THREE ESSAYS ON FINANCIAL DISTRESS

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To my family, friends and teachers

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Sumaira Ashraf

Three essays on financial distress

Abstract

Large corporate failures and scandals in recent years indicate the shortcomings of current risk assessment tools and highlight the need for more extensive research on predicting financial distress (FD). The main objective of this thesis, comprised of three independent essays, is to provide empirical evidence on the factors affecting financial distress of firms. The *first essay* compares the accuracy of traditional distress prediction models at predicting the early warning signs of financial distress. The results reveal that the prediction accuracy of models declines for both early and more progressed financially distressed firms, when applied to an emerging market, Pakistan. The study results suggest that the researchers and practitioners should periodically revise the distress prediction models to adjust them with the dynamic changes in the business environment. The *second essay* for the first time investigates the benefit of combining accounting, market-based and financial reporting quality (FRQ) measures to predict financial distress of the developed and emerging market firms, UK and Pakistan, respectively. The resulting model shows good prediction accuracy for firms in the developed and emerging market, showing that the FRQ plays a significant role in the financial distress of firms. The findings of the study suggest that the researchers should use this hidden information of financial reports to predict financial distress of firms. The *third essay* explores the importance of board committee independence for firms operating in a developed market, the UK, and an emerging market, China. Our overall results support current best practice for corporate governance, which recommends more independent board members in compensation and nomination committees to ensure the unbiased selection and evaluation of corporate leadership.

Keywords: Financial distress, financial reporting quality, panel data, corporate governance, board committee's independence, conditional logit analysis

Três Ensaios sobre Empresas em Dificuldades Financeiras

Resumo

Nos últimos anos observou-se a falência de grandes empresas, bem como vários escândalos financeiros, o que se tornou indicativo da existência de falhas ao nível das actuais ferramentas de avaliação de riscos, bem como da necessidade de estudos relacionados com a previsão da existência de empresas em dificuldades financeiras (FD). O principal objetivo desta tese, composta de três ensaios independentes, é fornecer evidências empíricas sobre os fatores que afetam as empresas em FD. O *primeiro ensaio* compara a exatidão dos modelos tradicionais de previsão de *stress* em prever os primeiros sinais de alerta de FD nas empresas. Os resultados revelaram que a exactidão da previsão dos modelos diminui no caso das empresas em fase inicial ou mais avançada de FD, quando aplicados ao mercado emergente Paquistão. Os resultados do estudo sugerem que tanto investigadores como profissionais devem periodicamente rever os modelos de previsão de FD por forma a os ajustar às mudanças dinâmicas do ambiente de negócios. O *segundo ensaio* investiga, pela primeira vez, o benefício da combinação de medidas contabilísticas, baseadas no mercado e na qualidade dos relatórios financeiros (FRQ), para prever se as empresas dos mercados desenvolvido e emergente, Reino Unido e Paquistão, respectivamente, se encontram em FD. O modelo final resultante mostra uma boa precisão de previsão para as empresas dos mercados desenvolvidos e emergentes, mostrando que a FRQ desempenha um papel significativo no FD das empresas. Os resultados do estudo sugerem que os investigadores devem usar essa informação, oculta dos relatórios financeiros, para prever o nível de FD das empresas. O *terceiro ensaio* explora a importância da independência do conselho do quadro de directores para as empresas que operam quer num mercado desenvolvido, Reino Unido, quer num mercado emergente, China. Os resultados globais fundamentam a prática da melhor governança empresarial, o que conduz à recomendação de um quadro de directores mais independente, ao nível dos comités de remuneração e nomeação, como forma de garantir uma selecção e avaliação da liderança empresarial não enviesadas.

Palavras-chave: aperto financeiro, qualidade de relatórios financeiros, dados em painel, governança empresarial, independência dos comités do quadro de directores, modelos Logit condicionais

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Chapter 1: Introduction

Understanding the predictors of financial distress (FD) has been one of the most challenging tasks in the field of finance. Several seminal studies on the topic occurred in the 1960s, but in the past decade, there has been a string of major financial crises resulting in FD for firms in both developed and emerging nations. Despite a vast academic literature, there is a dearth of studies aimed at understanding the differential impact of a key predictor of FD in different economies of the world. The main objective of this thesis is to fill this research gap. This thesis, organized into three separate essays, contributes to the distress prediction literature by focusing on the topics that are important for investors, creditors, managers, and policymakers. The first essay tests the predictive accuracy of traditional distress prediction models, by widening the previous definition of FD used in research in emerging markets. The second essay introduces a financial reporting quality (FRQ) measure into the FD prediction models by developing a new distress prediction score with a set of accounting, market-based, and FRQ measures. The third essay explores the importance of corporate governance measures, specifically whether board committee independence impacts on the FD of firms operating in both developed and emerging markets.

This chapter gives an overview of the importance of FD along with a brief review of the literature. The research objectives and contribution of this thesis are also presented.

1.1. Financial distress and its importance

FD is a company's inability to pay current financial obligations and can ultimately lead to business closure. However, in order for all companies to operate and grow, they must, in one way or another, have some form of debt. An organized and diligent structured business plan will always involve a financial plan that includes both short-term and long-term debt. If a company’s assets are less than their debts overall value, a loan or debt restructure may be needed, which will then put the company in good financial standing with their debtors.

A business’s core purpose is to maximize its profit; however, with there being many factors which affect a firm’s ability to achieve those objectives, both internally and externally. For a business to remain profitable, it must focus on proper management control; environmental changes that affect their business directly and indirectly; and good financial planning.

Because a company facing FD may experience great loss, being able to investigate FD before it occurs is important to a business's success. The effects of a company in debt affect all its stakeholder; the employees, shareholders, managers, investors, and creditors. Companies, both locally and internationally, have experienced damaging consequences from ignoring the early warning signs of FD and the effects it has on a business's stability and growth. With the use of FD prediction models, many companies have seen a significant difference in their financial stability and have even been able to decrease their chance of going into bankruptcy.

A thorough and accurate FD prediction tool guide investors to legitimate and profitable financial opportunities, as well as help managers and executives, adjust their managerial and executive strategies accordingly. These tools have, also, been proven significant to insurance companies, policy makers, banks, financial analysts and foreign buyers.

1.2. Brief review of the literature

There is a plethora of financial distress prediction models in the literature which have been developed and tested by many researchers. Research practitioners frequently used FD prediction models to estimate the financial health of the companies. Since the seminal work of Beaver (1966), the literature on FD has flourished with several bankruptcy prediction models having been developed using this study. Altman (1968) extended the work of Beaver (1966), by employing multiple discriminant analysis with different accounting ratios to determine the most statistically significant ratios to envisage the distress. Over the last five decades, a number of researchers including Li & Rahgozar (2012), and Mizan & Hossain (2014) demonstrated that it is an accurate bankruptcy prediction model. After Altman's work, Ohlson (1980) developed a new accounting-based measure using logit analysis which requires fewer statistical assumptions than MDA. Zmijewski (1984) criticized that the sample in the bankruptcy literature is biased by the over-estimation of the troubled firms and only including those with complete data, he developed probit model after overcoming these limitations in the literature.

Another stream of literature consists of introducing market-based variables in the distress prediction literature. Shumway (2001) developed a hazard model with a set of accounting and market variables. His model was further tested by Chava & Jarrow (2004), Campbell et al. (2008) and Bonfim (2009). Later, a number of researchers highlighted an importance of market-based variables in distress prediction literature. Balcaen & Ooghe (2004) argue that, if researchers are only using financial ratios they make strong implicit assumptions that annual accounts are reflecting both internal and external information. Moreover, Tinoco and Wilson (2013) articulate that financial accounts do not reflect all important information related to bankruptcy and market variables could overcome this deficiency. Further, Beaver et al. (2005) stated that market-based variables are more suitable to predict FD, because the probability of default is embedded in the stock prices, and moreover they increase the predictability of distress prediction models (Agarwal & Taffler, 2008). Trujillo-Ponce et al. (2014) suggested that a combined model with both accounting and market-based variables is the best option, as both types of information are important for FD prediction.

The literature hitherto discussed could be described by critics as data-mining. Indeed, Blums (2003) emphasized that a model should be developed based on a strong theoretical framework which is arguably lacking in Altman's (1968) bankruptcy prediction model (Wilcox, 1971; Blum, 1974; and Scott, 1981). He proposed a D-Score model, based on the accounting and market-based variables within a stronger conceptual framework. Researchers subsequently continued to add new variables to the distress prediction literature based on stronger a-priori hypotheses (Tykvová & Borell, 2012; Korol, 2013).

The aforementioned studies in the literature classify distressed firms based on two criteria; a firm's legal state (Altman, 1968; Wu et al., 2010, Almamy et al., 2016), and entrance into a distress state (Lau, 1987; Cheng & Li, 2003; Hensher et al., 2007). The warning signs of a firm about to enter FD can be detected many years prior to failure, therefore researchers have also attempted to capture a firm transitioning through different stages of the phenomenon, from early containable stages to full-blown bankruptcy. For example, Foster (1978) defines four stages of FD based on product power and default on the debt, dividend, and bonds. Lau (1987) defines five states related to stability, dividend omission, loan default, protection under the bankruptcy act and, finally, bankruptcy filing. More recently, Cheng & Li (2003, 2006) used this definition of FD and broadly defined them into two states.

From the late 1980s to the mid-1990s, some authors (Hambrick & D'Aveni, 1988; Gilson, 1990; Daily & Dalton, 1994; Gales & Kesner, 1994) started to explore the relationship among bankruptcy and corporate governance variables. Results prove that corporate governance practices of a firm play a significant role in the FD of a firm. This is consistent with the conjectures from agency theory, that a conflict of interest between management and stakeholders can lead to deleterious impacts on the firm if the former does not internalize the interests of the latter (Donker et al., 2009). Recent researches also confirmed that corporate governance variables provide significant information to predict the likelihood of FD (see Fich & Slezak, 2008; Chang, 2009; Laitinen & Laitinen, 2009; Brédart, 2014; Schultz et al., 2015; Manzaneque et al., 2016).

1.3. Research objectives and main contributions

FD can cause severe, negative, social and economic consequences for society. The main objective of this thesis is to investigate the roles of the different factors which predict FD. This thesis is divided into three separate essays with the common aim of understanding the differences in the impact of accounting ratios, market-based variables, and corporate governance practices on the likelihood of FD of firm's operating in developed and emerging countries.

The first essay to test the predictive ability of traditional distress prediction models for the emerging markets with respect to early warning signs of FD. The second essay develops a model with a set of accounting, market-based, and financial reporting quality measures and test the differences in their impact on developed and emerging markets. The final essay explores the differences in the impact of corporate governance variables, specifically board committee independence, on the likelihood of FD for the firms operating in both developed and emerging economies.

The first essay contributes to the literature in two ways. First, it tests the generalizability of traditional distress prediction models (Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Shumway, 2001; Blums, 2003), which were constructed solely for US companies, to the less researched emerging market, Pakistan. This essay also analyses the performance of prediction models in terms of accuracy during the global financial crisis. Second, it extends the definition of FD for the emerging markets to account for the lack of proper databases, which clarify whether a company is financially stable or distressed. In addition to common distress types used in the literature (for instance, delisting, suspension, liquidation, winding-up, and bankruptcy), we also explored other warning signs such as face value, dividend/bonus declaration, annual general meeting, and listing fee to identify deteriorating condition of firms operating in Pakistan.

The second essay introduces financial reporting quality (FRQ) variables in the distress prediction modeling, along with a set of previously used accounting ratios, and market-based variables. To the best of our knowledge, the inclusion of financial reporting quality measures, earning and accruals quality, has not hitherto been considered in the literature. The presented model is constructed with a data from a developed market, the United Kingdom (UK), using a panel logit model, and then the model is applied to data from an emerging market, Pakistan. Another contribution is the testing of the model's robustness during the financial crisis, to understand how generalizable the model is.

The third essay assesses the relationship between board committee independence and FD, along with other common corporate governance variables for firms operating in a developed market (United Kingdom) and emerging market (China). Another contribution of this paper is the use of propensity score matching to match firms and then the use a conditional logit analysis to estimate how board committee independence influences the probability of FD. It tests the restrictive assumptions of models used in the previous literature. Many previous studies match distressed firms based on a subset of control variables, most commonly, firm size, industry, and year. This study contributes to the literature by testing these restrictive assumptions, through finding matches for distressed firms along all observable control characteristics, to verify the robustness of the overall model.

The thesis findings reveal that, although traditional distress prediction models can predict FD of the Pakistani equity market, there is a significant decrease in predictive accuracy during times of financial crisis. Hence, it is essential for the regulators, practitioners, academics, to periodically study and enhance the distress prediction models, to adjust them according to the dynamic nature of a firm's financial position. Moreover, the study findings reveal that the hidden portion of annual reports, measured with financial reporting quality proxies, plays a significant role in the FD of firms. This study offered a new distress prediction model with accounting, market-based, and financial reporting quality measures, which shows overall good prediction accuracy for both developed and emerging market. The results of the study also suggest that independent members of board committees play a significant role in the financial position of firms operating in both developed and emerging markets. Therefore, the firms should adopt corporate governance practices, with an increased level of independent directors to ensure unbiased decision making while appointing and evaluating the persons, who decide the future of business.

The three essays are presented in the similar structure to the papers submitted for consideration for publication in distinct journals, including international journals of CEFAGE-UE Journal Ranking. Since the three papers were prepared to read independently, there is a repetition of literature and concepts, given that they are all based on a common topic. The remainder of the thesis is organized as follows. The next three chapter presents three aforementioned independent essays, with the following structure: abstract, introduction, literature review, methodology, robustness test and concluding remarks. The last chapter summarizes the main conclusions of the distinct topics covered in this thesis and presents limitations and suggestions for future research.

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Chapter 2: Do traditional financial distress prediction models predict the early warning signs of financial distress?*

Abstract

This study aims to compare the prediction accuracy of traditional distress prediction models for the firms which are at an early and advanced stage of distress in an emerging market, Pakistan, during the period 2001-2015. An important contribution of the paper is the widening of the definition of financially distressed firms to consider the early warning signs related to a failure in dividend/bonus declaration, quotation of face value, annual general meeting, and listing fee. The results indicate that the three-variable probit model has the highest overall prediction accuracy for our sample while the Z-Score model more accurately predicts insolvency for both types of firms, i.e. those that are at an early stage as well as those that are at an advanced stage of financial distress. Furthermore, the study concludes that the predictive ability of all the traditional financial distress prediction models declines during the period of the financial crisis.

Keywords: Financial distress, emerging market, prediction models, Z-Score, logit analysis, probit model.

Jel Classification: G01, G11, G17, G32, G33

* This essay received a best paper award at 5th Annual Spain Business Research Conference and is currently submitted to Research in International Business and Finance Journal.

2.1. Introduction

Financial distress is a company's inability to fulfill their debt requirements; that is, going into bankruptcy, experiencing liquidation and another form of asset seizure and distribution (Sun et al., 2014). Because a company facing financial distress will experience huge losses, being able to predict financial distress before it occurs is paramount to a business's success. The degree to which a company's assets is less than the value of the debt may lead it to default on a contract, and ultimately affect all its stakeholders; its employees, shareholders, managers, investors and creditors alike (Chen & Merville, 1999). Pindado & Rodrigues (2005) argued that companies both locally and internationally have experienced damaging consequences, because of ignoring the warning signs of financial distress and the effects it has on a business's stability and growth. With the use of business failure prediction models, many companies have seen a significant difference in their financial stability and have even been able to lower their chances of going into bankruptcy. Bankruptcy prevention not only prolongs a firm's economic life and augments its financial performance, it also serves to improve a country's overall economic well-being.

Commonly used bankruptcy prediction models have been specially constructed for developed markets, as such, their relevance and prediction accuracy is questionable for emerging markets like Pakistan, with a large industrial manufacturing base[2]. Over the most recent two decades, many organizations in all economies have suffered financial distress so there is a need to recognize a model which may help investors to evaluate firms' financial issues and make judgments about their future. This can shield them from misfortunes arising out of the failure of organizations. We aim to answer three questions in this paper;

(a) Do traditional distress prediction models have the ability to predict financial distress of firms with early warning signs of bankruptcy;
(b) Which traditional distress prediction model (Altman (1968), Z-Score; Ohlson (1980), O-Score; Zmijewski (1984), Probit Model; Shumway (2001), Hazard Model and Blums (2003), D-Score model) can predict financial distress of Pakistani companies more accurately; and

[2] Many developed markets are witnessing the hollowing out of their manufacturing base which raises concerns of the applicability of financial distress models in emerging markets (Paolone & Rangone, 2015).

(c) What are the differences in the predictive ability of the models before, during and after the financial crisis?

A firm does not enter the state of financial distress at once, analysis of UK firms shows that a firm takes up to three years to enter the state of bankruptcy (Tinoco & Wilson, 2013). The case is the same for US firms, which tend to, on average, stop providing financial statements two years before bankruptcy (Theodossiou, 1993). Our study contributes to the literature by extending the definition of financial distress to apply also to firms that show early warning signs of financial failure, that is not only the firms that are well in the middle of financial distress. Our contention is that real benefit lies in identifying the signs of financial distress well before the ultimate disaster of liquidation sets in. Analyzing a firm's financial statements just before it goes into bankruptcy, or having a detailed investigation into what went wrong, serve little purpose for the investors or the economy at large. The material utility of financial distress prediction models is to pick up the signs early enough in order to start the financial reconstruction in good time. In addition to the other commonly available and applied definitions of financial distress, we selected those firms for our sample, who have failed to pay a listing fee, conduct an annual general meeting and whose shares are quoted at less than 50% of book value. We then tested the generalizability of the commonly used distress prediction models for the emerging market firms, which are at an early and advanced stage of distress. The manufacturing sector firms listed on one of the major stock exchanges of Pakistan, Karachi Stock Exchange during 2001 to 2015 are selected for this purpose. Further, the differences in the predictability of the models are tested before, during and after the financial crisis period. Additionally, a robustness test is conducted to check the differences in the predictive ability of models with respect to early-distressed firms.

Our overall results indicate that all five models are applicable for the emerging markets, but their prediction accuracy is slightly different than original studies in developed markets. The results show that the Probit model has the highest overall prediction accuracy, while the Z-score model more accurately predicts all the stages of the deterioration of a firm's financial position for the emerging market. A robustness test for each model also reflects the same results with respect to the early warning signs of financial distress. With this detailed evidence on the predictability of traditional distress prediction models, the current study suggests the practitioners in an emerging market like Pakistan with a large manufacturing base, can rely on the models proposed by Altman (1968) and Zmijewski (1984), to check the stage of firm's financial position and take decisions accordingly. Moreover, the empirical results suggest that there is a need to develop a model by identifying variables which will have a higher impact on the financial distress of firms operating in both developed and emerging markets and increases the overall prediction accuracy of the model.

The rest of the paper is organized as follows. The following section gives an overview of the previous literature in the area of distress prediction. Section three describes the data, sample, and methodology followed by empirical results in section four. The last section covers the conclusion and discussion of the result outcomes.

2.2. Literature review

Over the last five decades, financial distress prediction has been an interesting topic for researchers because of its incredible significance to companies, the economy and all other concerned parties (Wanke et al., 2015). To dissect the extensive literature on financial distress prediction, we divide our literature review into three parts. The first part covers the traditional bankruptcy prediction models, the second part analyzes the comparative studies on the distress prediction model, and the third part elaborates the criterion used to define financially distressed and stable firms.

