fit statistics

	"Accrual" Model 1	"Cash flow" Model 2		"Corporate Governance" Model 5		"Full" Model 3	
	Model 1	Model 2	Model 1 *less* Model 2	Model 5	Model 1 *less* Model 5	Model 3	Model 1 *less* Model 3
Obs (N)	8,850	8,850	-	8,850	-	8,850	-
McFadden R^2	0.510	0.534	-0.024	0.565	-0.055	0.585	-0.075
Cox-Snell R^2	0.424	0.437	-0.013	0.457	-0.033	0.469	-0.045
AIC	4,895.91	4,700.98	194.93	4,373.65	522.26	4,223.43	672.48
BIC	5,045.45	4,914.43	131.02	4,565.73	479.72	4,479.62	565.83
Log-Likelihood	-2,426.93	-2,320.44	-106.49	-2,159.81	-267.12	-2,075.71	-351.22
Deviance	4,853.92	4,640.92	213.0	4,319.61	534.31	4,151.44	702.48
Likelihood Ratio			213.06***		534.34***		702.52***
Wald chi-squared	987.12*** (DF,18)	1,030.67*** (DF,27)		1,116.72*** (DF,24)		1,203.96*** (DF,33)	

***Legend*:** ** Significant at 10 percent level, ** Significant at 5 percent level, *** Significant at 1 percent level*

Source: Author's compilation

Inclusion of cash flow-based ratios

Table 4.13 (columns 2 and 3) show the effect of accrual-based ratios; TATURN, NITA, WCTA and TLTA in the "accrual" model 1 compared to the "cash flow" model 2 is the same and insignificant at 0.10 level. On the other hand, the effects of market-based ratios; MVTL and MVBV in the "accrual" model 1 compared to the "cash flow" model 2 is different and this is significant at 0.01

level. The results suggest that, in improving the explanatory power of the "accrual" model 1, the cash flow-based ratios specifically improve the explanatory power of only market-based ratios but not accrual-based ratios. It is noteworthy to see that cash flow-based ratios do not improve accrual-based liquidity ratios (WCTA in our research). Regarding liquidity, the results suggest that rather than improve accrual-based liquidity, cash flow-based ratios introduced a *fresh* perspective to liquidity not assessed by accrual-based liquidity ratios. This finding is contrary to the conventional financial distress studies that use accrual-based liquidity ratios and cash flow-based liquidity ratios interchangeably. Nonetheless, the results support the finding by key studies by Atieh (2014); Barua & Anup (2015) that show distinct aspects of liquidity assessed by cash flow ratios and traditional accrual-based ratios.

From table 4.14, when cash flow based ratios (CBRs) are included in "accrual" model 1, AIC, BIC and Defiance and Log-likelihood improved by 194.93 , 131.02 and 213.0 and -106.49 respectively. Further, if CBRs are included in the "accrual" model 1, the resulting "cash flow" model 2 reports an improvement to the "accrual" model's ability to explain financial distress. This is shown by an improvement to the McFadden R^2 and Cox & Snell R^2 by 0.024 and 0.013 respectively. In addition, we observe an increase in the Wald chi-squared that suggests explanatory power of the model from 987.12 in model 1 to 1,030.67 in model 2, both tests significant at 0.01 level. This suggests the "cash flow" model 2 has an increased financial distress explanatory power with the inclusion of cash flow-based ratios in the model. The improved ability to explain financial distress again provides strong evidence of integrating cash flow-based ratios to the conventional accrual-based ratios and market-based ratios. Given that the resulting "cash flow" model 2 has better McFadden R^2, Cox & Snell R^2, AIC, BIC, Log-likelihood and Deviance compared to the base "accrual" model 1, we conclude that cash flow-based ratios improve the model fit and predictive power of accrual-based and market-based ratios. Our finding on model fit and explanatory power added by cash flow-based ratio is consistent with Laitinen (1994) who argues that cash flow information explains an aspect of cash liquidity that is not explained by accrual-based liquidity ratios. In the case of the Chinese equity market, the significance of including cash flow information is profound. The delisting system uses only accrual accounting information as designation criteria however, profitability and negative asset criteria of the delisting system do not assess "cash flow insolvency”. To comprehensively diagnose financial distress, both “cash flow insolvency” and “balance sheet insolvency” as defined by the Insolvency Act (1986) need to be assessed.

Inclusion of corporate governance factors

Further, in Table 4.13 (columns 4 and 5), the marginal effects of accrual-based ratios and market-based ratios in the “accrual” model 1 compared to the “corporate governance” model 5 is different and this is significant at 0.01 level. This suggests that the inclusion of corporate governance indicators improves the explanatory powers of both accrual-based and market-based ratios, especially market-based ratios.

From Table 4.14, where corporate governance factors are included in “accrual” model 1 instead of cash flow-based ratio, the resulting “corporate governance” model 5 reports an improvement to the “accrual” model’s ability to explain financial distress. This is shown by an improvement to the McFadden R^2 and Cox & Snell R^2 by 0.055 and 0.033 respectively. Further, the “accrual” model 1 fit is improved with the inclusion of corporate governance factors as suggest by AIC, BIC, Defiance and Log-likelihood that improved by 522.26, 479.72, 534.31 and -267.12 respectively. The resulting “corporate governance” model 5 has better McFadden R^2, Cox & Snell R^2, AIC, BIC, Log-likelihood, and Deviance compared to the base “accrual” model 1. Therefore, we conclude that corporate governance indicators improve the model fit and explanatory power of accrual-based and market-based ratios. Similar to the incremental explanatory power, our results suggest that corporate governance indicators provide better incremental model fit and predictive power to accrual-based and market-based ratios than cash flow-based ratios. The strength of corporate governance indicators in our study reflects the strong institution background of the Chinese equity market and the significance of corporate governance in China as shown by Li (2014). This result confirms our earlier finding that similar to the accrual-based and market-based ratios, cash flow-based ratios assess financial factors while corporate governance indicators assess non-financial factors that influence financial distress.

After including corporate governance indicators in the model 1, we observe the improvement in the explanatory power of model 5. This is suggested by the Wald Chi-squared increase from 987.21 for the “accrual” model 1 to 1,116.77 for the “corporate governance” model 5, both test significant at p< 0.01 (Table 4.14). Further, we observe the improvement that corporate governance indicators make to accrual-based and market-based ratios are better than those made by cash flow-based ratios. This is shown by the "corporate governance" model 5 with a Wald chi-squared of 1,116.77 that is better than the Wald chi-squared of 1,030.67 for the "cash flow" model 2. This result is expected and supports the finding by Li (2014) that corporate governance indicators that are non-financial factors are relatively less susceptible to manipulation compared to cash flow-based ratios that are financial factors. Second, corporate governance factors assess corporate governance which is an entirely different aspect of firm performance from financial statements.

Finally, when both cash flow-based ratios and corporate governance indicators are combined with accrual-based and market-based ratios, improved model fit and explanatory power in the resulting "full" model 3 is better than "cash flow" model 2 or "corporate governance" model 5. The explanatory power of model 1 is improved from a Wald chi-squared of 987.21 to 1,203.93. In addition, the likelihood ratio of model 1 is improved by 702.52 in model 3 which is significant at 0.01 level. Our finding suggests that a prediction model that integrates cash flow-based and corporate governance indicators provide better predictive results than a model concentrating solely on a single class of variable such as accrual-based ratios. This finding is consistent with prior studies by Wang & Li (2007) and Xie, Luo & Yu (2011) that found that models that include non-financial variables perform better than models with only financial variables. These studies argue that the diverse dimensions of financial distress in the Chinese equity market coupled with instances of creative accounting require a robust predictive model. Such a robust predictive model must combine an assessment of the relevant financial and non-financial performance of a firm.

4.2.4.2 Model Prediction Performance

Table 4.15 reports the assessment of the classification/predictive power for each of the four financial distress states in our multiple states nested models 1,2,3 and 5 using the baseline probability cut-off of 50%. In each panel, the bolded entries in the diagonal sequence are correctly classified observations while the rest of the entries are misclassified observations. The last column seven reports the percentage of accurate classification for each of the four financial distress states. Across the four models, the most accurate classification accuracy is observed in classifying firms in the NFDIS state (state 0) with a classification accuracy of 99.8%. The second most accurate classification across the four models is in classifying FWEAK firms (state 2). The worst classification performance of the four models is in classifying firms in the FDECL state second by the classifying firms in the FDIST state.

Overall prediction accuracy for the "accrual" model 1 (base model) is 93.3%. Despite being a multiple state model, the "full" model 3 prediction performance compares favourably with popular binary state models including Altman (1968) Z-score with 80% to 90% accuracy, Shumway (2001) Hazard method of 70.7% to 96.5% and Zhang et al. (2010)'s Z-China model.

Table 4.15: Model prediction performance (in Observations) using Cutoff of 0.5.

MODELS	OBSERVED	PREDICTED				PERCENT CORRECT
		NFDIS (State 0)	FDECL (State 1)	FWEAK (State 2)	FDIST (State 3)	
"Full" Model 3 ABR+MBR+CBR+CGI	NFDIS - State 0	**7,809**	22	1	0	99.8%
	FDECL - State 1	327	**226**	21	2	39.1%
	FWEAK - State 2	6	6	**445**	36	90.3%
	FDIST - State 3	0	0	53	**143**	73.0%
	Overall percent	89.5%	2.8%	5.7%	2.0%	**94.8%**
"Corporate Governance" Model 5 ABR+MBR+CGI	NFDIS - State 0	**7816**	15	1	0	99.8%
	FDECL - State 1	360	**186**	29	1	32.3%
	FWEAK - State 2	12	5	**439**	37	89.0%
	FDIST - State 3	0	0	453	**143**	73.0%
	Overall percent	90.0%	2.3%	5.7%	2.0%	**94.4%**
"Cash flow" Model 2 ABR+MBR+CBR	NFDIS - State 0	**7,812**	20	0	0	99.7%
	FDECL - State 1	381	**170**	23	2	29.5%
	FWEAK - State 2	7	4	**446**	36	90.5%
	FDIST - State 3	0	0	55	**141**	71.9%
	Overall percent	90.1%	2.1%	5.8%	2.0%	**94.2%**
"Accrual" Model 1 ABR+MBR	NFDIS - State 0	**7,821**	8	3	0	99.9%
	FDECL - State 1	447	**96**	30	3	16.7%
	FWEAK - State 2	19	2	**432**	40	87.6%
	FDIST - State 3	0	0	58	**138**	70.4%
	Overall percent	91.1%	1.2%	5.7%	2.0%	**93.3%**

Source: Author's compilation

The “accrual” model 1 predictive performance is impressive considering the model had to predict across four financial distress states which have more classification errors compared to a binary state model. We observe that the “accrual” model 1 had the least accuracy of 16.7% in classifying firms in the FDECL state with most Type I and II misclassification error resulting from classifying FDECL firms as NFDIS, FWEAK firms respectively. The “accrual” model 1 also suffered a lower accuracy of 70.4% in classifying firms in the FDIST firms with most Type I misclassification errors resulting from classifying FDIST firms as FWEAK firms. Our results suggest that although accrual-based ratios have a strong overall ability to discriminate between firms in different financial distress states, its weakness is in identifying firms at early FDECL state and firms at terminal FDIST state. The model classification weakness is seen in identifying early and terminal symptoms of financial distress. The classification weakness of the “accrual” model 1 draws from our finding in section 4.2.2. In that section, we found that there is no significant difference between firms in NFDIS and FDECL state in the aspects of liquidity, cash flow from operations, market valuation and financial leverage performance. Likewise, there is no significant difference between firms in the FWEAK state and FDIST state in regards to asset management efficiency, profitability, liquidity, cash flows, market valuation and corporate governance. Our FDECL state is analogous to Altman’s (1968) “grey area” which are performance areas shared by “financially healthy” and “financially distressed” firms. Although there is an overall difference between NFDIS and FDECL firms in terms of profitability, the instance of having ST (FDECL) firms on one-year net loss designated as NST (NFDIS) contribute to the Type I misclassification error in classifying FDECL firms. Since the “accrual” model 1 consist of only accrual-based ratios, there is no other factor by which the model could further classify firms across different financial distress states.