2.2.1. Traditional distress prediction models

The empirical literature on financial distress prediction is large and varied, in terms of explanatory variables and methodological techniques. Since Beaver's seminal work (1966) using a univariate discriminant analysis to compare the ratios of failed and non-failed firms, a number of bankruptcy prediction models have been developed and tested by the researchers. Altman (1968) extended the work of Beaver (1966) by employing Multiple Discriminant Analysis (MDA) to identify a group of distress prediction ratios. Later, MDA has been used by many researchers including Deakin (1972), Grice & Ingram (2001) and Agrawal & Taffler (2007). Most recently, El Khoury & Al Beaïno (2014) tested the performance of original Altman Z-Score model for manufacturing companies operating in Lebanon and found that it is still a valuable tool to predict financial distress of Lebanese manufacturing sector. The findings of the study are consistent with Li & Rahgozar (2012) and Ihsan et al. (2015). On the other hand, Almamy et al. (2016) found that the prediction accuracy of the original Z-Score model decline with the passage of time for the UK market, especially during the global financial crisis.

Since 1968, the Altman model has been widely used in the distress prediction literature, but the MDA technique is sharply criticized because of its restrictive assumptions about multivariate normality and the independence of explanatory variables (Ohlson, 1980). To overcome these limitations, Ohlson (1980) proposed a new model based on logit analysis with a set of nine accounting ratios. This resulted in the proliferation of studies using logit analysis and an improvement of financial distress predictability (Campbell et al., 2008; Sun et al., 2014; Jones et al., 2015; Jones et al., 2017). Furthermore, Zmijewski (1984) employed probit analysis and developed a three-variable distress prediction model, which was further tested by many researchers including Wu et al. (2010) and Kleinert (2014).

Shumway (2001) presented a further extension of financial prediction models, who criticized the static bankruptcy prediction techniques and developed a discrete hazard model with the addition of market-based variables, which led to increases in the overall classification accuracy of a model. His model was further tested by a number of researchers including Campbell et al. (2008) and Bonfim (2009). Later on, researchers including Chava & Jarrow (2004) and Agarwal & Taffler (2008) articulated that market-based variables reflecting both internal and external information increases the overall predictability of distress prediction models. Further, Trujillo-Ponce et al. (2014) suggested that a combined model with both accounting and market-based variables is the best option, as both types of information are important for distress prediction.

A major drawback of previous distress prediction models is the lack of strong theoretical framework, for example, one of the most widely used studies of Altman (1968) was developed with limited data and by searching right variable (Wilcox, 1971; Blum, 1974; and Scott, 1981). To address this problem in the literature, Blums (2003) proposed a D-Score model, based on the accounting and market-based variables with the strong conceptual framework. After that researchers continued to add new variables to the distress prediction literature with the strong theoretical background. For instance, Tykvová & Borell (2012) employed a set of liquidity, profitability and solvency ratios, moreover, Korol (2013) used a set of profitability, liquidity and activity ratios with a strong theoretical background.

2.2.2. Comparative position

The plethora of financial prediction models in terms of variables and techniques warrants research to investigate which variables and models perform the best at financial distress prediction. Begley et al. (1996) demonstrated that both the Z-Score and O-Score models did not perform well for US firms with data belonging to the 1980's. By contrast, Pongsatat et al. (2004) found that both models significantly predict defaulter firms operating in Thailand. Abdullah et al. (2008) found that the hazard model outperforms MDA and the Logit model for Malaysian firms. Nam et al. (2008), found similar results and reported that the hazard model has a higher accuracy level than the static logit model for the Korean firms. On the other hand, Kordlar & Nikbakht (2011) proved that the O-Score more accurately predicts financial distress for Iranian firms when compared with Z-score, probit, and hazard model. Further, Imanzadeh et al. (2011) compared the performance of Springate (1978) and Zmijewski (1984) models for firms on the Tehran Stock Exchange and found that Zmijewski’s (1984) model is the most accurate predictor of bankruptcy.

Recently Tinoco & Wilson (2013) tested the performance of the Altman (1968) Z-Score model for UK firms and noticed a significant decrease in the prediction accuracy of the model than the original study. On the other hand, Roomi et al. (2015) reported that the Z-score model is a good predictor for predicting financial distress of Pakistani firms. Moreover, Jaffari & Ghafoor (2017) found that the logit model is better than MDA, but the prediction accuracy of the models declines when applied to the Pakistani market. More recently, researchers including Mselmi et al. (2017) and Jones et al. (2017) reported that the logit analysis is the most accurate predictor for a French and US market, respectively. In sum, the literature reports mixed results with respect to the predictive ability of the traditional distress prediction models when applied to different economies of the world.

2.2.3. Definition of financial distress

Most of the previous studies on default prediction models differentiate financial distress in two ways; legal state (Altman, 1968; Shumway, 2001; Wu et al., 2010, Almamy et al., 2016); and, doorway to distress state (Lau, 1987; Hill et al., 1996; Cheng & Li, 2003; Hensher et al., 2007). Financial distress is the state wherein the firm has insufficient cash flows to meet its debt obligations (Wruck, 1990). The effects of financial distress can be detected in advance by witnessing a decrease in firm value before the actual default of a firm (Whitaker, 1999). A number of researchers make use of different states of financial distress based on the pre-warning signs. Foster (1978), for instance, defines four stages of financial distress based on debt payments, dividend payments, products power and bond default. Chen (1983) categorize companies based on three states; financial distress, financial imbalance, and bankruptcy. He defined financial distress as the state of power revenue, delayed debts and the shortage of cash flows. Furthermore, Lau (1987) defines five states of financial distress based on stability, missing or decrease in the dividend, loan payment default, protection under the bankruptcy act, and finally bankruptcy filing. Moreover, Cheng & Li (2003) modified financial administration stages of the Lau (1987) model and broadly defined them based on financial distress and financial stability with the four states of financial distress used in the original model. Later, Cheng & Li (2006) use this modified version of the model to develop a pre-warning model based on fuzzy regression.

If the net worth of the company's shares is less than its book value then the firm is in the stage of financial distress (Wang & Deng, 2006). Similarly, we define a firm is in the early stage of distress if the quotation of its shares is less than 50% of the book value for three consecutive years. In addition, akin to the previous literature (see e.g. Foster, 1978; Lau, 1987; Cheng & Li, 2006), we also classify financial distress as the reduction or omission of dividend payments for five consecutive years. Theodossiou (1993) articulated that firms stop publishing financial statements at least two years before filing for bankruptcy. If the firm is not publishing final accounts, it will not conduct an annual general meeting. Therefore, we argue that firms who do not publish their financial statements for at least three consecutive years are in the early stages of financial distress[3]. It is widely understood that the financially distressed firm face difficulties to meet its obligations and if the firm is not paying a listing fee of the stock exchange, it is in the state of distress. Hence, firms that failed to pay the annual listing fee for two consecutive years is in the early stages of distress and categorized as early distressed firm in our study.

Tinoco & Wilson (2013) argued that financial distress is costly for the creditors of the firm and they want to minimize the cost of it by taking necessary actions. Therefore, a reliable financial distress prediction model should have the capability to predict all the stages of a firm's financial position, the early stage of distress, and the advanced stage of financial distress. We contribute

[3] It should be noted that this study covers data relating to financial years up to FY 2015 when the new Companies Act 2017 had not come into force, which entails provisions for the automatic delisting of companies that fail to file annual accounts or hold annual general body meetings within the prescribed time limits

to the literature by testing the predictive ability of five well-known traditional distress prediction models by including early distressed firms in our sample. Moreover, existing studies on the financial distress literature suffered from a few limitations for emerging markets. The first issue is related to the selection criteria for the distressed firms because there are no databases available with financial information pertaining to these companies. The current study addresses this problem by selecting companies based on the financial criteria used for developed markets from popular databases along with that we extended the definition of financial distress and included early distressed firms in our sample. The second issue has been limited availability of financial distress data for the emerging markets. There was a need to collect more historical data with the large time frame and sample, to comment better on the predictive ability of traditional distress prediction models. The extant study addresses this issue by using the large time frame of fifteen years for all the companies listed on one of the emerging markets to test the applicability of the models. Thirdly, according to the best of our knowledge, none of the studies focused on the differences in the predictive ability of the models with respect to the financial crisis for emerging markets. The current study checks the difference by dividing the sample into three periods; pre-crisis period (2001-2006), financial crisis period (2007-2009) and post-crisis period (2010-2015).

2.3. Sample and methodology

2.3.1. Construction of sample

Our sample first meet the following inclusion criteria: (1) the company is listed on the Karachi stock exchange (KSE) during 2001 to 2015, (2) the company belongs to the non-financial sector, (3) financial statement data is available in the annual reports published by the State Bank of Pakistan from 1998 to 2015. Using these criteria, a sample of 431 companies was selected, which were further classified based on their financial position. This study used two criteria to classify firms to compare the results with those from previous studies; i) common death types used in the literature by many researchers (Taffler, 1982; Opoku & Abor, 2009; Christidis & Gregory, 2010; Almamy et al. 2016). ii) an additional criterion which includes defaulter firms who did not fulfill their listing requirements and obligations (see table 2.1).

Table 2.1: Definition of financial distress stages

Stages of financial position	Description	Degree of financial position
State 0	Financial stability	Stable
State 1	Defaulter firms with below reasons for default: (i) Less than 50% quotation of book value for consecutive 3 years (ii) Failure of dividend/bonus declaration from continuous 5 years (iii) Failed to conduct AGM for consecutive 3 years (iv) Failed to pay the yearly listing fee for 2 years. Delisted/Suspended/Liquidation/Winding up/Bankruptcy	Financial distress

Using the above criterion, 179 companies were classified as distressed from 2001 to 2015. The study uses an un-paired sampling technique frequently employed in the distress prediction literature by many researchers (Ohlson, 1980; Taffler, 1982; Zmijewski, 1984; Begley et al., 1996; Wu et al., 2010; Almamy et al., 2016), and includes 252 remaining manufacturing sector companies listed on the Karachi Stock Exchange during any year from 2001 to 2015 as financially stable firms. The total listed companies of KSE differ every year which gives us the sample of total 5,265 observations for both distressed and stable firms from ten[4] major industrial sectors.

Secondary data is collected from different sources: balance sheet analysis published by the State bank of Pakistan; analysis reports published by the Karachi Stock Exchange; Business Recorder (BR); Yahoo Finance; and, indices published by the World Bank.

[4] Textile; Sugar; Food Products; Chemicals & Pharmaceuticals; Other Manufacturing; Cement; Motor Vehicles, Trailers & Autoparts; Fuel & Energy; Coke & Refined Petroleum Products; Paper, Paperboard & Products; Electrical Machinery & Apparatus.

2.3.2. Distress prediction models

Over the last four decades, several distress prediction models have been developed by various researchers. Most commonly used are:

a) **Altman (1968), Z-Score Model**

$$\mathrm{Z} = 1.2\mathrm{WCTA} + 1.4\mathrm{RETA} + 3.3\mathrm{EBITTA} + 0.6\mathrm{MCTL} + 1.0\mathrm{STA} \tag{1}$$

b) **Ohlson (1980), O-Score Model**

$$\mathrm{O} = \left\{1 + \exp\left(-\begin{bmatrix} -1.3 - 0.4\mathrm{OSIZE} + 6.0\mathrm{TLTA} - 1.4\mathrm{WCTA} \\ +0.1\mathrm{CLCA} - 2.4\mathrm{OENEG} - 1.8\mathrm{NITA} \\ +0.3\mathrm{FUTL} - 1.7\mathrm{INTWO} - 0.5\mathrm{CHIN} \end{bmatrix}\right)\right\}^{-1} \tag{2}$$

c) **Zmijewski (1984), Probit Model**

$$P = \Phi(-4.336 - 4.513\mathrm{NITA} + 5.679\mathrm{TLTA} + 0.004\mathrm{CACL}) \tag{3}$$

d) **Shumway (2001), Hazard Model**

$$\mathrm{H} = \left\{1 + \exp\left(-\begin{bmatrix} 13.303 - 1.982\mathrm{NITL} + 3.593\mathrm{TLTA} \\ -0.467\mathrm{RSIZE} - 1.809\mathrm{LExReturn} \\ +5.791\mathrm{LSigma} \end{bmatrix}\right)\right\}^{-1} \tag{4}$$

e) **Blums (2003), D-Score Model**

$$\mathrm{D} = -4.907 - 2.11\mathrm{NITA} + 0.0006\mathrm{TDTE} - 1.734\mathrm{META} - 0.016\Delta\mathrm{P} + 0.005\Delta\mathrm{S} + 5.885\mathrm{CLTA} \tag{5}$$

Table 2.2 shows a summary of the variables and analysis technique for each model. Using an up-to-date data set from the emerging market, we compare the prediction accuracy of these models.

Table 2.2: Summary of distress prediction models and variables employed

Model	Analysis Techniques	Variables	Description
Altman (1968), Z-Score Model	Multiple Discriminant Analysis	*WCTA*	Working capital/Total assets
		RETA	Retained earnings/Total assets
		EBITTA	Earnings before interest & taxes/Total assets
		MCTL	Market value of equity/Book value of total liabilities
		STA	Sales/Total assets
Ohlson (1980) O-Score Model	Logit	*OSIZE*	Log (Total assets/GNP price-level index)
		TLTA	Total liabilities/Total assets.
		WCTA	Working capital/Total assets
		CLCA	Current liabilities/Current assets.
		OENEG	One if total liabilities exceed total assets, zero otherwise
		NITA	Net income/Total assets
		FUTL	Funds provided by operations/Total liabilities
		INTWO	One if net income was negative for the last two years, zero otherwise
		CHIN	$\frac{NIt - NIt\_1}{\lvert NIt\rvert + \lvert NIt\_1\rvert}$ where NI_t and NI_{t_1} is the net income for the most recent and the preceding year respectively. The variable measures the change in net income.
Zmijewski (1984) Probit Model	Probit	*NITA*	Net income/Total assets
		TLTA	Total liabilities/Total assets
		CACL	Current assets/Current liabilities
Shumway (2001) Hazard Model	Hazard	*NITL*	Net income/Total liabilities
		TLTA	Total liabilities/Total assets
		RSIZE	Log (the number of outstanding shares multiplied by year-end share price then divided by total market value)
		LExReturn	Cumulative return of Company in year *t-1* less cumulative return of KSE in year *t-1*
		LSigma	Standard deviation of residual derived from regressing monthly stock returns of company on market return in year *t-1*
Blums (2003) D-Score Model	Logit	*NITA*	Net income/Total assets
		TDME	Total Debt/Market equity
		META	Market Equity/Total assets
		ΔP	6-month Stock Price change
		ΔS	3-year Sales Growth
		CLTA	Current liabilities/Total assets

The methodology involves constructing model scores for both financially distressed and stable firms and then comparing the prediction accuracy of the models with the original position. To check the prediction accuracy of models, we used original cut-off points of the models; 2.67 for Z-score, 0.038 for O-score, and 0.5 for the remaining three models. Predictive ability of the models is evaluated based on overall precision accuracy together with Type I and Type II error. Table below shows Type I and Type II errors along with different types of costs linked with each.

Table 2.3: Type of errors

Actual Position	Model's Prediction	
	Distressed	Stable
Distressed	Correctly predicted	Type I Error
Stable	Type II Error	Correctly predicted

2.4. Empirical results

2.4.1. Descriptive statistics

The descriptive statistics of variables from all five models are shown in table 2.4. The variables from all models are categorized into five groups: profitability; liquidity; leverage; company size; and, market-based variables. The table lists mean, median and standard deviation for both distressed and stable firms. There are clear differences in the mean value of distressed and stable firms. The average mean of *profitability* variable, *sales growth* (*ΔS*) is quite low -0.01 for distressed firms than the stable firms, indicating the declining sales of distressed firms. The distressed firm's ability to pay short-term debts, as indicated by the *liquidity ratio* (*WCTA*) which is quite low for distressed firms (-3.55) than the stable firms (0.03). The mean of the *leverage ratio*, *total liabilities to total assets* (*TLTA*) for distressed firms (4.54) is quite high than that for stable firms (0.61). Similarly, *Relative Size (RSIZE)* of stable firms has a higher mean of -1.8 than the distressed firms with the mean of -2.71. The table also lists the two-sided t-test values, which shows that the mean of both groups is significantly different for most variables, at 1% and 5% level.

Table 2.4: Descriptive statistics of distressed and stable firms

Independent Variables	Distressed N = 1724			Stable N = 3541			T-test [a]
	Mean	Med	SD	Mean	Med	SD	
Profitability							
EBITTA	0.65	0.00	0.56	0.11	0.09	0.01	0.17
STA	0.69	0.51	0.02	1.36	1.12	0.05	0.00**
NITA	0.06	-0.03	0.12	0.04	0.03	0.00	0.86
CHIN	0.31	0.00	0.43	0.17	0.03	0.23	0.76
ΔS	-0.01	0.00	0.02	0.14	0.11	0.01	0.00**
Liquidity							
WCTA	-3.55	-0.19	0.71	0.03	0.03	0.01	0.00**
CLCA	26.71	1.70	5.45	1.28	0.94	0.05	0.00**
FUTL	0.13	0.00	0.12	0.11	0.09	0.01	0.75
INTWO	0.40	0.00	0.01	0.10	0.00	0.01	0.00**
OENEG	0.39	0.00	0.01	0.04	0.00	0.00	0.00**
CACL	3.26	0.59	0.74	1.48	1.07	0.06	0.00**
CLTA	15.47	0.59	5.14	0.46	0.44	0.00	0.00**
Leverage							
RETA	-50.66	-0.10	15.18	0.25	0.26	0.01	0.00**
MCTL	2.68	0.12	0.76	1.65	0.42	0.26	0.10*
TLTA	4.54	0.86	0.72	0.61	0.61	0.01	0.00**
NITL	-0.19	-0.03	0.77	0.12	0.06	0.01	0.56
META	4.73	0.13	1.21	0.51	0.25	0.05	0.00**
Company Size							
OSIZE	1.33	1.41	0.01	1.79	1.76	0.01	0.00**
RSIZE	-2.71	-2.87	0.02	-1.80	-1.67	0.02	0.00**
Market							
LExReturn	-0.23	-0.28	0.01	-0.11	-0.15	0.01	0.00**
LSigma	0.17	0.14	0.00	0.14	0.12	0.00	0.00**
ΔP	0.20	0.00	0.02	0.28	0.07	0.02	0.00**

[a] P-Value of two-sided t-test to check the mean differences between distressed and stable firms.
*, ** indicating significance at 10% and 5%, respectively.

2.4.2. Prediction accuracy of models

We compare the overall accurateness of all five models, along with Type I and Type II error. Type I is the incorrect classification of distressed companies, while Type II error is the incorrect classification of stable companies. As shown in table 2.5, the prediction accuracy of D-Score model is higher (86.3%) for the distressed companies then only 22.9% for the stable, indicating that the model over-estimates the sample companies as distressed and shows only 43.6%

overall prediction accuracy. The overall prediction accuracy of O-Score and Hazard model is 61.9% and 70.7% respectively, but the Type I error is higher for both models with the value of 94.5% and 88.3%, which indicates that the models over-estimate the companies as financially strong. According to Hsieh (1993), the cost linked with Type I error is higher than the Type II error, so the best model should have the lowest Type I error. The remaining two models Z-Score and Probit perform well for the Pakistani equity market with the overall prediction accuracy rate of 67% and 73.8%, with a Type I error of 20.9% and 35.2% respectively. The results indicate that the overall prediction accuracy of the models decreases than the original studies, Blums (2003) D-Score model from 71.8% to only 43.6%, Ohlson (1980) O-Score from 96.4% to 61.9%, Altman (1968) Z-Score 95% to 67%, Shumway (2001) Hazard model 96.5% to 70.7%, Zmijewski (1984) Probit model 98.2% to 73.8%.