The integration of cash flow-based ratios (CFOTL, CFFTA and DPS) results in the “cash flow” model 2 with an overall classification accuracy of 94.2% which is an improvement from 93.3% by the “accrual” model 1. Likewise, the integration of corporate governance indicators (CEO_DUAL and INST_OWN) resulted in the “corporate governance” model 5 with an overall classification accuracy of 94.4% which is an improvement from 93.3% by the “accrual” model 1. When cash flow-based ratios and corporate governance indicators are integrated into accrual-based ratios, the overall classification accuracy is improved to 94.8%. Improvement is observed in classifying

FDECL, FWEAK and FDIST firms although a greater portion of the improvement is observed in classifying FDECL firms. Regarding the accuracy in classifying FDECL firms, this improved from 16.7% in the “accrual” model 1 to 29.5% in the “cash flow” model 2 and 32.3% in the “corporate governance” model 3 and 39.2% in the “full” model 3. The accuracy in classifying FDIST improved from 70.4% in the “accrual” model 1 to 71.9% in the “cash flow” model 2 and 73% in both the “corporate governance” model 3 and “full” model 3. The accuracy in classifying FWEAK is improved 87.6% in the “accrual” model 1 to 90.5% in the “cash flow” model 2 and 89% in the “corporate governance” model 3.

The result shows that the inclusion of cash flow-based ratios or corporate governance indicators introduces the necessary explanatory variables required to diagnose early distress symptoms (discriminate FDECL from NFDIS firms) and diagnose terminal distress symptoms (discriminate FDIST and FWEAK firms). Notably, the “accrual” model 1 that consists of only accrual-based and market-based ratios is limited in its ability to diagnose the *vague* difference between FDECL and NFDIS firms. Besides the FDECL, we observe that the FDIST state received the second poorest prediction accuracy across the four models from Table 4.15. Chinese listed firms at the highest delisting risk (SSTDelisted firms on FDIST state) are most likely to engage in earnings management and other creative accounting practices to remain listed (Chen, Chen & Huang, 2010; Yang et al., 2012). Where FDIST firms engage in creative accounting then the firm’s financial statements and financial ratios may not capture the true financial distress situation of the firm. In this case, our “accrual” model 1 would classify or predict the financial ratios of FDIST firms to belong to firms in the second-worst state that is, the FWEAK state. We observe from Table 4.15 that across the four MLR models, misclassified FDIST firms are classified as FWEAK firms. The inclusion of cash flow-based ratios and corporate governance in the “full” model 3 significantly improved the classification of FDIST from the base “accrual” model 1. Results from the “accrual” model 1, “cash flow” model 2 and “corporate governance” model 5 suggests that cash flow-based ratios or corporate governance indicators significantly improve the explanatory power of accrual-based ratios in the Chinese equity market. Our study found that combining both cash flow-based ratios and corporate governance indicators further improves the overall classification power of the model especially regarding the discriminating FDECL from NFDIS firms.

Similar to the goodness-of-fit/predict performance results, we observe that corporate governance indicators make a slightly greater classification performance improvement to accrual-based ratios than cash flow-based ratios. Our finding on corporate governance indicators is contrary to Kim et al. (2016) that argue that non-accounting variables such as corporate governance indicators do not provide incremental explanatory power in predicting the turnaround of ST firms and removal of ST designation. Our finding on the incremental explanatory power of cash flow-based in the Chinese equity market supports the finding by Stewart (2016) in the Australian equity market and Casey & Bartczak (1985), Bhandari & Rajesh (2013) and Sayari & Mugan (2013) in various equity markets. Our finding on the incremental explanatory power of corporate governance in the Chinese equity market supports the finding by Liang et al. (2016) and Chenchehene (2019) in the UK equity market.

4.2.5 Model Validation

For the sake of validating our "full" model 3, our sourced data of non-financial listed Chinese firms in the SSE and SZSE between 2009 and 2018 is split into estimation and validation sample datasets. The "full" model 3 was applied to the validation dataset and the validation performance compared to the estimation performance are reported in Table 4.17. Table 4.17 show that overall model classification accuracy experienced a very small decline when the model is tested on the validation sample, from 94.8% for the estimation dataset to 93.6% for the validation dataset. Model fit as represented by AIC, BIC and Deviance are almost the same between the estimation and validation datasets. Model predictive accuracy also slightly decline from McFadden R^2 and Cox-Snell R^2 of 0.581 and 0.469 for the estimation dataset to 0.571 and 0.462 respectively for the validation dataset. The very small differences (within one percent) between the model estimation and validation performance suggests the model performance and results is consistent when tested across samples.

Table 4.16: Full Model validation result

MODELS	McFadden R^2	Cox-Snell R^2	AIC	BIC	Deviance		Correct Prediction
Validation sample **"Full" Model 3**	0.575	0.462	4,236.32	4,487.74	4,162.53	**NFDIS - State 0**	99.5%
						FDECL - State 1	38.5%
						FWEAK - State 2	91.1%
						FDIST - State 3	70.8%
						Overall percentage	**93.9%**
Estimation sample **"Full" Model 3**	0.581	0.469	4,223.45	4,479.62	4,151.45	**NFDIS - State 0**	99.7%
						FDECL - State 1	39.2%
						FWEAK - State 2	90.3%
						FDIST - State 3	73.0%
						Overall percentage	**94.8%**

Source: Author's compilation

4.3 Chapter Summary

Chapter four addresses the four research objectives of this research using the two-stage multinomial logit and binary logit models. Both models are controlled for firm and industry heterogeneity, state ownership and macroeconomic factors.

This research found that profitability, liquidity, asset management efficiency, financial leverage, market valuation, ownership structure and board structure all have a significant *negative* effect on the probability of a firm belonging to the FDECL, FWEAK and FDIST states in the Chinese equity market. This association is *positive* for the probability of a firm being in the NFDIS state. Marginal effects analysis revealed that changes in predicted probabilities increase as the variable increases but then declines and slows down at larger values of the variable. For instance, while an increasing asset management efficiency initially increases the chances of the firm being "*financially healthy*", our results indicate that the effects seem to slow down when the firm attains higher efficiency levels. Inversely, financial leverage and cash flow from finance have a significant positive effect on the probability of a firm belonging to the FDECL, FWEAK and FDIST states in the Chinese equity market. This relationship is positive for the probability of belonging in the NFDIS state. The direction of association between financial ratios and corporate governance factors and financial distress as shown by the log coefficients are as expected and, consistent with the predicted probabilities, marginal effects and prior financial distress studies.

This research found that profitability (NITA) and asset management efficiency (TATURN) had the greatest effects in our multiple state model. amongst corporate governance indicators. The magnitude of the effect of financial ratios or corporate governance indicators is particularly captured in the steepness of the predicted probabilities curve for the respective financial distress state. We observe that with all the regressors, the strongest marginal effects magnitude is at the NFDIS state followed by the FDECL and the FWEAK, with the least effect at the FDIST state which is almost flat. There are grey areas of performance that both "financially healthy" firms in NFDIS state and firms in financial distress- FDECL and FWEAK states share in common. For instance, both financially healthy firms and firms in financial distress could experience a single year's net loss. This phenomenon is captured in the predicted probabilities curves of financial ratios and corporate governance indicators for the FDECL and FWEAK states that initially assume the same relationship direction with NFDIS firms but with increasing values of the variable, assume a different direction. This highlights the non-linear relationship between financial ratios and corporate governance indicators and financial distress states. Analysis of predicted probabilities shows that substantive effects of financial ratios and corporate governance indicators on predicted probabilities at different financial distress states: the FDECL, FWEAK and FDIST relative to the NFDIS state, vary greatly, even for a given odds ratio. Our study examined the effects of Individual explanatory variables (when other variables are held constant). Our findings indicate that the improvement of the individual aspect of firm performance has very little or no effect on late or terminal financial distress states which in our study is the FDIST state. Such changes during restructuring have slim chances of changing the overall financial distress health of the firm.

Furthermore, we show that the four financial distress states in this research are mutually exclusive and indeed statistically and significantly different from one another by the reason of the distribution of explanatory variables in each distress state. This implies we are correct to treat them as such in satisfying the IIA assumption of the multinomial logit. Other than net losses (profitability) criteria used efficiency, reduced dividend payment, increased cash flow from finance, reduced institutional ownership and weak board structure that determine the FDECL state. Otherwise, there is no difference between firms in FDECL and NFDIS states in regards to liquidity, financial leverage, market valuation and cash flow from operations. When firms deteriorate to the FWEAK state (state 2), in addition to determinant factors that are significant at FDECL state, we observe declining liquidity, reduced market valuation and weak cash flow from operations distinguishable between firms in the FWEAK state (state 2) and firms in the NFDIS state (state 0). Otherwise, there is no difference between firms in the FDECL, FWEAK and NFDIS states in regards to financial leverage. When firms deteriorate to the FDIST state (state 3), all "symptoms" as determinant factors of financial distress become obvious including financial leverage. In essence, determinant factors of the FDECL, FWEAK and FDIST states relative to the NFDIS state are different. In addition, determinant factors become evident in an ordinal manner-NFDIS, FDECL, FWEAK and then FDIST state that is the terminal state. Overall, accrual-based ratios are less effective in diagnosing early financial distress and this emphasizes the importance of cash flows and corporate governance information that are less susceptible to manipulation by management.

The study also found that the explanatory factors in a multiple state model and a binary state model are different. In the same vein, the effects of financial ratios and corporate governance indicators on the probability of financial distress in a multiple state model are different from a binary state model. Marginal effects in a binary state model are stronger. Predicted probabilities (likelihood) of financial distress are strongest at the FDIST and FWEAK states in a multiple state model, then the FDIST state in a binary state model and weakest at the FDECL state in a multiple state model.

The inclusion of cash flow-based ratios or corporate governance indicators improves the overall explanatory power of accrual-based and market-based ratios in a model. Specifically, cash flow-based ratios improve the explanatory power of market-based ratios only but not accrual-based ratios. On the other hand, corporate governance indicators specifically improve explanatory power in both accrual-based and market-based ratios. In addition, corporate governance indicators make better improvements to accrual-based and market-based ratios goodness-of-fit and predictive power than cash flow-based ratios since they measure non-financial aspects of firm performance. Cash flow-based ratios do not improve the explanatory powers of liquidity rather, explain a unique aspect of liquidity not assessed by accrual-based liquidity ratios. Empirical results suggest that although accrual-based and market-based ratios have a strong overall ability to identify or classify firms in different financial distress states, its weakness lies in identifying firms at early FDECL state and firms at terminal FDIST state. This is because accrual-based ratios are the most susceptible to creative accounting manipulation and where financial results can be manipulated, firms are also able to manipulate market results Cheng & Li (2015a). Cash flow-based and corporate governance factors make up for the gaps in classification accuracy performance by accrual-based and market-based ratios. Specifically, cash flow-based ratios and corporate governance factors are efficient in assessing firms in the early FDECL state that may share common significant explanatory factors with a healthy NFDIS state. This presents strong evidence to support the inclusion of cash flow-based ratios and corporate governance indicators in the final "full" model 3. It is also clear that cash flow-based ratios and corporate governance indicators explain aspects of financial distress that accrual-based and market-based ratios do not.

CHAPTER FIVE

SUMMARY AND CONCLUSION

Chapter five presents the conclusions on the key findings in achieving the four research objectives of this research and discusses the contribution and implications of the findings of this study. Section 5.1 presents key conclusions on the effects of financial ratios and corporate governance indications and how these effects differ at different financial distress states and in a binary state model. Section 5.2 discusses the contributions made by the findings of this research to the financial distress literature. It also discusses the implications of the findings of this research for the Chinese equity market regulators and the listed Chinese firms. Section 5.3 discusses the limitations of this research and offers recommendations for further research. Section 5.4 is the chapter summary.

5.1 Key Empirical Findings

This research examines the effects of financial ratios and corporate governance indicators on multiple states of financial distress, how the effects differ at different financial distress states and how the effects differ in a binary state of financial distress. This research further investigates the incremental information that cash flow and corporate governance add to accrual-based and market-based ratios. The maximum likelihood estimation is the main estimation method employed while the two-stage control function multinomial logit model is the main model used. Using the 2SCFMLR, this research used firm size, firm age and state ownership to control for firm-level heterogeneity, industry dummies to control for industry-level heterogeneity, and gross domestic product rate and lending rate to control for confounding influence bias. An unbalanced panel data consisting of 8,850 firm-year observations of 1,415 Chinese non-financial listed firms between 2009 and 2018 was used. From the literature review, nineteen explanatory variables were selected from accrual-based ratios, cash flow-based ratios, market-based ratios and corporate governance indicators. Following the likelihood ratio test method, eleven financial ratios and corporate governance indicators that made the greatest contribution to our model were selected for our research. Financial ratios are TATURN, NITA, WCTA, TLTA, CFOTL, CFFTA, DPS and corporate governance indicators are CEO_DUAL and INST_OWN. The conclusions on the four research objectives of this research are as follows:

5.1.1 Effects of Financial Ratios, Corporate Governance Factors on Multiple State Distress

The *first research objective* is to examine the effects of financial ratios and corporate governance indicators on the probability of multiple state financial distress. The empirical finding shows a significant negative effect of assets management efficiency, profitability, liquidity, market valuation, cash flow from operations, cash dividend, board structure and ownership structure on the probability of a firm being in *financial distress*, FDECL, FWEAK and FDIST states. These explanatory variables have a positive effect on the probability of a firm being in a *financially healthy*, NFDIS state. This implies that improving the aspect of firm performance that relate to these explanatory variables decrease the probability of the firm being in financially distressed, FDECL, FWEAK and FDIST state and at the same time, increases the probability of the firm staying financially healthy (NFDIS state), other factors held constant. Conversely, financial leverage and cash flow from finance have a significant positive effect on the probability of a firm being in *financial distress*, FDECL, FWEAK and FDIST state and a negative effect on the probability of a firm being in *financial health*, NFDIS state. The direction of the associations between financial ratios is expected and consistent with prior studies including Altman (1966), Chancharat (2008), Zhou et al. (2012), Zhou (2013), Zhang et al. (2010), Liang et al. (2016) Tinoco et al. (2018). Our finding on ownership structure is consistent with Lai & Tam (2017) that found that access to market information reduces investment risk for institutional investors in such a way that their ownership stake in a firm decreases as the probability of the firm becoming financially distressed increases. Further, the effects of board structure on financial distress support the findings by Li (2014), Lai & Tam (2017) and Chenchehene (2019) that separating the positions of the CEO and board chairman results in significant improvement in board efficiency and reduces financial distress risk.

From empirical findings, profitability showed the greatest magnitude of effect across the four financial distress states; the magnitude of the effect of profitability at least double that of board structure that displayed the second greatest effect. The magnitude of the effect of cash flow from finance, cash dividend and asset management efficiency ranked third, fourth and fifth respectively. There is no doubt that the Chinese equity market delisting system that designates firms based on two years of consecutive losses has driven the magnitude of the effect of profitability to a great extent and asset management efficiency to some extent. Liquidity, financial leverage and market valuation made the least effect in our study. Assessing late financial distress state reduced the magnitude of the effect of these explanatory variables but not their significance. We observe that factors such as profitability, asset management, cash flow from finance and cash dividend that assess early financial distress state made the greatest magnitude of effect. The board structure is significant in several studies including the study by Chenchehene (2019) in the UK market, the indicator made the second greatest magnitude of effect in our research which communicates a higher significance in the Chinese equity market. The CEO or general manager position wields a dominant power in China and such power increases the risk of power abuse and reduces board effectiveness (Lai & Tam (2017). The reorganization carried out by financially distressed firms is an opportunity to make further changes to their board structure such as merging the positions of the CEO and board chairman which further drives the effect of the CEO_DUAL indicator. The effects of ownership structure explain the situation where institutional investors in the Chinese equity market have better access to insider and privileged equity market information compared to individual investors.

Although a significant positive or negative association can be established between financial ratios and corporate governance indicators and financial distress, we observe from our marginal effects analysis that the true nature of these associations is nonlinear. Nonlinear positive association with NFDIS implies the curve slopes up from left to right and concave up while the negative association with financial distress, FDECL, FWEAK and FDIST states implies the curve slopes down from left to right and concave down. The *negative* effect of asset management efficiency, profitability, liquidity, market valuation, cash flow from finance, dividend payment, board and ownership structure and, financial distress tends to be skewed to the right. On the other hand, the *positive* effect of cash flow from finance and financial leverage tends to be skewed to the left. The nonlinear, skewed shape of the relationships further implies that each change in a financial ratio or corporate governance indicator will not always bring about the same effect on each of the four financial distress states. This situation is partly explained by the initial performance of a firm within a certain performance area (Wulff, 2015). For instance, a one-off net loss by a *financially healthy* NFDIS firm may not result in an increase in the probability of the firm going into financial distress however, repeated net losses by the firm do increase the probability of becoming financially distressed. Nonlinearity is strongest with factors such as profitability, board structure, asset management efficiency and board structure with the greatest magnitude of effect on financial distress. At initial lower values of these factors, the slope of the early FDECL state shows the same association direction as the NFDIS state however, the association direction changes with higher values of the factor. Notably, none of the other financial distress states - FWEAK and FDIST showed this attribute. This finding explains the “grey” area according to (Altman, 1983) where the performance of financial healthy firms overlaps with those of firms in early financial distress FDECL state. For instance, both financially healthy NFDIS firms and firms in early financial distress FDECL may suffer a decline in revenue, incur net losses and acquire external debt. At the instance of these performances, the curve for firms in both states assumes the same direction of the association. However, after a sustained period of performance in a particular aspect, the association direction begins adapting.

The effect of financial ratios and corporate governance indicators is lower for firms at FWEAK state and lowest for firms at FDIST state with the state showing an almost a flat curve. This corroborates the finding by Laitinen (1991) and Johnsen & Melicher (1994) that the further a firm’s financial health deteriorates, the lesser their chances of recovery. Our study further shows a very slim chance of firms in FDIST to recover by way of improved asset management efficiency, profitability, liquidity, market valuation, cash flow or corporate governance practice. On the other hand, the effects of financial ratios and corporate governance indicators are greatest for NFDIS firms with that state showing the steepest curve. Although NFDIS firms are deemed *financially healthy*, they are also the most *volatile* compared to the rest of the states. There is a high propensity for them to either stay financially healthy or show signs of declining financial health. This implies that the NFDIS firm is continuously on its way to financial health improvement or deterioration, and it *steeply* stays that course. Consequently, the marginal effect curve for firms at the NFDIS is the steepest amongst the other states.

5.1.2 Explanatory Factors and their Effects on Multiple State Financial Distress

In the *second research objective*, we examine the explanatory variables at each of the four financial distress states. Table 5.1 presents the conclusion on the significant financial ratios and corporate governance indicators and financial distress that determine firms in the four financial distress states. The orange coloured boxes indicate where explanatory factors become significantly (at a 1% level) different relative to the reference NFDIS state.