Table 2.5: Prediction accuracy of models

Model Prediction	Distressed		Stable		Overall
	Distressed	Type I Error	Stable	Type II Error	
Z-Score	1364	360	2165	1376	5265
	79.1%	20.9%	61.1%	38.9%	67.0%
O-Score	95	1629	3163	378	5265
	5.5%	94.5%	89.3%	10.7%	61.9%
Hazard	201	1523	3522	19	5265
	11.7%	88.3%	99.5%	0.5%	70.7%
Probit	1118	606	2766	775	5265
	64.8%	35.2%	78.1%	21.9%	73.8%
D-Score	1487	237	810	2731	5265
	86.3%	13.7%	22.9%	77.1%	43.6%

This table presents the overall prediction accuracy of models along with type I and type II error. Results are displayed in both numeric and percentage form for each model. The first column is the list of models, second and third column reports classification results for distressed firms, third and fourth column reports the classification results for stable firms and the final column shows overall classification accuracy of models.

Our results showed that the Probit model of Zmijewski (1984) has the higher overall prediction accuracy for the Pakistani equity market than all other models in the study. The findings of our study are consistent with Oude (2013), who tested the prediction accuracy of Altman (1968), Ohlson (1980), and Zmijewski (1984) models for the Dutch firms. Similar results were reported by Wu et al. (2010), who compared five distress prediction models for US firms by using data from 1980 to 2006. While doing the comparison of Ohlson (1980) and Altman (1968) model, we found that the Ohlson model performs worse than the Altman model. Our results are consistent for the UK and Malaysian market as reported by the studies of Agrawal et al. (2007) and Abdullah et al. (2008), respectively. The opposite results were found by Begley et al. (1996) and Jaffari (2017) for the US and Pakistani market, respectively. Our results also showed that the prediction accuracy of Shumway (2001) model is quite lower for the Pakistani Equity Market, inconsistent with the findings of Wu et al. (2010) and Kordlar et al. (2011) for US and Irani market, respectively.

2.4.2.1. Pre-crisis (2001-2006)

In addition to the prediction accuracy of the model for the whole sample period from 2001 to 2015, we also tested the prediction accuracy of the models before, during and after the financial crisis. Table 2.6 indicates that the results of the models before the financial crisis are consistent with the overall time period results. D-Score leads to higher Type I errors while the O-Score and Hazard's model show higher rates of Type II errors. The Probit model has the highest overall prediction accuracy (75.6%) while the Z-Score prediction accuracy is slightly lower (67.1%).

Table 2.6: Prediction accuracy of models before financial crisis

PRE-CRISIS					
Model Prediction	**Distressed**		**Stable**		**Overall**
	Distressed	**Type I Error**	**Stable**	**Type II Error**	
Z-Score	654	208	850	530	2242
	75.9%	24.1%	61.6%	38.4%	67.1%
O-Score	21	841	1350	30	2242
	2.4%	97.6%	97.8%	2.2%	61.2%
Hazard	96	766	1376	4	2242
	11.1%	88.9%	99.7%	0.3%	65.7%
Probit	573	289	1122	258	2242
	66.5%	33.5%	81.3%	18.7%	75.6%
D-Score	770	92	284	1096	2242
	89.3%	10.7%	20.6%	79.4%	63.5%

This table presents the prediction accuracy of models before the financial crisis in numeric and percentage form.

2.4.2.2. During crisis (2007-2009)

A large number of companies around the world faced difficulties in survival during the financial crisis (Duchin et al., 2010; Vermoesen et al., 2013). According to the Economic

Survey 2009-10 published by the Government of Pakistan, there was a 33% decrease in the after-tax profits of the listed companies at KSE. The study uses 2007 to 2009 as the crisis years as considered by Dietrich & Wanzenried (2011). As shown in table 2.7, the overall prediction accuracy of the Probit model is higher (69.5%) than the Z-Score model while the Z-Score more accurately (82.4%) predicts distress during the crisis time period. There was a significant decrease in the prediction accuracy of both models at the time of financial crisis; Z-Score decreases from 67.1% to 62.9%, and Probit model from 75.6% to 69.5%.

Table 2.7: Prediction accuracy of models during financial crisis

DURING CRISIS					
Model Prediction	**Distressed**		**Stable**		**Overall**
	Distressed	**Type I Error**	**Stable**	**Type II Error**	
Z-Score	308	66	355	325	1054
	82.4%	17.6%	52.2%	47.8%	62.9%
O-Score	8	366	669	11	1054
	2.1%	97.9%	98.4%	1.6%	64.2%
Hazard	42	332	677	3	1054
	11.2%	88.8%	99.6%	0.4%	68.2%
Probit	247	127	486	194	1054
	66.0%	34.0%	71.5%	28.5%	69.5%
D-Score	150	224	317	363	1054
	40.1%	59.9%	46.6%	53.4%	44.3%

This table presents the prediction accuracy of models during the financial crisis (2007 to 2009) in numeric and percentage form.

2.4.2.3. After crisis (2010-2015)

There was a significant increase in the number of companies with financial difficulties which lead to the downward trend in Karachi Stock Exchange after the global financial crisis (Hameed et al., 2013). The comparison of performance in table 2.8 depicted that Type I error is quite lower (17.3%) for the Z-Score model than the Probit model (38.1%) after the financial crisis, which indicates that the Z-Score more accurately predicts financially distressed companies.

Table 2.8: Prediction accuracy of models after financial crisis

AFTER CRISIS					
Model Prediction	**Distressed**		**Stable**		**Overall**
	Distressed	**Type I Error**	**Stable**	**Type II Error**	
Z-Score	402	86	960	521	1969
	82.4%	17.6%	64.8%	35.2%	69.2%
O-Score	6	482	1452	29	1969
	1.2%	98.8%	98.0%	2.0%	74%
Hazard	64	424	1468	13	1969
	13.1%	86.9%	99.1%	0.9%	77.8%
Probit	297	191	1158	323	1969
	60.9%	39.1%	78.2%	21.8%	73.9%
D-Score	226	262	554	927	1969
	46.3%	53.7%	37.4%	62.6%	39.6%

This table presents the prediction accuracy of models after the financial crisis in numeric and percentage form.

When we compare the differences in the prediction accuracy of traditional distress prediction models before, during and after the financial crisis, results indicate that the prediction accuracy of the models decreases during the period of crisis. Similar results of the decrease in the prediction accuracy of discriminant analysis during the period of the financial crisis were reported for the Italian and UK market by Teti, et al. (2012) and Almamy et al. (2016), respectively. Moreover, Fahlenbrach et al. (2012) and Dietrich et al. (2011) reported the same effect of a crisis on the performance of accounting ratios for US and Swiss banks.

2.4.3. Robustness test

The characteristics of a firm experiencing financial problems differ from the healthy firms, and the signals of the firm's deteriorating condition are produced successively for many years before the failure (Theodossiou, 1993). Therefore, a more accurate distress prediction models should have an ability to predict such shifts in the financial positions of firms as soon as they begin. To test the robustness of the models with respect to the early warning signs of financial distress, we re-classify firms into three stages based on the degree of their financial position; stable (financially stable firms), early-distressed (an additional criterion to represent firms which are at an early stages of distress), and distressed (common death types used in the literature to classify distressed firms). The description of different stages is presented in table 2.9.

Table 2.9: Stages of financial distress.

Stages of financial position	Description	Degree of financial position
State 0	Financial stability	Stable
State 1	Defaulter firms with below reasons for default: (i) Less than 50% quotation of book value for consecutive 3 years (ii) Failure of dividend/bonus declaration from continuous 5 years (iii) Failed to conduct AGM for consecutive 3 years (iv) Failed to pay the yearly listing fee for 2 years.	Early distressed
State 2	Delisted/Suspended /Liquidation/Winding up/Bankruptcy	Distressed

Using the above criteria, 179 companies with 1724 firm-year observations were in the state of distress during 2001 to 2015. As there are two states of distressed firms in our study, so we further classify these observations into early distressed and distressed states, which gives us 1104 observations for the early distressed firms and 620 observations for the distressed firms. After dividing the financial position of firms into three states, we compare the prediction accuracies of all five models. Table 2.10 presents the overall classification accuracies of models along with Type I (incorrect classification of early distressed and distressed firms), and Type II error (incorrect classification of stable firms). The classification accuracy results in table 2.10 are robust after dividing the sample into three stages of financial distress. The results indicate that the overall classification accuracy of the probit model is higher (73.8%) as compared to the other four models. The D-score overestimates the early distressed and distressed firms, while O-score and hazard model overestimates the stable firms. Furthermore, the Z-score has an overall higher prediction accuracy of 80.8% for distressed and 78.2% for early distressed firms, respectively, along with 67.0% overall prediction accuracy.

Table 2.10: Prediction accuracy of models with three stages of financial distress

Model Prediction	Distressed		Early Distressed		Stable		Overall
	Distressed	Type I Error	Early Distressed	Type I Error	Stable	Type II Error	
Z-Score	501	119	863	241	2165	1376	3529
	80.8%	19.2%	78.2%	21.8%	61.1%	38.9%	67.0%
O-Score	18	602	24	1080	3163	378	3205
	2.9%	97.1%	2.2%	97.8%	89.3%	10.7%	60.9%
Hazard	45	575	65	1039	3522	19	3632
	7.3%	92.7%	5.9%	94.1%	99.5%	0.5%	68.9%
Probit	395	225	722	382	2766	775	3883
	63.7%	36.3%	65.4%	34.6%	78.1%	21.9%	73.8%
D-Score	503	117	988	116	810	2731	2301
	81.1%	18.9%	89.5%	10.5%	22.9%	77.1%	43.7%

This table presents the overall prediction accuracy of models for all three states of companies. Results are displayed in both numeric and percentage form for each model. The first column is the list of models, second and third column reports classification results for distressed firms, third and fourth column reports the classification results for early distressed firms, fifth and sixth column shows the classification results for stable firms and the final column shows overall classification accuracy of models.

2.5. Conclusion

Empirical researchers and practitioners frequently use traditional financial distress prediction models constructed by using data from developed markets. This poses a potential problem of the reliability of the models for emerging markets because traditional models were developed using economically advanced countries data. In this paper, the empirical performance of five financial distress prediction models constructed particularly with the data from developed markets are tested on the emerging market with up-to-date data from 2001 to 2015. Many companies were financially distressed and filed for bankruptcy during the recent global financial crisis (Li & Zhong, 2013). Recent studies of Teti et al. (2012) and Almamy et al. (2016) proved that the accuracy of the discriminant model decreases during the period of financial crisis. This poses a question of the applicability and the prediction accuracy of distress prediction models during the period of crisis. In addition to the testing of distress prediction models for the whole sample period, we also compare the accuracy of the distress prediction models before, during and after the financial crisis to check the differences in the prediction accuracy of the models with regard to the financial crisis. Detection of a firm’s movement towards failure at an early enough stage is beneficial for all stakeholders of the business, researchers developed several distress prediction models by keeping this purpose in mind (Theodossiou, 1993). To capture the predictive ability of traditional distress prediction models for the firms that are at an early stage of financial distress, we classify them as a separate state in the robust test and compared the prediction accuracy of all five models.

Our results indicate that all five models are applicable to the Pakistani equity market, but their prediction accuracy decreases with the passage of time. The logit model of Ohlson (1980), D-Score model of Blums (2003) and hazard model of Shumway (2001) performs poorly relative to other two models with the overall prediction accuracy of 43.6%, 61.9%, and 70.7%, respectively. The results also showed that the D-Score model over-estimate the financially distressed companies, while the other two models over-estimate the companies as financially strong indicating the poor ability of the models to discriminate between the financially strong and weak firms.

Both the Z-Score and Probit model performs well for the emerging market. When we look at the overall prediction accuracy of the models, the Probit model of Zmijewski (1984) more accurately predicts companies than the other four models during the whole time period of the study whereas the prediction of Z-Score is the best for firms at an early and advanced stages of distress with the minimum Type I error of 19.19% and 21.83%, respectively. If Type I error is considered costlier than Z-Score model would be more ideal than the Probit model.

Our overall conclusion is that both conventional accounting-based models by Altman (1968) and Zmijewski (1984) are still valuable for predicting financial distress of emerging markets and can be used by businessmen, financial specialists, administrators and other concerned parties who are thinking to invest into an organization and/or want to enhance their organization performance. When we look at the differences in the prediction accuracy of traditional distress prediction models before, during and after the financial crisis, the results indicate that the prediction accuracy of these traditional models decreases during the period of crisis, consistent with the findings of Almamy et al. (2016).

This study contributes to the literature by finding the most accurate predictor of financial distress for the emerging markets after conducting the more comprehensive and detailed comparison of the traditional distress prediction models, constructed primarily for developed markets. There are no available financial databases for the Pakistani equity market which indicate the financial status of the companies based on the company's performance. The study added to the literature by utilizing various information sources to classify companies based on liquidation, suspension, default, delisting and winding up of companies. We contribute to the literature by extending the definition of financial distress by adding firms which failed to quote, pay dividend/bonus, listing fee and to conduct an AGM. Our study uses a long-time frame of fifteen years to check the differences in the predictive ability of the models with respect to the financial crisis for the emerging markets. We also provide evidence on the predictive ability of models with respect to the early warning signs of financial distress.

Even though our sample includes all companies listed on the stock exchange of the emerging market with the large time span of fifteen years, it has certain limitations. Including more emerging markets would help to comment better on the generalizability of the financial distress prediction models with respect to the early warning signs of financial distress. In addition, there is a need for the financial distress prediction model with the most accurate ratios, which are stable and increases the overall prediction accuracy of models for both developed and emerging markets.

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Chapter 3: Development and testing of augmented distress prediction model: A comparative study on developed and emerging market[**]

Abstract

This study presents a financial distress (FD) prediction model by combining accounting, market-based, and financial reporting quality (FRQ) measures. It was estimated with the data of UK firms during the period 2001-2015, under a panel logit framework, and then tested for an emerging market, Pakistan. The results reveal that the hidden area of financial reports, measured with FRQ proxies, is strongly related to FD. So, it was demonstrated the utility of FRQ measures, which represent earning management tactics of managers for income smoothening, in the distress prediction modeling. Overall, the FRQ measures are significant predictors of FD, in both the UK and Pakistani markets with good predictive accuracy. A robustness check shows, also, that predictive accuracy remains high during different tranches of the business cycle.

Keywords: Financial distress, panel logit analysis, financial reporting quality, earning management

Jel Classification: G01, G11, G17, G32, G33

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3.1. Introduction

The entry and exit of firms is a fundamental part of the functioning of the economic system. Every year, thousands of firms have prospered, while others face financial difficulties and ultimately failed. Although no businesses wish to fail, continual ignorance of financial problems can have serious negative consequences for all stakeholders of the business. Investors, creditors, managers, shareholders, and regulatory authorities demand continuous assessment and timely reporting on the corporate likelihood of financial distress (FD). The recent global financial crisis highlights the weaknesses of the debt management policies, practiced in both developed and emerging markets. It also demonstrates the shortcomings of the risk assessment tools used by creditors and rating agencies for anticipating the financial health of firms.

Financial information, reported in the annual accounts, incorporate the impact of both economic conditions and firms' activities, which, in turn, vary according to the different stages of the business cycle (Jenkins et al., 2009). If economic conditions influence the financial status of firms, it can be anticipated that the forecasting ability of distress prediction tools varies during the global financial crisis (Filip & Raffournier, 2014). Several studies examine financial reporting during the global financial crisis. According to Liao et al. (2013), fair value accounting decreases the severity of crisis for firms. Habib et al. (2013) state that the managers of financially distressed firms tend to use earning management tactics to show less income in the financial statements. Moreover, Dimitras et al. (2015) also confirm that companies tend to manipulate financial reports to hide financial problems during the recession. These studies are, however, limited in scope and none of them incorporate this hidden part of earning management tactics in a distress prediction model.

Firm failure is a common occurrence in developed and emerging economies (Altman et al., 1979) and there is a significant increase in the number of financially distressed firms over the past two decades in both types of economies (Ngwa, 2016). As such, researchers are continuously motivated to develop an early warning system to detect financial problems of firms (Sayari & Mugan, 2017; Jones et al., 2017; Altman et al., 2017; Beaver et al. 2011; Shumway, 2001; Ohlson, 1980; Altman, 1968). The focus of these studies is to highlight the importance of financial ratios and market-based variables in detecting early warning signs of FD. However, these or similar studies seldom take financial reporting quality (FRQ) proxies into account. The shortcomings of these studies motivate novel research to detect which FRQ measures play a significant role in predicting the financial health of firms.

The objective of this study is to develop a distress prediction model with FRQ measures along with a set of previously used accounting ratios and market-based variables. This is to confirm whether existing accounting and market-based measures consistently predict the financial health of firms. Following Mselmi et al. (2017), this study adopted backward elimination to select the most significant set of accounting and market-based measures which predict distress. To the best of author’s knowledge, there is no published work focusing on the use of FRQ measures for a distress prediction model. As a result, this study contributes to the extant literature by including an important but previously overlooked determinant of FD. In doing so, we test proxies of earning and accruals quality measures along with a well-established set of accounting and market-based measures which enhance the predictive model.

This study contributes to the growing knowledge of FD prediction literature in three ways. First, presenting a distress prediction model estimated with the data of a developed market, the United Kingdom (UK), which has the third largest stock market in the world, the London Stock Exchange. Second, we identified a set the most significant accounting and market-based measures for predicting distress and find the majority of the ratios are significant in predicting the financial health of a firm. Third, and perhaps most important, for the first time in distress prediction literature, this study collectively tests three types of variables: financial ratios, market variables, and FRQ measures. The model is estimated with a panel data methodology for discrete dependent variables, which allows time-varying covariates and controls for unobservable heterogeneity (Pindado et al., 2008; Tinoco & Wilson, 2013).

Empirical evidence from the UK sample validates the econometric specification of the proposed model, in terms of significance and expected signs. Specifically, for FRQ measures, our results indicate that distressed firms have a poor quality of reported earnings and high value of discretionary accruals which is a telltale sign of firm’s facing financial difficulties. The model demonstrates high accuracy as demonstrated by the high percentage of correctly classified distressed firms. Moreover, the variables show stable signs and significance during the global the financial crisis period (2007-2009). Overall, the results show that the model is useful in predicting financial health of firms during different stages of the business cycle.

Furthermore, the robustness check performed using data pertaining to an emerging market, Pakistan, which has a large manufacturing sector, validates the stability of model in terms of expected signs, significance, and prediction accuracy during both the whole study time period and crisis.

The rest of the paper is organized as follows. Section two covers a brief review of the literature, section three describes the methodology used for the model development, section four describes the empirical results of the study and the last section concludes the paper.

3.2. Literature review

The literature is divided into two groups; studies which focus on accounting and market-based ratios, and those which estimate the relationship between FRQ and the probability of firm distress.

3.2.1. Accounting and market-based measures

The empirical bases of bankruptcy prediction date back to early 1930's with the initial study of Fitzpatrick (1932), who compared 13 financial ratios of failed and non-failed firms and reported differences in the financial ratios of both groups. He identified two significant ratios; Net Worth to Debt and Net Profits to Net Worth. Merwin (1942) confirm his findings and identified working capital to total assets and the current ratio as significant indicators of financial failure.

Early researchers did not use advanced statistical methods, instead, they relied on simple comparisons of financial ratios between failed and surviving firms to deduce informative financial ratios. In 1966, Beaver's pioneering study introduced univariate discriminant analysis and found that several indicators including net income to sales, net income to debt, net income to net worth and cash flow to debt convey crucial information of firm's future health.

Altman (1968) argued that one ratio can influence another, therefore there is a need to predict distress with multiple ratios in a multivariate framework. He developed a five-factor multivariate discriminant function based on profitability, liquidity, and financial leverage to forecast bankruptcy of manufacturing firms.

The Multivariate discriminant analysis is a restrictive statistical technique which does not take into consideration the probabilistic nature of firm's operations (Ohlson, 1980). To overcome the limitations of MDA, Ohlson (ibid.) used a logit model - multivariate conditional probability model to predict bankruptcy based on size, leverage, liquidity, and performance measures. Jones et al. (2017) compared the predictive performance of 16 distress prediction models and found that the logit analysis is the best statistical technique for predicting distress.

A further addition to the bankruptcy prediction literature was made by Zmijewski (1984), who developed a three-factor probit model with the addition of a new statistically significant ratio of total liabilities to total assets. This new ratio is consistently statistically significant in default prediction (Chava & Jarrow, 2004).

A further advancement in the distress prediction literature is the inclusion of market-based variables along with accounting ratios. Shumway (2001) argued that there is a need to develop a model with market-based variables. He introduced three statistically significant market variables including market size, past market returns, and returns variability. Further, Beaver et al. (2005) used a set of three accounting and three market-based variables and reported that market-based variables are better predictors of bankruptcy while the two accounting ratios return on assets and earning to total liabilities became no longer significant.

Previous researchers provide various reasons why researchers ought to include market-based variables in a distress prediction model. First, stock prices reflect the future information of expected cash flows (Rees, 1995) while the accounting information only represents past performance. Second, market prices represent additional information beyond accounting statements (Hillegeist et al., 2004). Third, market prices tend to be unaffected by accounting policies (Agarwal & Taffler, 2008). Fourth, the endogenous nature of information represented by market prices may increase the timeliness of a distress prediction model (Beaver et al., 2011). Fifth, market prices provide estimates of volatility which improves the predictability of a distress model (Tinoco & Wilson, 2013).

The research discussed before is mainly cross-sectional in nature. However, recent researchers argue that a panel logit methodology is more appropriate for distress prediction because it allows time-varying covariates and adjusted for unobservable heterogeneity (Altman & Sabato, 2007; Pindado et al., 2008; Nam et al. (2008); Altman et al., 2010; Tinoco & Wilson, 2013).

Researchers who focus on the re-estimation of the models including Grice & Ingram (2001), Wu et al., (2010), Almamy et al. (2016) provide evidence that the statistical significance of models declines in recent periods. Hence, there is a need to identify variables with a more stable pattern in terms of sign and significance.

In sum, the literature provides mixed results and demonstrates that market variables, as well as financial ratios, are significant predictors of firm's FD. As a result, they are both incorporated into the model predicting the FD of firms.

3.2.2. FRQ and financial distress

Accounting reports are the primary source of information for all stakeholders of the business including creditors, investors, managers, regulators and even government. According to FASB, accounting reports should be clear, transparent, relevant, and reliable for all concerned parties. Poor quality documentation may cause premature decisions and resources misallocation (Yetman & Yetman, 2012). Also, poor reporting quality may create difficulties in assessing a firm's position regarding the payment of debts and dividends (Bharath et al., 2008). Moreover, Verdi (2006) documented that better quality of financial reports may increase investment efficiency by minimizing the asymmetry in financial information, and the earnings would draw a much clearer picture of future cash flows (García-Teruel et al., 2009). Similarly, Bushman & Smith (2001) articulated that the superior quality of financial reporting improves the investment efficiency and future economic performance of the firms. Improvement in investment efficiency creates a positive link between conservative accounting (early loss realization in the financial statements than gain) and future profitability of firms (Ahmed & Duellman, 2011; Lara et al., 2016).

Francis et al. (2005) used earning quality as a proxy of FRQ and showed a relationship between earning quality and expected returns of the company. Furthermore, Rajgopal & Venkatachalam (2011) proved that the changes in FRQ and return volatility are positively related to each other. Companies with better quality of financial reporting enjoy higher financial performance (Martínez-Ferrero, 2014), which lead to the decrease in the probability of FD. If the accounting income is informative, the stock returns will integrate all the available information and reflects the superior quality of accounting reports (Ashbaugh at al., 2006). Habib et al. (2013) examined the behavior of financially distressed firms during the global crisis and concluded that the managers of distressed firms are involved more in the earning management than healthy firms.

From the above-mentioned literature, there is evidence to suggest FRQ is a clear indicator of the financial health of a company. Managers manipulate accounting reports to engage in earning smoothening tactics across different years to maintain the confidence of their shareholders. To the best of the author's own knowledge, no studies employ FRQ for FD prediction. This study addresses this limitation of the literature and tests two main aspects of FRQ; earning quality and accruals quality in the distress prediction model.

3.3. Empirical methodology

3.3.1. Sample and data selection

To meet the aim of this research, we collect data from developed and emerging markets to build a predictive model that works for both types of markets. Therefore, our sample contains companies operating in two countries; UK and Pakistan. More specifically, the sample consists of a panel of non-financial sector companies listed on the London and Karachi Stock Exchange and includes financial information relating to the period between 2001 and 2015. The reason for the selection of this period is to cover a large time span before and after the financial crisis. For the UK sample, data of accounting ratios, market-based variables, and stock prices are from Datastream and the Amadeus database. The data on indices are derived from the website of the World Bank. We excluded those observations from the sample which do not fulfill the data requirements. The constructed variable, quality of financial reporting, requires at least eight observations to run cross-sectional industry regressions, this leads to a further reduction in the sample. Table 3.1 provides a brief overview of the observations and number of firms. The final sample is categorized into two distinct groups, namely financially distressed and non-distressed. A firm is classified as financially distressed whenever it meets the following two conditions; i) inactive, merged, suspended, dissolved, liquidation (voluntary and court order), bankrupt or equivalent, and ii) its net income is negative for consecutive three years.

Table 3.1: Sample for UK and Pakistani market

	UK		Pakistan	
	Firms	Obs	Firms	Obs
Initial Sample	920	14,098	431	5,265
Financially Distressed (FD)	430	6,241	179	1,724
Non-Distressed (ND)	490	7,857	262	3,541
Final sample	546	3,996	418	4,947
Financially Distressed (FD)	213	1,726	159	1,650
Non-Distressed (ND)	333	2,270	256	3,112

With respect to Pakistani firms, we collected data of all non-financial sector companies listed on a Karachi stock exchange. As there are no financial databases for Pakistani firms, we use various secondary sources to fulfill the data requirements. Share prices data is derived from the website of the business recorder and the data on the face value of shares stems from the analysis reports published by the Karachi Stock Exchange. The data of remaining accounting and market ratios belong to the balance sheet analysis published by the State Bank of Pakistan. Like the UK, we exclude those firms from the sample which do not fulfill the data requirements. The final sample comprises of 418 firms, listed on the Karachi Stock Exchange from 2001 to 2015 (Table 3.1). To identify financially distressed firms, we use similar criteria for the Pakistani firms.

3.3.2. Initial ratios selection

The initial features selected for empirical analysis involve five main groups, i.e. profitability, liquidity, leverage, firm size, and market-based measures, which provides comprehensive information on the firms' financial position. In the distress prediction literature, profitability ratios commonly measure the financial performance of firm (Joseph & Lipka, 2006), liquidity ratios measure the short-term debt paying capacity of a firm and some authors view lower liquidity ratios as a reliable indicator of firm distress (Bunn & Bedwood, 2003). Leverage/Solvency represent the soundness of a firm, distressed firms tend to have more leverage and lower repayment capacity (Mselmi et al., 2017). Market-based measures capture information from other sources beyond accounting reports and can improve the predictive accuracy of a distress prediction model (Beaver et al., 2005). Each model is composed of several financial ratios, frequently used in the distress prediction literature by a number of researchers including Beaver (1966), Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001), Blums (2003), Beaver et al. (2005), Teti et al. (2012), and Tinoco & Wilson (2013). Table 3.2 summarizes the initial set of 18 financial ratios used in this study.

Table 3.2: Initial set of financial ratios

Variable	Description	Variable	Description
Profitability		**Firm Size**	
FR_1	Net income/total assets	FR_{12}	Log (Total assets/GNP price-level index)
FR_2	$\frac{NIt - NIt\_1}{\|NIt\| + \|NIt\_1\|}$ where NI_t and NI_{t_1} is the net income for the most recent and the preceding year respectively.		
		Leverage/ Solvency	
FR_3	3-year sales growth	FR_{13}	Total liabilities/total assets
FR_4	Sales/total assets	FR_{14}	Market equity/ total liabilities
FR_5	Net income/total liabilities	FR_{15}	Total equity/total assets
FR_6	Earnings before interest & taxes/total assets	FR_{16}	Market equity/total assets
Liquidity		**Market-Based**	
FR_7	Working capital/total assets	FR_{17}	Cumulative return of company in year *t-1* less cumulative return of market in year *t-1*
FR_8	One if total liabilities exceed total assets, zero otherwise	FR_{18}	One-year stock price change
FR_9	Current liabilities/current assets.		
FR_{10}	Current liabilities/total assets		
FR_{11}	Operating funds/total liabilities		

This table presents the initial set of financial ratios collected for financially distressed and non-distressed firms. FR indicates the financial ratios.

To identify an optimal set of financial ratios, we chose features by stepwise selection. The reduced set of ratios reflecting profitability, liquidity, leverage/solvency, size, and market features are presented in table 3.3. We then incorporated two proxies of FRQ in this set to improve the quality of the model.

Table 3.3: Financial ratios selected by stepwie regression

Financial Ratios		Rank
FR_4	Sales/total assets	1
FR_7	Working capital/total assets	4
FR_{12}	Log (Total assets/GNP price-level index)	2
FR_{13}	Total liabilities/total assets	3
FR_{16}	Market equity/ total assets	6
FR_{18}	Cumulative return of company in year *t-1* less cumulative return of market in year *t-1*	5

This table presents the reduced set of financial ratios. Column 2 indicates the rank of the ratio in the stepwise selection process.

3.3.3. Proxies of FRQ

There is no universally accepted measure of FRQ (Dechow et al. 2010). Taking previous literature into account, we employed two main aspects of FRQ; earnings quality, and accruals quality.

3.3.3.1. Earnings quality

Earnings quality is one of the most widely employed proxies of FRQ. If the reported income is consistently informative, stock returns should adjust after incorporating this and all other available information, which reflects the high quality of financial reporting (Ashbaugh et *al*., 2006). To capture the information context of earnings, we use Collins & Kothari (1989) model of earning management. The model equation is:

$$ERES_{it} = \propto_1 NIPS_{it} + \propto_2 \Delta NIPS_{it} + \propto_3 NEG_{it} + \propto_4 NIPS_{it} * NEG_{it} + \epsilon_{it} \qquad (1)$$

Where, $ERES_{it}$ is the current year stock return, $NIPS_{it}$ is the current year net income per share, $\Delta NIPS_{it}$ is the change in current and previous year net income per share, NEG_{it} is an indicator variable equal to one if the firms make a loss zero otherwise and $NIPS_{it}*NEG_{it}$ is the interaction variable between the net income per share and their sign. The residuals are estimated separately for each two-digit SIC code sector that has at least eight firm-year observations. We then calculated the standard deviation of residuals higher value represents a poor quality of information.

3.3.3.2. Accruals quality

FD and difficult market conditions may lead some companies to adopt fraudulent accounting practices for example, by understating the cost of goods sold, R&D expenses, and relaxing credit terms to increase revenues. Discretionary accruals could be adjusted for earning smoothening among different fiscal years. As observed by Garcia et al. (2005), total accruals can be divided into two components:

$$Total\ Accruals = Non - Discretionary\ Accruals + Discretionary\ Accruals \quad (2)$$

Different researchers attempt to measure appropriate factors reflected in non-discretionary accruals. For example, Jones (1991) argued that normal accruals are a function of revenues and property, plant, and equipment; Dechow et al. (1995) deducted account receivables from revenues; Larcker & Richardson (2004) added operating performance and book to market ratio. Kothari et al. (2005) added return on assets into their model to control for measurement errors. The managers could increase or decrease the remaining portion of discretionary accruals for earning smoothening among different fiscal years. Hence, a lower quality of accruals represents the firm's probability of going into default.

After reviewing the extent of earnings management literature, we identified five models to measure non-discretionary accruals. We use the Larcker & Richardson (2004) model to separate non-discretionary and discretionary accruals. The remaining four models are explained in Appendix 1. Following Larcker & Richardson (2004), we estimated the following model:

$$TCA_{it} = \alpha_0\left(\frac{1}{TA_{it-1}}\right) + \alpha_1(\Delta REV_{it} - \Delta AR) + \alpha_2 PPE_{it} + \alpha_3 BM_{it} + \alpha_4 OCF_{it} + \epsilon_{it} \quad (3)$$

Where TCA_{it} are total current accruals, measured as (ΔCurrent assets-ΔCash-ΔCurrent liabilities-ΔShort term Debt-Depreciation Expense); ΔREV is the annual change in revenue; ΔAR is the change in account receivables; PPE_{it} is the value of property, plant, and equipment; BM_{it} is the book to market ratio, and OCF_{it} are the operating cash flows for firm i in year t. All variables are scaled by lagged total assets, TA_{it-1}. Like the earning quality measure, we run the cross-sectional industry regressions of the firms for every year in the same two-digit SIC code and with minimum eight firm-year observations. The absolute value of residuals is multiplied by -1 and denoted by AQ, the higher value represents the high level of discretionary accruals and reflects the lower quality of financial reporting.

3.3.4. Model development

Following Pindado et al. (2008), we ran a multivariate panel logistic regression because it is based on less restrictive assumptions of multivariate normality and covariance matrices as well as its relative insensitivity to outliers due to the non-linear transformation of input data.

More specifically, we employ two types of panel logistic regressions. First, the following fixed effects logit is specified:

$$P(Y_{it} = 1|X_i) = \frac{e^{(\alpha_i + x_{it}\beta)}}{1 + e^{(\alpha_i + x_{it}\beta)}} \tag{4}$$

Where, Y_{it} is the outcome of the binary variable in period t; one in the case of a distressed firm, zero otherwise, x_{it} is a vector of the independent variables which predict FD in period t, β is a vector of the slope coefficients of the independent covariates and α_i is an unobserved firm-level fixed effect. The benefit of using this model is that it controls for unobserved firm-level heterogeneity. However, one drawback is that its estimation relies on time-variant dependent variables therefore observations with time-invariant binary indicators are removed from the sample and so it is less efficient than other panel data models.

Second, we run a random effects model which assumes the firm-level fixed effect is normally distributed with a mean of zero and a standard deviation, σ:

$$\propto_0 \sim N(0, \sigma_\alpha) \tag{5}$$

This accounts for random unobserved and unexplained variability in financial distress and non-distress across firms. However, it relies on a stronger assumption that firm-level fixed effects are not correlated with the vector of covariates albeit this is less likely to hold. It also relies on a restrictive assumption that the random effect follows a specific parametric function (i.e. normal distribution).

3.4. Empirical results

3.4.1. Descriptive statistics

To estimate the differences in variance and mean between financially distressed and non-distressed firms, we use the Levene's test for equality of variances and t-test for equality of means. Table 3.4 reports summary statistics of variables including mean, standard deviation, and significance level for both the Levene's and t-test. Group A and group B show the results for the UK and Pakistani sample, respectively.

Table 3.4: Descriptives and independent sample test

	Levene's test for equality of variances			t-Test for equality of means			
	FD	ND	Sig.	FD	ND	Sig. (2-tailed)	Mean difference
Group A: UK Firms							
STA	0.825	0.658	0.000*	0.799	1.043	0.000*	0.244
WCTA	0.349	0.185	0.000*	0.024	0.201	0.000*	0.211
TLTA	6.275	0.214	0.013*	0.923	0.458	0.000*	-0.465
META	2.240	2.064	0.000*	3.594	4.376	0.000*	-0.219
SIZE	0.488	0.517	0.003*	2.305	2.663	0.000*	0.358
LgExRet	0.822	0.566	0.000*	-0.011	-0.134	0.000*	-0.122
EQ	0.359	0.241	0.000*	0.350	0.233	0.000*	-0.116
AQ	0.147	0.072	0.000*	0.091	0.058	0.000*	-0.033
Group B: PK Firms							
STA	0.755	0.779	0.071**	0.745	1.265	0.000*	0.520
WCTA	0.576	0.248	0.000*	-0.309	0.067	0.000*	0.376
TLTA	0.564	0.235	0.000*	0.953	0.583	0.000*	-0.369
META	2.844	2.770	0.000*	0.628	1.295	0.000*	0.666
SIZE	0.401	0.344	0.000*	1.445	1.792	0.000*	0.346
LgExRet	0.564	0.466	0.000*	-0.222	-0.108	0.000*	0.113
EQ	0.357	0.245	0.000*	0.356	0.278	0.000*	-0.078
AQ	6.185	1.070	0.000*	0.669	0.166	0.000*	-0.503

This table reports Levene's test for the equality of variances, and t-test for the equality of means. FD and ND represent financially distressed and non-distressed firms, respectively. *, ** indicate significance at the 1% and 5% level, respectively.

The results show that the variances and means of financial ratios are significantly different at the 1% level for both distressed and non-distressed firms in both groups A and B, while the variance of *STA* belonging to group B is statistically different at the 5% significance level. Consistent with the findings of Altman (1968), our results for both groups confirms that the sales generating capacity of distressed firm's assets (STA) is lower than non-distressed firms.

Similarly, the results of *WCTA* ratio are consistent with the fact that financially distressed firms have lower current assets due to consistent operating losses. As expected, the solvency ratio *(TLTA)* is higher for distressed firms as compared to the non-distressed firms, confirming that distressed firms tend to have higher levels of long-term liabilities. A higher value of *META* indicates that the market value of firm's assets shows more decline for the distressed firms as compared to the non-distressed firms. As opposed to distressed firms, non-distressed firms, on average, are larger in size showing that the sizeable firms are less prone to FD and have a higher capacity to meet their financial obligations. Additionally, our results with respect to Lgexret confirm the findings of Shumway (2001) whereby firms' past excess returns are able to predict FD as well as market capitalization. Moreover, we find that the earning and accruals quality of financially distressed firms is lower than the non-distressed firms, indicated by the higher average value of poor information content of earnings (EQ) and discretionary accruals (AQ).

3.4.2. Panel models results

Table 3.5 reports the estimation results of the fixed and random effects models, respectively. Conclusions from the Hausman test were indefinite as a negative test statistic was produced. Moreover, since the results of the test are indeterminate, and it is difficult *a priori* to determine whether fixed or random effects is the correct relation, this study follows Arellano & Honoré (2001) by presenting the results from both models. This study presents two ex-ante models for testing the contribution of FRQ measures in distress prediction models, based on accounting and market-based measures. Model 1 presents the 'initial accounting and market based' model based on Sales to total assets (STA), Working capital to total assets (WCTA), Total liabilities to total assets (TLTA), Market equity to total assets (META), Firm size (SIZE), and Lag ex return of company (LgExRet). Model 2 is the complete model, incorporating, in addition to the initial set of accounting and market-based variables, two FRQ measures; Earnings quality (EQ) and Accruals quality (AQ).