Figure 5.1: Significant explanatory factors at the four financial distress states

NFDIS – State 0	FDECL – State 1	FWEAK– State 2	FDIST – State 3
Weak assets efficiency	Weak asset mgmt efficiency	Weak asset mgmt efficiency	Weak assets efficiency
Poor liquidity & WC	Poor liquidity & WC	Poor liquidity & WC	Poor liquidity & WC
Poor Profitability	Poor Profitability	Poor Profitability	Poor Profitability
Increased Fin. Leverage	Increased Fin. Leverage	Increased Fin. Leverage	Increased Fin. Leverage
Poor Cash flow-Operation	Poor Cash flow-Operation	Poor Cash flow-Operation	Poor Cash flow-Operation
Increased Cashflow-Finance	Increased Cash flow-Finance	Increased Cash flow-Finance	Increased Cash flow-Finance
Little or No dividend	Little or No dividend	Little or No dividend	Little or No dividend
Low Market Valuation	Low Market Valuation	Low Market Valuation	Low Market Valuation
Different CEO& Chairman	Different CEO& Chairman	Different CEO& Chairman	Different CEO& Chairman
Low institutional ownership	Low institutional ownership	Low institutional ownership	Low institutional ownership

Source: Author's compilation

Our results show that different explanatory factors determine whether a firm enters different financial distress states. Our finding that different financial ratios and corporate governance indicators are driving different financial distress states is not consistent with the conventional assumption by several studies on the financial distress process by Tinoco (2018), Farooq et al. (2018) and Yi (2019). These studies studied the financial distress process, however, the same factors have been assumed or found to influence firms in different financial distress states. The delisting system mainly uses two years of consecutive losses (that is profitability) to designate firms into the ST status. In addition to net losses, our study found that firms in the FDECL state have poor asset management efficiency, increased cash flow from finance, declining cash dividend payment, low institutional ownership and poor board structure compared to firms in the NFDIS state. Profitability and asset management efficiency were the only accrual-based ratios that explain the early financial distress state of FDECL. The effect of these two factors has been driven by the "profit-based" delisting system in the Chinese equity market, otherwise, these factors are expected to be insignificant at the early FDECL state. Firms in the FWEAK state experience the same explanatory factors at the FDECL state in addition to weaker liquidity, poorer cash flow from operations and lower market valuation compared to firms in the NFDIS state. Firms in the terminal FDIST state experience the same explanatory factors at the FDECL and FWEAK states in addition to having the higher financial leverage compared to firms in the FDIST state.

Following the afore finding, it is tempting to assume that explanatory factors- *symptoms* (for instance, poor profitability) that are significant across two or more financial distress states would exhibit the same magnitude of effect across the distress states they are significant. The empirical finding suggests that that the magnitude of the effect of financial ratios and corporate governance indicators on the FDECL state compared to the NFDIS are not the same except for liquidity, cash flow from operations, market valuation and financial leverage. Further, we observe the magnitude of the effect of financial ratios and corporate governance indicators on the FWEAK state compared to the NFDIS are not the same except for financial leverage. Finally, the magnitude of the effect of financial ratios and corporate governance indicators on the FDIST state compared to the NFDIS are not the same for all firm performance areas assessed in our model.

5.1.3 Effects of Financial Ratios, Corporate Governance Factors in Binary State Vs Multiple State

In the *third research objective*, we examine explanatory variables and their effects in the multiple state financial distress model compared to the binary state financial distress model. From our results, we conclude that financial ratios and corporate governance indicators significant at the FDECL and FWEAK states in a multiple state "full" model 3 are significantly different from those in the FDIST state in the binary state "full" model 4. However, we note that explanatory factors significant at the FDIST state in a multiple state "full" model 3 and the FDIST state in a binary state "full" model 4 are the same. This means the FDIST state is a terminal distress state in both models where all explanatory variables are observed to be significant.

From our findings, we conclude that the effects of financial ratios and corporate governance indicators are different for all four financial distress states (multiple state model) and two financial distress states (binary state model). That is, in the binary state "full" model 3, the effect of an explanatory variable across the distress states is pooled rather than reported individually. On the other hand, the multiple state "full" model 3 reports the results of the effects of explanatory variables in each financial distress state. This results in the effects of explanatory variables being most likely greater in a binary state model than in the individual states of a multiple state model. Our conclusion from the comparison of the two models shows the importance of separating different financial distress states. Our empirical results also suggest that the statistical approach employed does influence the explanatory power of the regressors in the model.

5.1.4 Incremental Explanatory Power Cash Flow-Based Ratios and Corporate Governance Factors

The fourth research objective investigates the incremental information added by the cash flow and corporate governance to accrual-based and market-based ratios. Our research found that the inclusion of cash flow-based ratios and corporate governance factors improved the overall explanatory powers, goodness-of-fit and classification power of accrual-based and market-based ratios. Empirical findings suggest that corporate governance factors make better improvements to accrual-based and market-based ratios goodness of fit and predictive power than cash flow-based ratios since they measure non-financial aspects of firm performance that cash flows do not. The results show that cash flow-based ratios do not improve the explanatory powers of liquidity rather, explain a unique aspect of liquidity not assessed by accrual-based liquidity ratios which is consistent with the findings by Sharma (2001) on the distinction between accrual and cash flow liquidity.

Empirical results suggest that although accrual-based and market-based ratios have a strong overall ability to identify or classify firms in different financial distress states, its weakness lies in identifying firms at early FDECL state and firms at terminal FDIST state. This is because accrual-based ratios are the most susceptible to creative accounting manipulation and where financial results can be manipulated, firms are also able to manipulate market results Cheng & Li (2015a). cash flow-based and corporate governance factors make up for the gaps in classification accuracy performance by accrual-based and market-based ratios. Specifically, improvement cash flow-based ratios and corporate governance factors are observed identifying firms in the early FDECL state that share common significant explanatory factors with a healthy NFDIS state. This presents strong evidence to support the inclusion of cash flow-based ratios and corporate governance factors in our final “full” model 3. It is also clear that cash flow-based ratios and corporate governance factors explain aspects of financial distress that accrual-based and market-based ratios do not.

5.2 Contributions of the Study

Firstly, this research is among the first to comprehensively investigate the association between financial ratios and corporate governance factors and financial distress in the Chinese equity market with unique market structures and institutional backgrounds. This research extends the conventional approach of studying the linear relationship between these variables, by exploring the nonlinear and dynamic associations while controlling for endogeneity. This research shows how changes in explanatory variables affect the probability of multiple financial distress states rather than assume these effects are the same. Rather than assume this association is equal, this research show changes in explanatory variables effects changes in the association with the probability of multiple financial distress states. Further, this research expands current financial distress literature by adopting the definition of financial distress from the InsolvencyAct (1986), focusing on cash flow insolvency and balance sheet insolvency. Consequently, this research provides further understanding of key factors that are critical to defining and diagnosing financial distress by connecting financial distress definition to these key factors. In addition, this research extends the understanding of the definition of financial distress to the financial distress process perspective. In addition, the findings from this research provide a further understanding of the *grey areas* of firm performance shared by both *financially healthy* firms and firms in *financial distress.*

This research shows how the explanatory power and magnitude of effects of explanatory variables may differ from one equity market and jurisdiction to another. Although factors such as assets management efficiency, cash flow from finance and dividend payment are relevant to financial distress, they were not commonly used in financial distress studies in developed markets according to Rossari & Rahman (2005). However, in our research in the Chinese equity market, these factors showed strong explanatory power in explaining financial distress. We found that profitability and board structure make the greatest effect in the Chinese equity market because of the current delisting system and the institutional background in China. These factors may not make as much effect in studies elsewhere as they do in the Chinese equity market, and the context of every market will always influence the magnitude of the effect of explanatory variables.