The results of model 1 indicate that all accounting and market-based variables have their theoretically expected signs and are statistically significant at the 1 to 10% level, suggesting that they are good predictors of FD. The profitability variable, Sales to total assets (STA) has an inverse relationship with the probability of FD, indicating that a decline in the sales leads to firms being in distress (Altman, 1968). Similarly, the liquidity variable (WCTA) also displays the expected negative sign, confirming the result of Bunn & Redwood (2003). Furthermore, the coefficient estimates of total liabilities to total assets are positive, indicating a highly leveraged firm is more likely to be in FD. This evidence is consistent with the seminal studies of Zmijewski (1984) and Tinoco & Wilson (2013). Our findings confirm that, there is an inverse relationship between market-based measure of capital structure (META) and the firm's probability, indicating an increase in market perceived prospects for the firm. In line with the findings Shumway (2001), our results confirm that past stock return (lgexret) plays a significant role in predicting the probability of FD. Additionally, the sign on the variable Size confirms the findings of Ohlson (1980), suggesting that lower the size of a firm, the higher its probability of FD. The likelihood ratio test and Wald test indicate the high explanatory power of all the variables in both fixed and random effect models, respectively. Both tests reflect the increase in explanatory power of variables when applied to the testing sample of emerging market. Moreover, the additional test in the random effects model (see ρ=0, $\chi 2$) verifies the presence of unobservable heterogeneity and confirms the findings of Pindado et al. (2008) that the model should be validated using panel data.

Model 2, in addition to a previous set of financial ratios, incorporates two FRQ measures, EQ and AQ, which represent poor information quality and high discretionary accruals of a firm, respectively. Both are statistically significant at 1 to 10% level in fixed and random effect models. Moreover, all the variables initially included in model 1 retain the relative magnitude of their coefficients and statistical significance in model 2. The signs of both measures are as predicted in this study, the positive signs of the EQ and AQ represent that firms with poor information quality of their earnings and higher discretionary accruals have a higher probability of FD. The results of the study suggest that a higher level of earning management practices is associated with a lower FRQ, and thus, a higher probability of FD. Our results show that the additional ratios increase the overall significance of the model, in both the fixed effects (see likelihood ratios, LR), and the random effects models (see Wald tests).

Table 3.5: Results of the panel data models for the financial status

Dependent variable: Financial Status								
	Results from the UK				Results from the PK			
	Fixed effect model		Random effects model		Fixed effect model		Random effects model	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
STA	-0.908 (0.272)*	-0.905 (0.275)*	-1.704 (0.243)*	-1.044 (0.250)*	-1.326 (0.166)*	-1.341 (0.169)*	-1.448 (0.151)*	-1.471 (0.153)*
WCTA	-0.881 (0.465)***	-0.897 (0.464)***	-0.953 (0.457)*	-0.979 (0.457)**	-0.713 (0.307)**	-0.756 (0.312)**	-1.177 (0.317)*	-1.222 (0.321)*
TLTA	2.184 (0.477)*	2.154 (0.472)*	2.520 (0.482)*	2.483 (0.479)*	0.996 (0.371)*	1.060 (0.375)*	1.704 (0.360)*	1.772 (0.363)*
META	0.022 (0.008)*	-0.021 (0.008)*	0.025 (0.007)*	-0.024 (0.007)*	-0.224 (0.077)*	-0.228 (0.078)*	-0.134 (0.046)*	-0.136 (0.046)*
SIZE	-1.714 (0.518)*	-1.767 (0.524)*	-3.044 (0.397)*	-3.053 (0.405)*	-5.555 (0.565)*	-5.240 (0.569)*	-6.233 (0.448)*	-5.991 (0.445)*
LgExRet	-0.311 (0.104)*	-0.322 (0.106)*	-0.210 (0.104)**	-0.225 (0.106)**	-0.333 (0.112)*	-0.347 (0.113)*	-0.368 (0.113)*	-0.383 (0.114)*
EQ		0.648 (0.242)*		0.786 (0.245)*		0.490 (0.205)**		0.580 (0.205)**
AQ		1.153 (0.380)***		1.577 (0.715)**		0.097 (0.205)*		0.110 (0.039)**
Log Lik	-461.63	-456.49	-1241.63	-1234.34	-654.12	-647.41	-1337.12	-1328.63
LR χ2	81.09 (6)	91.39 (8)			285.83 (6)	299.24 (8)		
ρ			0.926 (0.011)	0.927 (0.011)			0.831 (0.020)	0.829 (0.020)
ρ=0 χ2			2235.62 (1)	2197.02 (1)			1479.24 (1)	1483.67 (1)
Wald χ2			113.71 (6)	122.81 (8)			338.40 (7)	347.92 (8)

i) Dependent variable: Status is a dichotomous variable equal to one for financially distressed firms, and zero otherwise; ii) heteroskedasticity consistent asymptotic standard errors are written in parentheses; iii) statistical significance at the 1%, 5% and 10% levels are denoted *, **, and ***, respectively; iv) The LR test is a maximum likelihood ratio test of goodness of fit, asymptotically distributed as χ^2 under the null hypothesis of no joint significance of the coefficients of the two models, degrees of freedom in parentheses; v) when ρ=0 the panel-level variance component is unimportant, and the panel estimator is no different from the cross-sectional estimator, it tests the joint significance of the individual effects, asymptotically distributed as χ^2 under the null hypothesis of no joint significance, degrees of freedom in parentheses; and vi) Wald is also a test of goodness of fit, asymptotically distributed as χ^2 under the null hypothesis of no joint significance of the coefficients, degrees of freedom in parentheses.

Table 3.6: Prediction accuracy of the model

Group A: UK firms				
	Actual Position	Prediction		Total
		FD	ND	
	FD	1519 (88%)	207 (12%)	1726 (100%)
	ND	544 (24%)	1726 (76%)	2270 (100%)
The overall prediction accuracy of the model for UK firms is 81.2%				
Group A: PK firms				
	Actual Position	Prediction		Total
		FD	ND	
	FD	1485 (90%)	165 (10%)	1650 (100%)
	ND	341 (11%)	2771 (89%)	3112 (100%)
The overall prediction accuracy of the model for PK firms is 89.4%				

After checking that the variables used in the model have an explanatory power and are supported by theory, the next step is to check the prediction accuracy of a model for both groups. Table 3.6 presents the prediction accuracy of the model for the UK and Pakistani firms. For the UK sample, the model correctly classifies 88% of distressed and 76% of non-distressed firms, with an overall prediction accuracy of 81.2%. When the model is applied to the PK sample, the percentage of distressed and non-distressed firms increases to 90% and 89%, respectively, with an overall classification accuracy of 89.4%. One possible reason for this increase in the prediction accuracy of the model is the presence of FRQ variables which demonstrates that the Pakistani firms tend to have a lower quality of financial information, hence, the model has more explanatory power for them. Another possible reason could be sample size; the number of observations is higher for the Pakistani sample.

3.4.3. Robustness test for FD during the financial crisis

Many firms face financial difficulties during the global financial crisis (Vermoesen et al., 2013) and the predictive power of traditional distress prediction models declines during the time of financial crisis (Almamy et. al, 2016). The objective of this section is to estimate the stability of the model during the global financial crisis. We followed Dietrich & Wanzenried (2011) and considered 2007 to 2009 as the crisis period. The second and third columns of Table 3.7 provide the estimation results for the UK and PK firms, respectively. The estimated coefficients have the expected signs and remain significant in both cases; that is, the probability of FD is negatively affected by the profitability variable (STA), liquidity variable (WCTA), solvency variable (META), firm size (SIZE), and market-based variable (LgExRet), and is positively affected by the leverage variable (TLTA) and FRQ variables (EQ and AQ).

Table 3.7: Results of the model during the crisis

Dependent variable: Financial Status		
	Results from the UK	Results from the PK
STA	-0.460 (0.157)*	-2.148 (0.234)*
WCTA	-1.157 (0.409)*	-2.462 (0.461)*
TLTA	1.033 (0.390)*	2.315 (0.484)*
META	-0.013 (0.007)***	-0.014 (0.045)***
SIZE	-1.518 (0.190)*	-3.151 (0.339)*
LgExRet	-0.366 (0.116)*	-0.421 (0.203)**
EQ	0.557 (0.264)**	1.208 (0.317)*
AQ	1.656 (0.618)*	4.183 (0.161)*
Wald $\chi2$	102.27	190.44
Observations	815	953
ND	515	621
FD	300	332

i) statistical significance at the 1%, 5% and 10% levels are denoted *, **, and ***, respectively; ii) Wald $\chi2$ is a goodness of fit test, asymptotically distributed as χ^2 under the null hypothesis of no joint significance of the coefficients, degrees of freedom in parentheses; iii) observations stands for the number of observations during the financial crisis; iv) ND stands for non-distressed and FD stands for financially distressed observations.

Overall results presented in this section verify that the model remains useful for predicting FD of firms operating in different institutional and legal settings. Moreover, due to the estimation of the model using a large timeframe of before and after the Great Recession period, the estimated signs and coefficients of the model remain stable during the financial crisis time.

3.5. Conclusion

FD prediction attracts significant research attention because of its importance for all external and internal parties of a firm. This study offers attempts to predict FD using a panel logit framework for non-financial sector companies operating in a developed country's market; United Kingdom. The study also tests whether the model can be applied successfully to an emerging market; in this case, Pakistan. Even though predicting FD has been a well-researched line of inquiry for many decades, an optimal set of financial ratios that can predict FD in companies operating in both developed and emerging markets have not been found. Additionally, none of the models in the literature take into consideration the FRQ of firms, which capture firm earning management tactics that are also a clear sign of a firm's FD. Furthermore, the expected signs and significance of variables remains constant, when the model is applied to an emerging market. Indeed, developing a model with a significant set of variables for both type of economies is often considered a challenge by researchers.

For model development, firstly this study identifies a set of accounting and market-based variables frequently used in the distress prediction literature. Second, backward selection identifies a set of ratios that effectively discriminate between financially distressed and non-distressed firms. Our findings show that six ratios have the higher discriminant ability for the financial status of firms, namely sales to total assets, working capital to total assets, total liabilities to total assets, market equity to total liabilities, firm size, and past stock returns of the firm. Our results confirm the findings of previous studies that distressed firms tend to have lower profitability, liquidity, solvency, and past stock returns. Those firms tend to be smaller in size and more leveraged compared to non-distressed firms. Third, this study identifies two statistically significant proxies of FRQ, i.e. earning and accruals quality, that best estimate the firm's probability of FD. We found that the firms with high earning management practices have more chances of FD. Fourth, the specification of the model based on accounting ratios, market-based measures, and FRQ measures is tested using panel data models to control for unobservable heterogeneity.

To test the validity of the model for the emerging market, the study used data on a subset of Pakistani firms. The results obtained confirm the statistical significance of variables and again show expected signs. Moreover, the model showed better prediction accuracy for the emerging market, where managers tend to use more earning management tactics and have a lower quality of financial information than those from the UK. At last, the model is estimated for the crisis period to check the stability of variables and expected signs. The results validate the stability of the variables in terms of significance and expected signs for both countries.

Overall, this study provides a valuable contribution to the distress prediction literature with a new approach to distress prediction by uncovering hidden earning management tactics of firms, represented by FRQ proxies, as significant predictors. The estimated model with the previous accounting ratios, market-based variables, and FRQ proxies is stable in terms of significance and expected signs of variables when applied to both developed and emerging market. The development of a model with robust and stable variables would make a practical value for all concerned parties. i.e. managers, investors, creditors, and regulatory authorities. In fact, early detection of FD is crucial for all stakeholders of a firm, and particularly for shareholders to protect their investment. Although we added a large timeframe and data from both a developed and emerging market, this study still needs to be tested in more developed and emerging markets. Further, the stability and impact of governance variables can be tested for the firm's probability of FD.

Appendix 1: Estimation results of remaining four accruals quality proxies

This study tested five proxies of accruals quality and selected one which increases the overall significance of remaining variables and produces a high value from the Wald test. The estimation procedure is the same as explained for Larcker & Richardson (2004) model. Table 3.8 presents the estimation results.

Table 3.8: Results of the model for accruals quality proxies

Dependent variable: Financial Status								
	Results for the UK				**Results for PK**			
Variables	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
SALESTA	-1.039 (0.251)*	-1.042 (0.250)*	-1.046 (0.250)*	-1.048 (0.249)*	-1.467 (0.153)*	-1.470 (0.153)*	-1.472 (0.153)*	-1.459 (0.152)*
WCTA	-0.966 (0.457)**	-0.970 (0.456)**	-0.985 (0.458)**	-0.959 (0.456)**	-1.199 (0.321)*	-1.213 (0.322)*	-1.214 (0.321)*	-1.215 (0.321)*
TLTA	2.455 (0.480)*	2.454 (0.480)*	2.490 (0.481)*	2.505 (0.481)*	1.775 (0.364)*	1.770 (0.364)*	1.745 (0.363)*	1.708 (0.362)*
MCTL	0.024 (0.007)*	0.024 (0.007)*	0.024 (0.007)*	0.024 (0.007)*	-0.147 (0.046)*	-0.140 (0.047)*	-0.136 (0.047)*	-0.138 (0.047)*
SIZE	-3.062 (0.406)*	-3.054 (0.405)*	-3.088 (0.405)*	-3.081 (0.404)*	-5.985 (0.446)*	-6.040 (0.445)*	-6.019 (0.447)*	-6.125 (0.446)*
LgExRet	-0.216 (0.106)**	-0.216 (0.106)**	-0.233 (0.106)**	-0.232 (0.106)**	-0.383 (0.114)*	-0.384 (0.114)*	-0.367 (0.114)*	-0.364 (0.113)*
EQ	0.797 (0.246)*	0.790 (0.246)*	0.779 (0.244)***	0.783 (0.244)*	0.586 (0.206)***	0.570 (0.205)*	0.562 (0.205)**	0.562 (0.205)**
AQ1	0.846 (0.459)***				0.006 (0.003)**			
AQ2		0.790 (0.437)***				0.009 (0.004)**		
AQ3			0.793 (0.669)				0.033 (0.017)**	
AQ4				0.926 (0.708)				-0.142 (0.128)
Log(L)	-1233.92	-1234.72	-1236.14	-1236.00		-1330.42	-1331.57	-1332.77
ρ	0.927 (0.107)	0.927 (0.011)	0.926 (0.011)	0.926 (0.011)		0.831 (0.020)	0.829 (0.020)	0.830 (0.020)

Dependent variable: Financial Status								
	Results for the UK				**Results for PK**			
Variables	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
$\rho = 0\ \chi^2$	2201.04 (1)	2198.96 (1)	2201.62 (1)	2200.78 (1)		1484.56 (1)	1480.11 (1)	1479.83 (1)
Wald χ^2	121.25 (8)	121.59 (8)	120.87 (8)	121.32 (8)		345.31 (8)	345.20 (8)	342.85 (8)

i) Dependent variable: Status is a binary variable coded one for financially distressed firms, and zero otherwise; ii) heteroskedasticity consistent asymptotic standard errors in parentheses; iii) *, ** and *** indicate significance at the 1%, 5% and 10% level respectively; iv) ρ=0 is a test of the joint significance of the individual effects, asymptotically distributed as χ^2under the null hypothesis of no joint significance, degrees of freedom in parentheses; and v) Wald is a test of goodness of fit, asymptotically distributed as χ^2under the null of no joint significance of the coefficients, degrees of freedom in parentheses.

We followed Lin et al. (2014) and estimate coefficients of all accruals quality measures for all firms in a same two digits SIC code in each year. The residuals from all equations below represent the discretionary accruals, the absolute value of which is multiplied by -1. The higher value of discretionary accruals shows poor quality of financial reporting.

Model 3 is based on Jones (1991) model:

$$TCA_{it} = \alpha_0\left(\frac{1}{TA_{it-1}}\right) + \alpha_1 \Delta REV_{it} + \alpha_2 PPE_{it} + \epsilon_{it} \qquad (6)$$

Where TCA_{it} are total current accruals (ΔCurrent assets-ΔCash-ΔCurrent liabilities-ΔShort term Debt-Depreciation Expense); ΔREV is the annual change in revenue; PPE_{it} is the value of property, plant, and equipment; All variables are scaled by lagged total assets, TA_{it-1}. The absolute value of residuals represents the high level of discretionary accruals and reflects the lower quality of financial reporting.

Model 4 is based on Dechow et al. (1995) model:

$$TCA_{it} = \alpha_0\left(\frac{1}{TA_{it-1}}\right) + \alpha_1(\Delta REV_{it} - \Delta AR) + \alpha_2 PPE_{it} + \epsilon_{it} \qquad (7)$$

Where ΔAR is the annual change in account receivable scaled by lagged total assets, the definitions of all other variables are same as used in Jones model.

Model 5 is based on Kothari et al. (2005) model:

$$TCA_{it} = \alpha_0\left(\frac{1}{TA_{it-1}}\right) + \alpha_1 \Delta REV_{it} + \alpha_2 PPE_{it} + \alpha_3 ROA_{it} + \epsilon_{it} \qquad (8)$$

Where ROA is the return on asset for firm i in year t and the remaining variables are the same as used in Jones model.

Model 6 is based on McNichols (2002) model:

$$\Delta WC_{it} = \alpha_0\left(\frac{1}{TA_{it-1}}\right) + \alpha_1 OCF_{it-1} + \alpha_2 OCF_{it} + \alpha_3 OCF_{it+1} + +\alpha_4 \Delta REV_{it} + \alpha_5 PPE_{it} + \epsilon_{it} \qquad (9)$$

Where ΔWC is a change in working capital; OCF_{it-1}, OCF, OCF_{it+1} are the cash flow from operations for the previous, present and future year for firm i. The remaining variables are the same as defined previously.

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Chapter 4: Does board committee independence affect financial distress likelihood? A comparison of China with the UK[††]

Abstract

This study explores the relationship between board committees' independence and financial distress of firms in China and the UK. Akin to the previous literature, we estimate this relationship between 2007 and 2016 using a conditional logit model on a sample of matched pair firms (one distressed firm to every non-distressed firm). Our overall results show higher levels of audit committee independence is associated with financial distress in Chinese firms, while the opposite relationship was found for compensation and nomination committees in both countries. These results support corporate governance policies which increase the level of independence of compensation and nomination committees as they can benefit the financial health of firms. A robustness test demonstrates that the results are robust to the assumed functional form imposed by the conditional logit model.

Keywords: Financial distress, conditional logit analysis, propensity score matching, corporate governance, board independence, board committees

Jel Classification: G01, G32, G33, G34

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4.1. Introduction

After the global financial crisis of 2007-2009, financial distress prediction of firms remains an important topic of interest for all business stakeholders including entrepreneurs, creditors, investors, managers and other concerned parties. Since the seminal work of Beaver (1966), several financial distress prediction models have been developed which incorporate accounting and market-based variables as predictors of financial distress (Altman, 1968; Ohlson, 1980; McGurr & DeVaney, 1998; Shumway, 2001; Almamy et al., 2016). From the late 1980's, some authors (Hambrick & D'Aveni, 1988; Gilson, 1990; Daily & Dalton, 1994) highlight the importance of corporate governance and its influence on financial distress. More recent researchers including Laitinen & Laitinen (2009), Brédart (2014), Schultz et al. (2015) and Manzaneque et al. (2016) also suggest that corporate governance practices significantly impact the likelihood of financial distress.

Governance mechanisms protect shareholders' interest by limiting managers pursuing their own self-interest instead of maximizing shareholder value. In other words, such mechanisms help to alleviate the "agency problem" (Jensen & Meckling, 1976). Agency theorists consider independent board members as vital in performing a monitoring role of managers (Fama & Jensen, 1983; Jensen, 1993). The board can better perform its duties when most directors which sit on its committees are independent and work freely without influence from management (Hadani et al, 2011). Also, the firm's financial performance may significantly improve with the increase in the number of independent directors in board committees (Puni, 2015), which may ultimately decrease the firm's likelihood of financial distress. Most previous research (Carcello & Neal, 2000; Hsu & Wu, 2010) has explored the influence of audit committee independence on the likelihood of financial distress. However, it is still an open question whether nomination and compensation committee independence have an impact on financial distress in different countries with distinct institutions. This study strives to fill the gap in the literature by analyzing how the impact of board committees, namely audit, compensation, nomination, differ in an emerging and developed market, China and the UK, respectively.

Both countries have the same requirements for board committees that its members should be composed of directors, chaired by an independent director, and contain a limited number of independent directors (Chambers, 2005), but there are stark differences in their institutional, economic, and cultural environments. China, with its unique and large, state-sponsored capitalistic economy (Haveman et al. 2017), continues to face problems of poor or lax corporate governance practices in their companies. According to Forbes, in 2010 and 2011, several Chinese-based companies including China Media Express (CCME) and China Agritech (CAGC), who both had more than $500 million market capitalizations, attempted to go public with the reverse take-over (RTO) process. However, the process was marred by accusations of frauds, which were arguably the result of poor corporate governance practices. According to the report published by RAND Corporation[7], one of the major problems in Chinese corporate governance is the lack of independent directors. Moreover, Chinese firms suffer from serious agency problems including inefficient monitoring management mechanisms and moral hazard problems (Lin, 2001).

The UK, on the other hand, is considered to have better corporate governance practices than China (Liu, 2005). Since 2003, UK Combined Code on Corporate Governance stipulates that boards, committees, directors and even the company chairperson should be subject to performance appraisal. On the other hand, the Chinese Securities Regulatory Commission (CSRC) in 2001 states that the board of a listed company “may” establish remuneration and appraisal, audit, and nomination committees. Although, the formation of these committees and their independence is at the discretion of the board in UK and shareholders in China, there is a tradition of voluntary compliance in UK as shareholders can voice their opinions, while in China where there is less focus on board committees due to a concentrated ownership structure and a weak institutional environment. There are some other interesting differences with respect to board independence, between China and the rest of the world. As stated in the guidelines issued by CSRC in 2001, the inclusion of independent board members is mandatory, but they should publicly disclose their opinion on important board decisions. However, this is potentially undermined by the fact that an individual can be an independent director of up to five listed companies, making them professional independent directors. In China, the appointment and evaluation of managers are often done by state owners or controlling shareholders and the board tends to simply rubber stamp decisions (Li et al., 2014). It would be interesting to see, how independent board members can play their role in board committees, which are responsible for managerial appointment and evaluation, on the likelihood that a firm is in financial distress.

[7] RAND, a center for corporate ethics and governance is a non-profit research organization.

Our primary contribution to the literature is to test the impact and the differences in the role of independent board committees' members on financial distress of firms operating in both emerging and developed market. Our analysis shows that audit and compensation committee independence have a significant positive and negative impact, respectively for China, while there is no impact for the UK from the conditional logit. Our findings support the view that independent audit committee members are not favorable for firm survival (Hsu & Wu, 2010). The results for compensation committee independence are in line with our argument that the firms operating in China encounter more issues while deciding the compensation for management, and there is a need to implement a similar performance appraisal system to the UK to help reduce the likelihood of financial distress of firms. Further, we demonstrate that nomination committee independence is significantly and negatively associated with financial distress for the firms operating in China and the UK, respectively. This implies that fewer independent members in the nomination committee result in increased chances of default, mainly due to poor and biased decision-making while selecting a person who decides the future of business.

We make two additional contributions to the literature. First, our results confirm that other governance attributes including board size, CEO duality, and board independence also play a significant role in the likelihood of financial distress, although their impact varies when applied to different economies of the world. Second, we use a propensity score matching technique to test the assumptions of models used in previous similar literature. Many previous studies involve an econometric identification strategy that relies on assumptions concerning the functional form of the relationship between different governance characteristics and financial distress. In other words, these studies match distressed firms to non-distressed counterparts based on a subset of control variables, most commonly, firm size, industry, and accounting year. Other control variables which may affect financial distress are included in a logit/probit regression on the partially-matched sample. This study tests this restrictive assumption in a robustness check which uses propensity score matching to find matches for distressed firms that are similar in terms of *all* observable control characteristics. The findings from this alternative estimation strategy reveal that the results are largely robust to different functional form assumptions. Hence testing the restrictive assumptions of matching can verify the robustness of the overall model.

The rest of the paper is organized as follows. Section 2 reviews the literature on corporate governance variables, section 3 describes the data and methodology used, section 4 analyzes the results, and section 5 discusses the conclusion.

4.2. Literature review and hypothesis development

A myriad of studies exists on investigating the determinants that predict firm financial distress (e.g., Beaver, 1966; Altman, 1968; Ohlson, 1980; Shumway, 2001; Agarwal & Taffler, 2008; Almamy et al., 2016). More recent studies (Laitinen & Laitinen, 2009; Lajili & Zéghal, 2010; Brédart, 2014) prove that corporate governance variables significantly improve the predictability of commonly used distress prediction models. There is a large literature that has been developed to explore the relationship between corporate governance and financial distress.

4.2.1. Board size

There are two perspectives regarding board size in the literature. On one hand, researchers argued that a smaller board are more efficient with low cost, efficient decisions and better coordination (Daily & Dalton, 1994; Jensen, 1993). In larger boards, people may be discouraged from sharing different ideas, communicating clearly, reaching a consensus or achieving corporate goals (Lipton & Lorsch, 1992). Moreover, Judge & Zeithaml (1992) and Rose (2007) found that large board size may adversely affect business performance and firm value due to increased coordination costs and decreased ability of monitoring management by larger boards (Hermalin & Weisbach, 2003; Hsu & Wu, 2010).

In contrast to the above studies, Resource Dependency Theory advocates that companies with larger boards have access to more resources and skillsets, which ultimately increases the financial performance of firms (Kiel & Nicholson, 2003). From this point of view, larger boards are more effective and the companies with larger boards tend to be less likely to fail due to a higher accountability because of the higher number of directors (Lamberto & Rath, 2008), a plurality of views, and potential for networking (Pfeffer & Salancik, 1978). Indeed, successful retailing firms tend to have larger boards than failed firms (Chaganti et al., 1985). Although these studies provide mixed evidence, most of them tend to support the need for larger boards. Therefore, we hypothesize that:

H1a: There is an inverse relationship between board size and the likelihood of financial distress for the Chinese market.

H1b: There is an inverse relationship between board size and the likelihood of financial distress for the UK market.

4.2.2. CEO duality

Board of directors has often conferred the power from shareholders to monitor managers of companies including Chief Executive Officers (CEO), (Fama & Jensen, 1983; Dalton & Kesner, 1987). In some cases, the CEO may also hold the position of board chairperson, which is often referred to as CEO duality. CEO duality has been linked with the increased possibility of corporate bankruptcy as well as increased chances of firms adopting unscrupulous practices such as earnings management techniques (Daily & Dalton, 1994). The agency perspective is that CEO duality gives rise to risks of the CEO maximizing his/her own wealth and creating less value for shareholders, which can ultimately advance a firm towards unavoidable bankruptcy (Eisenhardt, 1989). Indeed, more recently, Wang & Deng (2006) and Hiu & Jing-Jing (2008) also reported a positive relationship between CEO duality and the likelihood of financial distress.

In contrast to above views, Resource Dependency Theory advocates that CEO duality provides stronger leadership in the organization, with smoother information transmission, reduced coordination costs, and fewer chances of conflicts (Donaldson & Davis, 1991; Davis et al., 1997). However, a number of researchers (e.g. Pearce & Zahra, 1992; Simpson & Gleason, 1999) provide evidence that there is a negative relationship between duality and the likelihood of financial distress. Some researchers also report that there are hardly any dissimilarities between the firms which are in financial distress and the ones which are doing well, in terms of the authority of the CEO (Elloumi & Gueyié, 2001; Nahar Abdullah, 2006). According to the agency theory, we hypothesize that keeping the roles of chairperson and CEO distinct from each other decreases the firm's chances of distress.

H2a: There is a positive relationship between CEO duality and the likelihood of financial distress for the Chinese market.

H2b: There is a positive relationship between CEO duality and the likelihood of financial distress for the UK market.

4.2.3. Board independence

The relationship between principal and agents can be improved if external directors are appointed; as they are better able to monitor management activities (Fama & Jensen, 1983). Moreover, decision making, and control functions can be carried out effortlessly (Bathala & Rao, 1995) and the quality of financial reporting tends to increase with the rise in the number of independent directors (Rutherford & Buchholtz, 2007). In contrast to this view, Baysinger & Hoskisson, 1990) argue that outside directors do not have enough knowledge and expertise to work in the best interest of the company.

There is mixed evidence with respect to the relationship between board independence and the likelihood of financial distress. Researchers including Elloumi & Gueyié (2001), and Fich & Slezak (2008) showed that likelihood of financial distress is lower for firms with a larger number of independent directors, they help the organization to take necessary action to overcome failure. On the other hand, the recent study by Lajili & Zéghal (2010) and Brédart (2014) failed to detect a significant relationship between board independence and financial distress. According to the agency hypothesis, we suggest that board independence is favorable for the organization.

H3a: There is an inverse relationship between board independence and the likelihood of financial distress for the Chinese market.

H3b: There is an inverse relationship between board independence and the likelihood of financial distress for the UK market.

4.2.4. Audit committee independence

The audit committee not only helps in the reduction of firm cost but also serves an internal regulatory function (Forker, 1992). Audit committees play a pivotal role in assisting directors of the firm to effectively perform their responsibilities in the domains of corporate governance (Spira, 2003). Moreover, audit committees serve as a platform for the auditor to address issues such as the scope and nature of the audit with the management and highlight any important findings resulting from audits (Leung et al., 2009). Audit committees also empower non-executive directors to take independent and unbiased decisions for maximizing shareholder's wealth (Dignam, 2011). Additionally, Dey (2008), and Alderman et al. (2012) reveals that there is a positive relationship between audit committee independence and the firm's financial performance. The presence of audit committees may also affect agency costs in a positive manner when measured by revenue costs (Reddy et al., 2008). It has also been found that the presence of non-executive directors in the audit committee reduces the firm's chances of default (McMullen & Raghunandan, 1996). There is a negative relationship between audit committee independence and the likelihood of financial distress (Carcello & Neal, 2000). Thus, it can be hypothesized that:

H4a: There is an inverse relationship between the presence of independent board members on the audit committee and the likelihood of financial distress for the Chinese market.

H4b: There is an inverse relationship between the presence of independent board members on the audit committee and the likelihood of financial distress for the UK market.

4.2.5. Compensation committee independence

Recently major stock exchanges (e.g. NYSE and NASDAQ) have attempted to gain investor confidence by issuing a requirement for fully independent members of compensation committees. Compensation/remuneration committees are responsible for board decisions on so-called 'Fat Cat Payments' for directors and managers at the upper echelon of businesses (Conyon et al., 1995). The most common forms of these payments are salary, bonus, options, commission and profit sharing. Herdan & Szczepańska (2011) argue that along with the financial constraints of a firm, compensation committees also consider the qualifications, expertise and past achievements of the directors when designing remuneration packages. The committee deals with many sensitive issues while designing a compensation package for senior executives, which ultimately affect the firm performance as poor (well) performing managers who are (not) compensated generously may (not) stay on in the firm. Zhu et al. (2009) suggest that compensation committee independence has a strong relationship with executive compensation and firm performance. Indeed, more recently, Lee et al. (2016) also found that firms that do not have fully independent board members in the compensation committees do not perform well.

Agency problems may arise if the members of the compensation committee are biased when designing a compensation package for senior executives and serving the interests of the principal (shareholders). The presence of non-executive members on the compensation committee can decrease agency problems and, in turn, increase firm financial performance by working in the best interest of shareholders for adding value to the company, which ultimately reduces the firm's chances of default. Thus, it can be hypothesized that:

H5a: There is an inverse relationship between the presence of independent board members on the compensation committee and the likelihood of financial distress for the Chinese market.

H5b: There is an inverse relationship between the presence of independent board members on the compensation committee and the likelihood of financial distress for the UK market.

4.2.6. Nomination committee independence

The nomination committee ensures that the person with the best skills, qualification, and expertise is appointed to take the crucial strategic decisions of a firm (Financial Reporting Council, 2012; 2014). The directors selected by the nomination committee have the responsibility to act in the best interest of shareholders and improves the financial performance of a firm to add value to the shareholders. The nomination committee also ensures that the selected directors are independent and work freely without management influence (Petra, 2005). Vafeas (1999) showed a positive relationship between the quality of newly appointed directors and the presence of the nomination committee. Indeed, more recently, Agyemang-Mintah (2015) proved that the presence of a nomination committee has a significant positive impact on the return on assets (ROA) of UK firms.

The nomination committee independence significantly decreases nepotism to get rid of agency problem, improves firm's governance (Vafeas & Theodorou, 1998), which leads to better financial performance (Fauzi & Locke, 2012) and eventually decrease the firm's chances of default. The literature on nomination committees is still limited, few researchers attempted to see its impact on the financial performance of firm but none of them tested the impact of nomination committee independence on the likelihood of financial distress. From the above literature, it can be hypothesized that:

H6a: There is an inverse association between the presence of non-executive board members in the nomination committee and the likelihood of financial distress for the Chinese market.

H6b: There is an inverse association between the presence of non-executive board members in the nomination committee and the likelihood of financial distress for the UK market.

4.3. Empirical methodology

This paper studies the impact of corporate governance and board committees' independence on the likelihood of financial distress for the Chinese and UK market. A firm is financially distressed in our sample if a firm becomes dissolved, liquidated, administrative receivership and bankrupt. Following prior researches of Ohlson (1980), Taffler (1982), Zmijewski (1984), Begley et al. (1996), and Almamy et al. (2016), we use unpaired sampling technique for the selection of companies from both countries.

4.3.1. Sample and data

The objective of this research is to identify the key difference in the board committees' independence of financially distressed and non-distressed firms operating in an emerging market, China and a developed market, the UK. For both countries, we restrict our sample to publicly listed non-financial sector firms as there are fundamental differences in the accounting and governance practices of the financial and non-financial sectors. The data of financial distress and financial status is collected from a DataStream and Bloomberg database. The data of industrial classification is collected from a Bloomberg database. To include a maximum number of firms in our sample, the data of financial and governance variables are collected from both Bloomberg and DataStream databases during the period 2007-2016. We then exclude those firms from our sample which do not fulfill the data requirements.

Our initial sample for China consists of 162 listed firms from the Shanghai and Shenzhen Stock Exchange, out of which 29 are financially distressed. The initial sample of UK comprises of 261 listed firms of London Stock Exchange, out of which 96 are financially distressed. A summary of the initial sample is presented in table 4.1. The number of firms and observations distributed across industry sectors and years is presented in panel A1 for China, and panel A2 for the UK.

4.3.2. Propensity score matching and conditional logit model

To construct the final sample, a matched-pair sampling technique was used to control the impact of firm-specific factors including firm size, industry and period (Chen, 2008) on the likelihood of financial distress. In line with the previous literature (Peasnell et al., 2001; Manzaneque et al. 2016), each financially distressed firm was matched with non-financially distressed firms which have a similar size (total asset), same industry and the same accounting period. However, the matching procedure used in this study presents the innovation by matching firms using propensity score matching[8] with a caliper of 0.1[9]. The effect of board independence on firm financial distress is then inferred from the estimated coefficient on board independence. Other variables are controlled through their inclusion in the regression estimation.

The matching procedure resulted in a total sample size of 342 observations over the whole sample period (2007-2016), displayed in table 4.2. A simple t-test demonstrated that the matching worked as financially distressed and non-distressed firms were of a statistically similar size (t=0.13, p=0.89). The same procedure was repeated for UK firms resulting in a total sample of 1388 observation over the same accounting periods. Another t-test reveals that the matched-pairs do not differ significantly and statistically in size (t=0.51, p=0.61).

[8] Propensity Score Matching was performed using the user-written STATA module *psmatch2*.
[9] A caliper is the maximum tolerated difference in propensity score between matched firms. This was performed to ensure matched firms did not statistically significantly differ in size.