The binary distress states approach to financial distress that is popular in financial distress research focuses on what happens to a firm when it is financially healthy and when it is at a terminal financial distress state such as insolvency. This research contributes to the scanty empirical research on multiple state financial distress process in three ways. First, this research shows how approaching financial distress as multiple states rather than binary states improves the understanding of the financial distress process and the nature of the effects of explanatory variables. This research provides an understanding of explanatory variables, symptoms, driving diverse financial distress states which is relevant when determining a firm's financial distress state within the financial distress process. Second, this research shows how the magnitude of the effect of explanatory variables, symptoms, defer for firms at different financial distress states. Third, this research integrates explanatory variables (cash flows and corporate governance) that are less susceptible to creative accounting manipulation to facilitate the diagnosis of early symptoms of financial distress. The cash flow-based ratios and corporate governance factors are factors that have been largely left out in key financial distress process studies by Lau (1987), Jones & Hensher (2004), Yao (2009), Pozzoli & Paolone (2017) and Yi (2019). Integrating both cash flow and non-financial – corporate governance factors enhance the robustness of the output of the financial distress prediction model by ensuring the model is less susceptible to manipulation. We show how cash flow and corporate governance factors can improve the explanatory and predictive power of the conventional accrual-based and market-based ratios by explaining aspects of financial distress not captured by accrual accounting and market information. The financial distress process approach provides more information on the financial health of a firm as well as the information investors require to assess the risk of investing in a stock and managing their investment risk. Adopting a multiple state approach result in a model that predicts the probability of a firm being in a certain financial distress state rather than investors predicting whether a firm will “fail” or “not fail”. This research is also useful to investors, creditors and management in assessing the financial health of firms and for auditors, in establishing the going concern of firms.

5.3 Implications of the Study

Where financial distress cannot be correctly or appropriately measured then it makes identifying and modelling it challenging. In the absence of a consensus on what explanatory variables to employ in financial distress research, this research contributes to the financial distress theory. In making this contribution, this research makes several findings that have implications on the selection of explanatory variables in the financial distress study. The research shows that the effects of explanatory variables in studies that adopt the binary state “dichotomous” approach are most likely exaggerated. Also, this research shows that not all explanatory variables used in research directly explain financial distress (insolvency) as defined by insolvency laws for instance the InsolvencyAct (1986). Some explanatory variables measure cash-flow insolvency and others measure balance sheet insolvency with the former preceding the latter. This research also shows that liquidity cash flow-based ratios and accrual-based ratios measured different aspects of firm liquidity and one does not help explain the other. The summary implication of these findings is that researchers need to properly define financial distress and multiple states in the financial distress process modelled before progressing into the study. The definition should point to appropriate explanatory variables that are significant in assessing aspects of financial distress already defined. In selecting explanatory variables, this research shows that factors that closely define insolvency may not always have the strongest effect in a multiple state financial distress approach. In essence, the effects of factors from a multiple state financial distress process differ from their effect in the conventional dichotomous financial distress process approach. Regarding measuring liquidity, researchers may not interchange liquidity based on accrual accounting for liquidity based on cash flow accounting because these measure different aspects of liquidity.

The Chinese Government and China Securities Regulatory Commission are determined to set new delisting rules and tighten up the delisting mechanism in a bid to manage financially distressed firms in the Chinese equity market (Xinhua, 2018). Therefore, the implications of our research are profound for the Chinese equity market considering the dynamic market structure and the weak

EBL process. The significance of integrating cash flow-based ratios and corporate governance factors that are less susceptible to manipulation is key in the Chinese equity market where Lai & Tam (2017) and Zhang et al. (2012) show that firms manipulate the earning-based delisting system criteria. In the Chinese equity market, this research finding supports the restructuring of the current "profit-based" delisting system since this framework applies to Chinese listed firms at different ST designations. Our study implies that the current criteria for the delisting system need to be robust to effectively assess the financial health of listed firms in different financial distress states. To assess early financial distress, the delisting system needs to include corporate governance factors and cash flow-based ratios, while factors such as liquidity, cash flow from operations and market valuation help assess later financial distress states.

Although profitability makes a great effect on the Chinese equity market, it implies a higher risk of firms manipulating the *profit-based* delisting system due to the high emphasis it places on earnings. The benefits of including cash flow-based ratios and corporate governance factors in the delisting system designation criteria are two folds. First, in the Chinese equity market where much emphasis has been placed on profitability, it de-emphasizes firm earnings to the point that firms would be discouraged to engage in earnings management. On the other hand, it emphasizes the need for firms to maintain healthy cash flows and incorporate best practice corporate governance Codes. Second, it facilitates identifying firms in early financial distress states using cash flows and corporate governance criteria. Complying with best practice corporate governance codes has been an issue with SOE due to the involvement of the state government in the governance of State enterprises (Yu, 2013). Including cash flow-based ratios and corporate governance factors encourage SOE to focus on corporate governance-related performance which may be *easier* to achieve than operational turnaround and earnings-related targets. Studies by Moses (1990), Palinko & Savoob (2016) and Beaver (2016) found the relationship between diverse aspects of firm performance such as corporate governance, profitability, or operational efficiency. Following the results of these studies, improving corporate governance performance would be a means to improving operational efficiency which is an underlying problem for SOE in China according to Yu (2013).

Presently, the Chinese central and state government provide bailouts in the form of increasing loans from state banks, subsidies, and tax incentives to Chinese distress *zombie* firms irrespective of where these firms are on the financial distress process. Our study shows that the effect of such bailout to boost cash flow, profitability, and asset management efficiency, on the probability of SST firms on delist warning (FWEAK firms) recovery is very low. Thus, it would be worthwhile if such bailout is channelled to firms in early financial distress states with higher chances of recovery. This is because the bailout has a greater potential of turning ST (FDECL) firms around to normal NST listing status than it has in turning SST (FWEAK) or SSTDelisted (FDIST) firms around to normal listing.