Table 4.1: Initial sample description

Panel A: Initial full sample (period 2007 - 2016)

Sample firms and number of observations by industrial sector

Panel A1: China sample	Total				Distressed				Non-Distressed			
	Firms	%	Obs	%	Firms	%	Obs	%	Firms	%	Obs	%
Consumer Discretionary	22	13.58	177	14.26	3	10.34	20	9.66	19	14.29	157	15.18
Consumer Staples	13	8.02	92	7.41	2	6.90	15	7.25	11	8.27	77	7.45
Energy	7	4.32	63	5.08	0	0.00	0	0.00	7	5.26	63	6.09
Health Care	13	8.02	99	7.98	2	6.90	20	9.66	11	8.27	79	7.64
Industrials	37	22.84	270	21.76	10	34.48	70	33.82	27	20.30	200	19.34
Information Technology	12	7.41	86	6.93	0	0.00	0	0.00	12	9.02	86	8.32
Materials	34	20.99	267	21.51	4	13.79	29	14.01	30	22.56	238	23.02
Telecommunication	6	3.70	41	3.30	5	17.24	33	15.94	1	0.75	8	0.77
Utilities	18	11.11	146	11.76	3	10.34	20	9.66	15	11.28	126	12.19
Total	162	100.00	1241	100.00	29	100.00	207	100.00	133	100.00	1034	100.00

Panel A2: UK sample	Total				Distressed				Non-Distressed			
	Firms	%	Obs	%	Firms	%	Obs	%	Firms	%	Obs	%
Consumer Discretionary	66	25.29	541	25.16	35	36.46	294	37.36	31	18.79	247	18.12
Consumer Staples	21	8.05	175	8.14	2	2.08	16	2.03	19	11.52	159	11.67
Energy	22	8.43	175	8.14	8	8.33	55	6.99	14	8.48	120	8.80
Health Care	14	5.36	108	5.02	4	4.17	22	2.80	10	6.06	86	6.31
Industrials	68	26.05	581	27.02	28	29.17	264	33.55	40	24.24	317	23.26
Information Technology	19	7.28	158	7.35	10	10.42	80	10.17	9	5.45	78	5.72
Materials	38	14.56	304	14.14	6	6.25	30	3.81	32	19.39	274	20.10
Telecommunication	6	2.30	51	2.37	2	2.08	17	2.16	4	2.42	34	2.49
Utilities	7	2.68	57	2.65	1	1.04	9	1.14	6	3.64	48	3.52
Total	261	100.00	2150	100.00	96	100.00	787	100.00	165	100.00	1363	100.00

Number of observations per year

Panel A1: China sample										
Status	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
Distressed	48	69	91	114	118	121	127	127	134	85	1034
Non-Distressed	7	9	14	24	24	24	26	28	28	23	207
Total firms	55	78	105	138	142	145	153	155	162	108	1241

Panel A2: UK sample											
Status	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
Distressed	88	95	107	130	151	154	161	161	163	153	1363
Non-Distressed	55	62	71	81	84	86	87	90	89	82	787
Total firms	143	157	178	211	235	240	248	251	252	235	2150

Table 4.2: Matched sample description

Panel B: Matched pair samples by size, industry and year

Number of observations by industrial sector

Panel B1: China sample (171 distressed firms observations/171 non-distressed firms observations)

Status	Consumer Discretionary	Consumer Staples	Health Care	Industrials	Materials	Telecommunications	Utilities	Total
0	20	14	15	68	28	8	18	171
1	20	14	15	68	28	8	18	171
Total	40	28	30	136	56	16	36	342

Panel B2: UK sample (694 distressed firms observations/694 non-distressed firms observations)

Status	Consumer Discretionary	Consumer Staples	Energy	Health Care	Industrials	Information Technology	Materials	Telecom…	Utilities	Total
0	242	16	49	22	258	71	25	3	8	694
1	242	16	49	22	258	71	25	3	8	694
Total	484	32	98	44	516	142	50	6	16	1388

Number of observations by year

Panel B1: China sample

Status	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
0	2	6	13	21	21	21	23	25	23	16	171
1	2	6	13	21	21	21	23	25	23	16	171
Total	4	12	26	42	42	42	46	50	46	32	342

Panel B2: UK sample

Status	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
0	44	48	58	69	77	81	82	82	80	73	694
1	44	48	58	69	77	81	82	82	80	73	694
Total	88	96	116	138	154	162	164	164	160	146	1388

4.4. Model specification

The study employed a fixed-effects conditional logit model, which is broadly used in the distress prediction literature. This extension of the logit model was chosen to take advantage of the matched-pair design of this study which controls for confounding due industry-specific market conditions, accounting year and size of a firm (proxied by total assets). The conditional logit allows each matched-pair to have a different constant term which allows for unobserved heterogeneity amongst firms of different sizes and industries. The model fitted is of the form:

$$P(Y = 1|X) = \frac{\exp(\propto_i + \beta x)}{1 + \exp(\propto_i + \beta x)} \tag{3.1}$$

Where, Y=1 denotes a firm being in financial distress, where $\propto_i$ is the constant term for the $_i$th strata, and x denotes a vector of explanatory variables. There are three sets of explanatory variables, the first set contains financial control variables, well documented in distress prediction literature by many researchers including Altman (1968), Ohlson (1980), Zmijewski (1984), Chaganti et al. (1985), Daily & Dalton (1994), Shumway (2001), Elloumi & Gueyié (2001), Almamy et al. (2016), the second group represent corporate governance variables reflecting board composition, and third group is comprised of board committees' independence.

We estimate the below four different specifications for the conditional logistic regression models:

$$\mathrm{DIS}_{ict} = \alpha_{ot} + \beta_1 C_{ict} + \epsilon_{ict} \tag{3.2}$$

$$\mathrm{DIS}_{ict} = \alpha_{ot} + \beta_1 C_{ict} + \beta_2 CG_{ict} + \epsilon_{ict} \tag{3.3}$$

$$\mathrm{DIS}_{ict} = \alpha_{ot} + \beta_1 C_{ict} + \beta_2 BC_{ict} + \epsilon_{ict} \tag{3.4}$$

$$\mathrm{DIS}_{ict} = \alpha_{ot} + \beta_1 C_{ict} + \beta_2 CG_{ict} + \beta_3 BC_{ict} + \epsilon_{ict} \tag{3.5}$$

Where, DIS_{ict} represents the financial distress for firm i of country c, in year t, C_{ict} is the vector of financial control variables, CG_{ict} is the vector of corporate governance variables, BC_{ict} is the vector of board committee independence variables. Table 4.3 describes the summary of the variables employed. The final model with control and governance variables is estimated as:

$$DIS_{ict} = \alpha_0 + \beta_1(PROF) + \beta_2(\mathrm{LIQ}) + \beta_3(\mathrm{LEV}) + \beta_4(\mathrm{BSIZE}) + \beta_5(DUAL) + \beta_6(BIND) + \beta_7(AIND) + \beta_8(\mathrm{CIND}) + \beta_9(NIND) + \epsilon_{it} \quad (3.6)$$

Table 4.3: Summary of variables

Variables	Description
Dependent variable	
Financial distress	0 = Financially non-distressed firms 1 = Financially distressed firms
Independent variables	
Control variables	
Profitability *(PROF)*	Sales to total assets
Liquidity *(LIQ)*	Working capital to total assets
Leverage *(LEV)*	Total liabilities to total assets
Board size *(BSIZE)*	Total number of directors on the board.
Duality *(DUAL)*	An indicator variable equal to 1 when the CEO and chairman is same, 0 otherwise.
Board independence *(BIND)*	Percentage of independent directors to total directors of the board.
Board Committees Independence variables	
Audit committee independence *(AIND)*	Percentage of independent board members on the audit committee.
Compensation committee independence *(CIND)*	Percentage of independent board members on the compensation committee.
Nomination committee independence *(NIND)*	Percentage of independent board members on the nomination committee
Matching variables	
Firm size	Natural logarithm of total assets
Industrial Sectors	Consumer discretionary Consumer staples Energy Healthcare Industrials Information technology Materials Telecommunications Utilities

4.5. Empirical results

4.4.1. Summary statistics

Table 4.4 presents the summary statistics of the independent variables for the initial and matched pair sample of Chinese and UK firms. For Chinese sample, our financial control variables *(PROF, LIQ, LEV)* have initial (matched) sample mean of 0.742 (0.659), 0.118 (0.103), and 0.515 (0.569), respectively, indicating no significant difference in the mean of both types of samples. Similarly, average board size *(BSIZE)* of the initial (matched) sample is

9.915 (9.743), and the average number of independent board members for initial (matched) sample is 38.350 (38.579). Moreover, the percentage of minimum and maximum independent board committees' members represented by *AIND*, *CIND*, and *NIND* are exactly same, indicating the same pattern in both initial and matched sample, hence our matched sample is representative of the initial sample. The distressed firms have a slightly higher percentage (24%) of the same person serving as CEO and chairman *(DUAL)* than the non-distressed firms (21%).

Our results are consistent for the UK sample, indicating fewer differences in the initial and matched pair sample. Comparing the financial control variables, we find that both groups have similar mean levels for all variables, with an average of 1.014 (1.017), 0.095 (0.097), and 0.567 (0.566) for initial (matched) sample. Similarly, the minimum and a maximum number of the board members for initial and matched sample are 3 and 19, respectively, indicating no apparent difference in both groups. The mean number of independent board members in audit *(AIND)*, compensation *(CIND)*, and nomination *(NIND)* committee for initial (matched) sample are 98.299 (98.268), 94.105 (93.940), and 83.597 (83.363), respectively. Furthermore, there is no significant difference in the average size of firms in both samples. Unlike the Chinese sample, there is no difference in CEO duality *(DUAL)* of the distressed and non-distressed firms operating in the UK.

Table 4.5 presents the main differences in the summary statistics of the distressed and non-distressed firms along with the test of mean differences in significance. For Chinese firms, the Mann-Whitney U test indicates that there are systematic differences between the distressed and non-distressed firm with respect to board size, slightly higher in distressed firms as compared to non-distressed firms. Also, the percentage of independent audit committee members *(AIND)* is significantly greater in distressed firms (87.7%) than the non-distressed firms (82.5%). By contrast, the percentage of the same person serving as CEO and chairman *(DUAL)* is significantly greater in non-distressed firms (30%) than the distressed firms (12%). For UK firms, the Mann-Whitney U test and Pearson chi-square value indicates that there are systematic differences in the mean of both groups for financial control variable liquidity *(LIQ)*, significantly lower (5%) for distressed firms than the non-distressed firms (15.5%). Also, the leverage *(LEV)* shows significant differences between distressed and non-distressed firms. Likewise, the average percentage of independent board members in audit *(AIND)*, compensation *(CIND)*, and nomination *(NIND)* are significantly different for distressed and non-distressed firms. As expected, the percentages are lower for distressed firms than the non-distressed firms, indicating that the distressed firms tend to have a lower number of independent board members in their committees than the non-distressed firms. The results for the CEO duality *(DUAL)* are similar to the Chinese firms with a slightly higher percentage (7%) in non-distressed firms than the distressed firms.

Table 4.4: Summary statistics of initial and matched sample

Chinese sample										
Variables	Panel A: Initial sample before matching					Panel B: Sample after matching				
	Mean	Med	SD	Min	Max	Mean	Med	SD	Min	Max
Control variables										
PROF	0.742	0.612	0.501	0.079	3.302	0.659	0.560	0.429	0.083	2.751
LIQ	0.118	0.101	0.243	-0.704	0.886	0.103	0.091	0.226	-0.593	0.882
LEV	0.515	0.523	0.221	0.014	1.631	0.569	0.589	0.243	0.033	1.478
BSIZE	9.915	9	2.632	5	25	9.743	9	2.234	5	18
BIND	38.350	36.363	7.413	11.110	77.780	38.579	36.363	7.998	18.750	72.730
Board committee's independence variables										
AIND	80.782	67.000	18.016	33.333	100.00	85.121	100.00	17.356	33.333	100.00
CIND	71.917	66.670	15.813	0.000	100.00	71.427	67.000	15.857	0.000	100.00
NIND	71.921	66.670	14.769	0.000	100.00	71.873	67.000	14.789	0.000	100.00
Matching variable										
SIZE	16.660	16.572	1.734	11.852	20.496	17.043	17.216	1.655	13.282	20.496
Categorical control variable										

		Distressed firms	Non-Distressed firms
DUAL	Coded 1	24.00%	21.00%
	Coded 0	76.00%	79.00%

UK sample										
Variables	Panel A: Initial sample before matching					Panel B: Sample after matching				
	Mean	Med	SD	Min	Max	Mean	Med	SD	Min	Max
Control variables										
PROF	1.014	0.840	0.836	0.000	12.959	1.017	0.842	0.846	0.000	12.959
LIQ	0.095	0.081	0.197	-1.210	0.923	0.097	0.083	0.197	-1.210	0.923
LEV	0.567	0.567	0.228	0.002	2.447	0.566	0.567	0.230	0.002	2.447
BSIZE	8.690	8	2.234	3	19	8.688	8	2.243	3	19
BIND	57.872	57.143	12.863	6.670	92.860	57.518	57.143	12.820	6.670	92.860
Board committee's independence variables										
AIND	98.299	100.00	7.784	25.000	100.00	98.268	100.00	7.849	25.000	100.00
CIND	94.105	100.00	13.169	0.000	100.00	93.940	100.00	13.289	0.000	100.00
NIND	83.597	83.333	16.206	0.000	100.00	83.363	83.333	16.268	0.000	100.00
Matching variable										
SIZE	14.265	14.051	1.680	8.098	19.835	14.231	14.025	1.668	8.098	19.835
Categorical control variable										

		Distressed firms	Non-Distressed firms
DUAL	Coded 1	5.00%	5.00%
	Coded 0	95.00%	95.00%

Table 4.5: Summary statistics: distressed and non-distressed firms

Chinese sample

	Distressed firms					*Non-Distressed firms*					*Mann-Whitney U test*
Variables	Mean	Med	SD	Min	Max	Mean	Med	SD	Min	Max	
Control variables											
PROF	0.617	0.555	0.351	0.083	1.744	0.702	0.584	0.492	0.097	2.751	1.122
LIQ	0.062	0.038	0.223	-0.593	0.882	0.145	0.115	0.221	-0.265	0.818	**3.366***
LEV	0.588	0.591	0.268	0.072	1.478	0.551	0.588	0.214	0.033	0.892	-0.418
BSIZE	9.813	10	1.792	5	15	9.673	9	2.605	5	18	**-2.097****
BIND	37.670	36.363	7.020	18.750	60.000	39.487	36.360	8.796	21.050	72.730	0.938
Board committee's independence variables											
AIND	87.747	100.00	15.643	50.000	100.00	82.495	100.00	18.591	33.333	100	**-2.628*****
CIND	70.057	67.00	15.660	0.000	100.00	72.797	67.000	15.980	50.000	100	-0.179
NIND	70.881	67.00	12.516	0.000	100.00	72.863	66.67	16.734	33.333	100	-1.179
Matching variable											
SIZE	17.031	17.216	1.673	13.286	20.496	17.056	17.232	1.641	13.282	20.444	0.299
Categorical control variable											

		Distressed firms	Non-Distressed firms	Pearson Chi-Square
Duality	Coded 1	12%	30%	**15.833*****
	Coded 0	88%	70%	

UK sample

	Distressed firms					*Non-Distressed firms*					*Mann-Whitney U test*
Variables	Mean	Med	SD	Min	Max	Mean	Med	SD	Min	Max	
Control variables											
PROF	1.099	0.926	0.731	0.000	4.147	1.114	0.895	1.001	0.001	11.197	-1.009
LIQ	0.049	0.025	0.185	-0.708	0.739	0.155	0.120	0.224	-0.526	0.853	**9.499*****
LEV	0.615	0.632	0.211	0.126	1.483	0.553	0.541	0.239	0.039	2.107	**-7.035*****
BSIZE	8.370	8	2.0200	4	19	8.463	8	1.976	3	15	**1.640***
BIND	55.583	57.140	13.237	10.530	85.714	56.643	57.142	11.610	20.000	88.889	1.052
Board committee's independence variables											
AIND	97.028	100.00	10.399	25.000	100.00	98.446	100.00	7.128	33.333	100.00	**2.668*****
CIND	91.794	100.00	15.591	25.000	100.00	94.474	100.00	11.327	33.333	100.00	**2.830*****
NIND	80.470	80.000	17.606	0.000	100.00	84.462	83.333	14.555	33.333	100.00	**3.837*****
Matching variable											
SIZE	13.872	13.882	1.184	10.398	16.405	13.905	13.801	1.228	10.219	17.894	0.129
Categorical control variable											

		Distressed firms	Non-Distressed firms	Pearson Chi-Square
Duality	Coded 1	4.00%	7.00%	**10.375*****
	Coded 0	96.00%	93.00%	

*, **, *** indicating significance at 10%, 5% and 1% respectively.

The correlation for the independent variables is presented in table 4.6. For both samples, all bivariate Pearson correlations are less than 0.4 except for compensation committee *(CIND)*, which is positively correlated with board independence *(BIND)* and audit committee independence *(AIND)* at 0.402 and 0.420, respectively. Even though some significant correlation exists but the overall correlation matrix suggests the minimal existence of multicollinearity in the model, and its possible impact on the analysis, because all values are less than 0.7 (Tabachnick & Fidell, 1996).

Table 4.6: Correlation matrix for independent variables

Chinese sample									
	PROF	LIQ	LEV	BSIZE	DUAL	BIND	AIND	CIND	NIND
PROF	1								
LIQ	-0.004	1							
LEV	0.040	**-0.491*** **	1						
BSIZE	-0.035	-0.078	**0.114** **	1					
DUAL	**0.101***	0.088	0.052	-0.076	1				
BIND	0.057	0.033	0.027	**-0.194*** **	-0.034	1			
AIND	**-0.174*** **	**-0.154*** **	0.042	**0.279*** **	**-0.113** **	**0.188*** **	1		
CIND	**0.142*** **	0.075	-0.081	**0.272*** **	**-0.136*** **	**0.160*** **	**0.344*** **	1	
NIND	**-0.117** **	-0.010	-0.015	**0.322*** **	-0.045	**0.133*** **	**0.386*** **	**0.399*** **	1
UK sample									
	PROF	LIQ	LEV	BSIZE	DUAL	BIND	AIND	CIND	NIND
PROF	1								
LIQ	**-0.190*** **	1							
LEV	**0.352*** **	**-0.548*** **	1						
BSIZE	**-0.098*** **	**-0.168*** **	**0.130*** **	1					
DUAL	0.019	**-0.055** **	0.021	**0.137*** **	1				
BIND	**-0.093*** **	**-0.045***	0.001	**-0.094*** **	**-0.159*** **	1			
AIND	-0.022	0.035	0.000	0.004	0.035	**0.290*** **	1		
CIND	0.003	0.042	**-0.096*** **	**-0.108*** **	-0.010	**0.402*** **	**0.420*** **	1	
NIND	**0.056** **	0.021	-0.005	**-0.065*** **	**-0.060** **	**0.372*** **	**0.378*** **	**0.352*** **	1

*, **, *** indicating significance at 10%, 5% and 1% respectively.

4.4.2. Conditional logistic regression results

The study uses a conditional logistic regression to test the differential impact of corporate governance variables for both emerging and developed market. Financial status is a binary dependent variable, coded with 1 for financially distressed firms and 0 for non-distressed firms. Four main models are presented (Model 1, 2, 3, and 4). In model 1, we test the impact of financial control variables *(PROF, LIQ, and LEV)* on the likelihood of financial distress. In model 2, we re-estimate the model with three corporate governance variables *(BSIZE, DUAL, and BIND)*. For model 3, we again re-estimate the model with the committee's independence variables *(AIND, CIND, and NIND)*. Finally, we added all three sets of variables (financial controls, corporate governance and committee's independence) in our fourth model. We begin our analysis by testing all four models for the Chinese market.

Table 4.7 presents the results of the conditional logistic analysis for the Chinese sample. The log likelihood test for all four models is significant at 1% level, indicating that the overall validity of the models, and the association of independent variables with the likelihood of financial distress. The results of model 1 show that the financial variables, profitability *(PROF)* and liquidity *(LIQ)* are negatively associated with the likelihood of financial distress at 10% and 1% significance level, while the leverage *(LEV)* shows the expected sign, but not statistically significant. Our results are consistent with the argument that the firms with lower profitability and liquidity have more chances of default (Altman, 1968). After adding the corporate governance variables in model 2, the profitability variable is no more significant, however, the liquidity variables retain its statistical significance and the expected sign.

Our overall results for the corporate governance variable, board size *(BSIZE*) does not have an impact on the likelihood of financial distress for the firms operating in China, and thus our hypothesis H1a is not supported. These results contrast with previous studies who find a significant impact (e.g. Pearce & Zahra, 1992; Manzaneque et al., 2016). The impact of CEO duality *(DUAL)* on the likelihood of financial distress is negative, rejecting the hypothesis H2a. This result is consistent with the argument of Resource Dependency Theory (Pearce & Zahra, 1992; Nahar Abdullah, 2006), according to which duality promotes the unity of leadership and facilitates organizational effectiveness. However, the result is contrary to that obtained by (Daily & Dalton, 1994; Hiu & Jing-Jing, 2008), who find a positive impact of duality on the likelihood of financial distress. The impact of board independence *(BIND)* on the likelihood of financial distress for the Chinese sample is negative, supporting the hypothesis H3a. Our results are consistent with the findings of Manzaneque et al. (2016), Fich & Slezak (2008), and Elloumi & Gueyié (2001).

The results of model 3, in table 4.7 indicates that the board committees are statistically significant at 1-10% level, with the exception for compensation committee *(CIND)* which become significant in model 4. Our overall results for board committees conclude that audit committee independence *(AIND)* is positively related to the likelihood of financial distress. So, hypothesis H4a is not supported. This result supports Hsu & Wu (2010), who argued that an increase in a number of outside directors in audit committee is unfavorable for firm survival and increases its chances of going into bankruptcy. The coefficient of our new variables, nomination *(NIND)* and compensation committee independence *(CIND)* have a negative influence on the likelihood of financial distress, hence accepting both hypotheses H5a and H6a. Therefore, it can be argued that firms with independent compensation (Lee et al., 2016) and nomination committee members (Fauzi & Locke, 2012) exhibit lower financial performance and in due course have a negative impact on the likelihood of financial distress.