The implication of board size not being statistically significant in this research is that listed Chinese firms could determine the board size based on the company size and operations. Likewise, the percentage of non-executive and executive board members does not affect the probability of Chinese firms being in financial distress, rather these factors may be influenced by the firm size, qualification and experience composition of the board. In other words, the larger the firm size, the larger the board and percentage of non-executives. Board structure having the second greatest effect in this research shades light on the corporate governance practice of distressed Chinese non-financial listed firms especially SOEs whom there are concerns over their corporate governance practice. This study shows that separating the positions of the CEO and board chairman could result in better board and management efficiency which in turn reduces the probability of financial distress. Consequently, non-financial listed Chinese firms must consider separating the two positions irrespective of the firm size, age or state ownership status.

5.4 Limitations of the Study and Recommendations for Further Research

This research focused on the *symptoms* or explanatory variables evident at different financial distress states rather than the time firms stay in each financial distress state or time to each financial distress state. The conventional approach from pioneer financial distress research has been to predict the time taken by a firm to enter a terminal financially distressed state, usually terminal distress states. For instance, Altman (1968) Z score model claims to predict a firm's insolvency years before the event and so do other researches such as Ohlson (1980), Shumway (2001), Tinoco et al. (2018) and Yi (2019). Theoretically, this approach is superior since it puts investors in a better position to make investment decisions if they know, with high precision, how long a firm has before it enters a terminal financially distressed state such as insolvency or bankruptcy. Our research is limited in this aspect since the time that elapses for firms in different financial distress states is not accounted for. It would be ideal where the period spent in different financial distress states is modelled. It should be noted that exit options available to firms in financial distress, the influence of management strategies, equity market regulation and insolvency law process are some of the factors that influence "time" in a financial distress study. With these several latent factors, it is challenging to practically model the time a firm spends in each financial distress state or predict the time it takes for a firm to enter a particular financial distress state. This is because such a study must accurately measure and control these latent confounding factors influencing *time* in the study. In the case of China, the ineffectiveness of the delisting system coupled with the weak EBL process implies an SOE firm stays longer than expected in the ST or SST designation pool. We also believe that including time spent by firms at each financial distress state may complicate our assessment of the significance of explanatory variables at each financial distress. A viable opportunity for further research would be to assess the average time spent at each financial distress state and compare the results with an assessment of explanatory variables at each financial distress state. It is important that further study measures and control for factors that influence time in the study.

Investigating the causes of financial distress including comparing the causes of a firm's financial distress between state-owned enterprises (SOE) and non-state-owned enterprises in China is outside the scope of this research. This presents an opportunity for future research since Chinese SOEs receive many financial resources and government subsidies that non-SOE do not thus, causes of financial distress might differ for these categories of firms.

In modelling the relationship between financial ratios and corporate governance factors, this research controlled for *external factors* identified in Figure 2.2 except for environmental factors. However, it is challenging to control for latent environmental factor changes such as natural disasters and climate changes due to the uncertainty of these factors and the accuracy of proxies. The GDPR as a measure has been used to control macroeconomic as well as environmental factors in this study, however, we believe there could be a more accurate proxy to control for environmental factors.

Zhang et al. (2012) and Lai & Tam (2017) have found evidence as to the high likelihood of firms in financial distress (ST or SST) in the Chinese equity market to manipulate their results. Accrual-based ratios are the most susceptible to creative accounting manipulation (Zhang et al., 2012). Several accrual-based ratios were used in our study and corporate governance as non-financial factors have been employed in our model to mitigate instances of earnings management especially regarding profitability. Nonetheless, this approach does not eliminate the implications of manipulation of financial results and consequently accrual-based ratios. An opportunity for further research is to employ other non-financial factors that measure firm performance besides corporate governance, such as product or service quality, customer satisfaction and market share growth.

The sample of companies used in this research is limited to non-financial listed firms in the Chinese equity market. This may limit the generalization of the findings of this research to exclude listed financial firms and non-listed private firms that consist of mainly small and medium-sized firms. This bias may have higher implications for generalization for small and medium-size firms since they are more prone to financial distress according to Chan et al. (1985). A sample of listed financial firms has been excluded because of the unique nature of their balance sheets which would significantly skew the firms' financial ratios. A sample of non-listed private firms has been excluded due to the unavailability of their financial statements to the public. An opportunity for further research is to conduct similar research using a sample of listed financial firms or a sample of non-listed private firms where data is available.

The financial statements, market and corporate governance data and firm listing information for this research were primarily obtained from CSMAR data. Although the CSMAR is the key database of firms in the Chinese equity market, it should be noted that the findings of this research largely depend on the accuracy of this database.

5.5 Chapter Summary

This chapter provides the summary, contributions, implications, and limitations of the empirical findings of this research. The study found that asset management efficiency, profitability, liquidity, cash flow from operations, dividend payment and market valuation, board structure and ownership structure have a negative effect on the probability of a firm being in financial distress, FDECL, FEAK and FDIST state in the Chinese equity market. Inversely, financial leverage and cash flow from finance have a positive effect on the probability of a firm being in financial distress, FDECL, FEAK and FDIST state in the Chinese equity market. The nature of the effect of financial ratios and corporate governance factors on financial distress is nonlinear. This implies that a change in financial ratios and corporate governance factors does not bring about the same amount of effect on financial distress. This research also found that the financial ratios and corporate governance factors that explain different financial distress states - FDECL, FWEAK and FDIST are significantly different from the NFDIS state. In addition, the magnitude of the effect of these explanatory variables on different financial distress states - FDECL, FWEAK and FDIST are significantly different from the NFDIS state.

The findings of this research contribute to financial distress literature in several ways. This study contributes to the literature on the financial distress process and the explanatory factors that drive different financial distress states as well as the nature of the effect of these factors. The findings on determinants of different financial distress states will support the review of the designation criteria of the delisting system in the Chinese equity to make the system more robust in designating firms in financial distress. Our findings support the improvement of areas of firm performance to reduce the probability of a firm becoming financially distressed and increase the probability of a firm staying financially healthy. Our study also supports the approach of studying individual financial distress states rather than the *dichotomous* approach that does not capture the reality of firms in financial distress.

This research has not captured the time a firm spends in a financial distress state or predicting the time until a firm enters a financial distress state. This provides an opportunity for further study which may include proxies that sufficiently measure and control for confounding factors that may influence "*time*" in a financial distress study.

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