Table 4.7: Conditional logistic regression results - China

Dependent variable: Financial Status				
Variables	Model 1	Model 2	Model 3	Model 4
Control variables				
PROF	**-0.469 (0.079)***	-0.394 (0.164)	-0.327 (0.252)	-0.178 (0.566)
LIQ	**-1.915 (0.001)*****	**-1.630 (0.008)*****	**-1.711 (0.006)*****	**-1.364 (0.033)****
LEV	0.055 (0.918)	0.268 (0.630)	0.045 (0.937)	0.412 (0.483)
BSIZE		-0.015 (0.793)		-0.026 (0.679)
DUAL		**-1.101 (0.000)*****		**-1.250 (0.000)*****
BIND		**-0.031 (0.047)****		**-0.034 (0.040)****
Board committees independence				
AIND			**0.028 (0.001)*****	**0.033 (0.000)*****
CIND			-0.010 (0.243)	**-0.016 (0.089)***
NIND			**-0.019 (0.039)****	**-0.017 (0.087)***
No of observations	342	342	342	342
LR $\chi 2$	**16.44 (0.000)*****	**34.52 (0.000)*****	**31.71 (0.000)*****	**52.92 (0.000)*****
-2 log likelihood	-192.23727	-183.19974	-184.60431	-174.0013
Pseudo R2	0.041	0.086	0.079	0.132

*, **, *** indicating significance at 10%, 5% and 1% respectively.

Table 4.8 presents the results of conditional logistic regression for the UK sample. With the notable exception for the leverage variable *(LEV)*, all the financial control variables retain the same sign in all four models with 1-5% significance level, suggesting that the profitability

(PROF) and liquidity *(LIQ)* are consistent predictors of the likelihood of financial distress. Leverage *(LEV)* is kept in the models because it shows the expected sign and contributed positively to the overall significance of the final model.

Table 4.8: Conditional logistic regression results - UK

Dependent variable: Financial Status				
Variables	Model 1	Model 2	Model 3	Model 4
Control variables				
PROF	**-0.171 (0.013)*** **	**-0.224 (0.002)*** **	**-0.160 (0.021)*** **	**-0.198 (0.006)** **
LIQ	**-2.663 (0.000)*** **	**-2.930 (0.000)*** **	**-2.671 (0.000)*** **	**-2.887 (0.000)*** **
LEV	0.201 (0.521)	0.266 (0.404)	0.147 (0.646)	0.198 (0.540)
BSIZE		**-0.087 (0.004)*** **		**-0.091 (0.003)*** **
DUAL		**-0.879 (0.001)*** **		**-0.823 (0.002)*** **
BIND		**-0.015 (0.001)*** **		-0.005 (0.350)
Board committees independence				
AIND			-0.003 (0.671)	0.000 (0.953)
CIND			-0.008 (0.130)	-0.008 (0.124)
NIND			**-0.013 (0.002)*** **	**-0.013 (0.003)*** **
No of observations	1388	1388	1388	1388
LR $\chi 2$	**98.46 (0.000)*** **	**126.43 (0.000)*** **	**120.90 (0.000)*** **	**141.66 (0.000)*** **
-2 log likelihood	-839.048	-825.064	-827.828	-817.449
Pseudo R2	0.0410	0.0861	0.0791	0.1320

*, **, *** indicating significance at 10%, 5% and 1% respectively.

In terms of our governance variables, there are differences in the impact on the likelihood of financial distress for the firms operating in the UK. Unlike China, large board size *(BSIZE)* is an effective monitor for the UK firms and decrease their chances of default with better access to resources, and ability to control management, supporting hypothesis H1b. This result is consistent with the findings of Pearce & Zahra (1992). Moreover, board independence *(BIND)* shows the expected sign, but become insignificant when added to the final model, thus we can argue that the there is no significant impact of independent board members on the likelihood of financial distress for the firms operating in the UK, rejecting hypothesis H3b. The coefficient of the variable audit *(AIND)* and compensation committee independence *(CIND)* are not significant for the UK market, and thus our hypothesis (H4b, H5b) are not supported. Although the signs of both variables are similar to the Chinese sample, firm's likelihood of financial distress increases with an increase in independent audit committee members while it decreases when there are more independent members in compensation committee.

There are some similarities in the results for both markets. Our results of the variable CEO duality are consistent for both markets and supports Resource Dependency Theory, indicating that firms with the same person exercising the role of chairperson of the board and CEO are less likely to be in financial distress. Therefore, our hypothesis H1b is not supported. Lastly, for the variable, nomination committee independence *(NIND)* we obtain the same relationship, the estimated coefficient is negative, supporting hypothesis H6b. This would suggest that companies with more proportion of independent members in nomination committee have less likelihood of financial distress because the selection of directors is unbiased, and the nominated members could work freely in the best interest of a company.

4.4.3. Robustness test

The partial-matched econometric method used in this study (i.e. matching only on size and industry as well accounting period) produces unbiased parameter estimates only if there is an identical functional relationship between the control variables and the outcome variable for each type of firm - distressed or non-distressed.

The conditional logistic regression used in this study assumes that a linear functional relationship exists between the log of the odds ratio and the observable covariates. It is possible that this functional form is mis-specified leading to potentially erroneous conclusions on the effect of board committees' independence on the financial distress of companies. We test this assumption by specifically matching distressed firms with non-distressed firms that are similar across all covariates except for the outcome of interest (audit, compensation, nomination committee independence). The matching variables used for matching were: *PROF, LIQ, LEV, BSIZE, and DUAL*[10] as well as industry and accounting year. Both the Chinese and UK samples

[10] Board independence was included as a matching variable over concern that it is an endogenous variable with the other board independence variables. For example, a company with an independent nomination committee is more likely to have an independent board.

demonstrated balance in terms of matching covariates between distressed and non-distressed firms.

Table 4.9 presents the results of the propensity score matching estimation on both the Chinese and UK Sample. With regards to the Chinese sample, the propensity score matching results confirm the results of those found using the partial-matched econometric design used in the earlier analysis, albeit the impact of the nomination committee independence becomes less significant. The UK financially distressed firms consistently have a lower percentage point difference in board independence than their matched non-financially distressed counterparts. Further, the robustness check shows the impact of audit committee independence on financial distress is now statistically significant although the difference in percentage point terms is rather low. Taken together, the results from the robustness check suggest that results from the main analysis are largely robust to both econometric techniques employed in this study which have different functional form assumptions.

Table 4.9: Robustness check: Propensity score matching

Outcome	**Mean Percentage Point Difference**	**t-stat**	**Mean Independence Distressed**	**Mean Independence Non-distressed**
Panel A: Chinese sample (430 firms)				
Audit committee independence	**5.7***	**3.5*****	88.17	82.47
Compensation committee independence	-2.82	**-1.70***	71.27	74.10
Nomination committee independence	-2.12	-1.47	71.58	73.70
Panel B: UK sample (1574 firms)				
Audit committee independence	-1.56	**3.57*****	97.02	98.59
Compensation committee independence	-1.99	1.15	95.25	97.25
Nomination committee independence	-6.76	**2.83*****	82.76	89.52

4.6. Conclusion

This paper examines the impact of board committees' independence, namely audit, compensation, and nomination, on the likelihood of financial distress. Using data from publicly listed firms operating in China and the UK during the period 2007-2016, we compared the Chinese corporate governance characteristics with those from a developed market. The rationale of running the conditional logit model in two countries is to see if there is a differential impact according to institutional setting; where the requirements are the same in terms of having directors in committees, independent chairpersons, and a limit on the number of independent directors; but where the ownership structure and corporate governance practices are different.

Our overall results indicate that corporate governance characteristics play a significant role in the likelihood of financial distress, although there are differences in the impact for emerging and developed market. For both markets, our results show that board size and board independence are negatively related to the likelihood of financial distress, but the former is significant for the UK and the latter is significant for China. Similarly, CEO duality significantly reduces the financial distress of the firms operating in both markets. This result is consistent with the Resource Dependency Theory, that CEO duality reduces chances of conflict and increases organizational effectiveness. The results indicate that higher levels of audit committee independence are not beneficial for the firms operating in China and increases their chances of distress. On the other hand, there is no impact of independent audit committee members on the firms operating in the UK. The results reveal that compensation committee independence is negatively associated with the likelihood of financial distress for both markets, but only China showed significant results. These findings have important implications especially for Chinese firms to increase the number of independent board members to design fair compensation packages. Another interesting finding of our study is that there is an inverse relationship between independent board members on the nomination committee and the firm's likelihood of financial distress for both markets. Our results suggest that the role of nomination committee is crucial for the firm's survival, as it has the responsibility to select the most suitable persons to decide strategic moves of the firm.

Our results support the conjecture that the firms with larger proportions of independent board members have fewer chances of financial distress. We provide evidence for the first time that the compensation and nomination committee independence is negatively associated with financial distress. These results have important implications for policymakers and other stakeholders of the business, operating in both types of economies, suggesting that if the members of these well planned, structured and assigned committees are not independent, then the firm cannot take proper advantage of director's expertise to perform oversight and advisory functions. Specifically, the Chinese market, which is primarily state-controlled, with a high degree of concentrated ownership, and relatively less investor protected, demand special focus, in order to maintain strong economic performance. In such an economy, improvements in corporate governance practices are especially important to protect against possible misconduct by the controlling shareholders. Improving corporate policy in line with recommended practice has the added benefit of attracting external investments and which could stimulate even more investment for the most attractive country in the world for overseas investors.

The overall results of this study suggest that both countries could adopt corporate governance policies which increase the level of independent directors in their board to protect minority shareholder's interest, specifically during the process of director appointment and evaluation. Future researchers can enhance the literature by focusing on the impact of various attributes of board committees, especially nomination committee, on the likelihood of financial distress.

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Chapter 5: Conclusion

Corporate financial distress is of growing public concern due to recent financial crises which have led to the bankruptcy of major well-established companies. These recent business closures have raised the question as to whether financial distress prediction models are fit for purpose. However, financial distress prediction is still desirable as it has the potential to save the firm from potential losses and bankruptcy but only in the context when predictive models are well-specified. In light of these facts, this thesis investigates three important issues relating to financial distress. First, it tests the generalizability of traditional distress prediction models with a wider definition of financial distress. Second, it introduces a new distress prediction model developed with accounting ratios, market-based variables and financial reporting quality measures Finally, it tests the impact of corporate governance practices, board committee independence - on the financial distress of firms operating in both an emerging and developed markets.

The objective of the first essay was to test the generalizability of five most widely used distress prediction models constructed for the US market; Altman's Z-Score model (1968), Ohlson's O-Score model (1980), Zmijewski's probit model (1984), Shumway's hazard model (2001), and Blums D-Score model (2003), for the emerging market, Pakistan with respect to early warnings signs of financial distress. The results show Zmijewski's probit model, as having the highest prediction accuracy with Altman's Z-Score model returning more accuracy in predicting financially distressed firms. The other three models performed poorly relative to the D-Score model by over-estimating the number of distressed companies, while the Hazard and O-Score models over-estimating the economically stable businesses. The results also indicated that the prediction accuracy of the models decline during periods of financial crisis, suggesting that new and better models that cover large data frame need to be developed after the global financial crisis. The new model might show a better prediction accuracy, especially when used in the emerging markets. This paper also contributed to the literature by widening the definition of financial distress for emerging markets to include firms at the earlier stages of distress in the sample and with confirmed results in the robustness test.

The second essay focused on the development of a new distress prediction model using it before and after the financial crisis. The study used data from the United Kingdom, a developed market, and tested the model's prediction accuracy for Pakistan, an emerging market.

Consequently, while accounting and market-based variables have widely been used by a number of researches, this research incorporated the financial reporting quality measures: earnings and accruals quality as new variables. The overall prediction accuracy of A-Score model for the UK market is 81.2%. Besides, the model shows a relatively improved prediction accuracy of 89.4% for the emerging market, Pakistan. The research unveiled that there is a significant relationship between financial reporting quality and the firm's probability of financial distress, and that researchers should not ignore reporting quality while developing a distress prediction model.

Lastly, the third essay sought to investigate how corporate governance variables, specifically board committee independence, impact on the financial distress of firms operating in the emerging and developed markets. To achieve this objective, two well-known economies were chosen, China and the United Kingdom to represent emerging and developed markets, respectively. The results of the study revealed that the board committee independence plays a significant role in the financial distress of firms, although the impact differs for both types of economies. The number of independent board members in the audit committee increased the firm's chances of default for the firms operating in China, but it does not have any impact for the firms operating in the UK. On the other hand, compensation committee independence increases the probability of financial distress for the Chinese firms, but it does not have a significant impact on the businesses operating in the UK. The findings of the study reveal that nomination committee members' independence has a significant inverse relationship with the likelihood of financial distress for both markets. Our results suggest that the role of nomination committee is crucial for the long-term sustainability of the firm because it has the responsibility to select the most qualified and suitable personnel accountable for strategic decision making of the company.

Although this thesis tries to address multiple gaps identified in the previous research, it is still subject to a number of limitations. The first essay only included one emerging market to test prediction accuracy of traditional models with respect to early warning signs of financial distress, as it was difficult to collect data of emerging markets from multiple sources. It is important to mention here that there is not enough data for emerging markets in financial databases, therefore data was collected one by one from multiple sources for every variable. The data availability and data collection were more of a problem in this study.

Regarding the second essay, the data limited our analysis to only two markets to represent developed and emerging markets for model development in the second essay. Moreover, the data with the wider definition of financial distress was not available for the developed market that is why we used the most commonly used definition of financial distress for which data was available for both developed and emerging market.

With respect to the final essay, corporate governance variables for emerging markets are quite limited in financial databases and it was not possible to work on the same market for the third paper, therefore we changed the market in the third paper and include the one which had representative observations. Although, we tried our best and utilized two databases, Bloomberg and Datastream, to collect data of corporate governance variables, still the number of observations were quite less as compared to the developed market.

5.1. Theoretical and practical implications of research

This research was inspired by attempting to better understand the empirical phenomenon of financial distress and contributes new insights to this exciting and complex field of financial research. We contribute to the existing knowledge of literature by widening the definition of financial distress for the emerging markets, developing a new model with financial reporting quality variables which can be applied to both developed and emerging markets, and explored the differences in the impact of governance variables, more specifically board committee's independence on the probability of financial distress in an emerging and developed markets. Therefore, there are multiple contributions of this research for academia and practitioners:

5.1.1. Academic contributions

This thesis contributes to the scholarly literature of financial distress in various ways. First, the study attempts to expand the definition of financial distress for the emerging markets, by identifying firms from the sample which are still at the early stages of financial distress, where no financial databases are available with the classification of firms. The definition can aptly be used in the financial distress prediction literature to describe financially distressed firms from both emerging and developed markets.

Secondly, through comparison of the five well-known distress prediction models developed particularly for the US firms, this study finds a declining prediction accuracy when the models are applied to the emerging markets with different firm capitalization structure. Consequently, the findings of the study suggest that researchers should work on the development of new distress prediction models with more stable variables for the developed and emerging markets, as the study results show the prediction accuracy of existing models declines during and after a period of financial crisis.

Also, none of the existing distress prediction models which have incorporated accounting ratios, market-based variables as well as corporate governance attributes, covers hidden part of financial reports, represented by financial reporting quality measures. This study addresses this gap in the academic literature by developing a distress prediction model with financial reporting quality measures. Researchers may use financial reporting quality variables to predict the probability of financial distress for other markets.

Similarly, instead of developing a model using data from a US market, we used data from another established market, the United Kingdom, and then tested the prediction accuracy of the model on the emerging market, Pakistan. Our study finds that if the model includes variables which are statistically significant for both developed and emerging markets than the same model can be applied for the financial distress prediction of both types of economies.

Moreover, to the best of our knowledge, there is no existing previous research testing the impact of compensation and nomination committees independence on a firm's probability of financial distress. This study covers this gap in the literature and concludes that nomination committee plays an essential role in the firm's possibility of financial distress for the firms operating in emerging and developed market, as it is responsible for selecting personnel who will provide the company with strategic leadership and direction. Moreover, compensation committee independence is crucial for an emerging market, China, where all important decisions related to management appointment and evaluation are made by controlling shareholders while the board solely approves the decisions.

Lastly, this study contributes to the body of literature by finding differences in the impact of corporate governance variables on a firm's probability of financial distress for the emerging and developed market.

5.1.2. Practical contributions

Financial distress information is a critical decision component to entrepreneurs, investors, managers and other stakeholders keen on investing in either a new business or an existing business. It is also beneficial in financial performance analysis and comparison as it gives clear signals on the risk factor in an industry of interest to a stakeholder. However, theoretical development in this area is less advanced as compared to those of start-up and growth of the business.

Timely detection of financial distress is beneficial to all stakeholders. First, management may take pro-active actions to prevent potential losses or even full-blown bankruptcy. Secondly, it allows investors to perform adequate due diligence of financially distressed firms. Thirdly, it may permit auditors, as well as the company, to maintain their reputation and goodwill. Finally, shareholders retain their confidence that the going concern presumption of the business is appropriate.

Moreover, timely prediction of financial distress may end up preventing the occurrence of the actual financial distress, as management has afforded enough time to come up with strategies for saving the business from total collapse. Subsequently, this study presents a new model, with the capacity to predict financial distress of the firms operating in developed and emerging market.

An effective financial distress prediction model is advantageous to all investors, investment companies and other stakeholders as it allocates their resources efficiently. Early detection of the warning signs, therefore, reduces the cost of supervision and examination procedures usually undertaken before one makes an investment decision. This means that investors can utilize this model before deciding to make the investment.

In addition, analysts can use this model for evaluation of companies and thus may be able to give correct advice to company management and the corrective actions necessary to bring the company back to sustainability. Alternatively, the same information may be provided to investors to make rational decisions. The model is also beneficial to creditors who may want to evaluate the creditworthiness of an existing or potential client.

Another significant finding of this research is the implication that the number of independent board members would harmonize the agency conflicts between management and shareholders and safeguard the invested capital of shareholders. Therefore, to control conflict of interests, there should be a significant number of independent members in board committees to ensure that the managers performance is evaluated at the board level, and the board's legal responsibilities to reward, to fire or hire executives is purely based on merit and is not subject to any external influence.

Moreover, we find that the nomination committee plays a vital role in the firm's probability of financial distress in both developed and emerging markets, as it is responsible in selecting a firm's strategic leaders who ultimately are left with the heavy responsibility of charting a firm's future direction. Thus, the policymakers and practitioners should ensure that the company maintains a significant number of independent members in the nomination committee to reduce the firm's chances of default.

Although our results have several implications and contributions to the financial distress literature, we provide some suggestions that we believe deserve further research. Foremost, the estimated model would also benefit with some additional refinements. One of them to develop a generalizable model which has sufficient predictive accuracy for firms operating in different geographical locations. The literature hitherto rarely tested the applicableness of their models to both emerging and developed markets. In addition, it would be interesting to see the impact of financial reporting quality variables on the financial distress of firms in other markets. Moreover, future researchers may test the different attributes of board committees especially compensation and nomination committee, and their impact on the firm's probability of financial distress.

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