Predicting Financial Distress Using Corporate Efficiency and Corporate Governance Measures

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Statement of Originality

This thesis has been composed by myself and contains no material that has been accepted for the award of any other degree at any university.

A part of this thesis has been published in the *Journal of the Operational Research Society:*

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Permission to include text from that paper has been gained from the publisher and the authors.

To the best of my knowledge and belief this thesis contains no other material previously published by any other person except where due acknowledgment has been made.

Zhiyong Li

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Table of Contents

List of Tables

List of Figures

List of Abbreviations

AANN	Auto Associative Neural Networks
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANOVA	Analysis of Variance
AUC	Area under ROC
BCBS	Basel Committee on Banking Supervision
BCC	Banker, Charnes and Cooper
BIS	Bank of International Settlements
BN	Bayesian Networks
BPNN	Back Propagation Neural Networks
BTSCS	Binary Time Series Cross Sectional
CART	Classification and Regression Trees
CBR	Case-based reasoning
CCNN	Cascade Correlation NN
CCR	Charnes, Cooper and Rhodes
CEO	Chief Executive Officer
CNY	Chinese Yuan
CRS	Constant Returns to Scale
CSRC	China Securities Regulatory Commission
DA	Discriminant Analysis
DD	Distance to Default
DEA	Data Envelopment Analysis
DHM	Discrete Hazard Model
DLP	Dual Linear Programming
DMU	Decision Making Unit
DT	Decision Tree
EBIT	Earnings Before Interest and Tax
EC	Efficiency Change
ES	Expert System
FP	Fractional Programming
FSA	Financial Services Authority
GA	Genetic Algorithm
GCI	Corporate Governance Index
IID	Independent and Identically Distributed
IPO	Initial Public Offerings
IRS	Increasing Returns to Scale
k-NN	k-Nearest Neighbour
KS	Kolmogorov-Smirnov
LLSV	La Porta, Lopez-de-Silanes, Shleifer, Vishny
LP	Linear Programming
LPM	Linear Probability Model
LR	Logistic Regression
LVQ	Learning Vector Quantisation
MARS	Multivariate Adaptive Regression Splines
MDA	Multiple Discriminant Analysis
MI	Malmquist Index
MNL	Multinomial Logit
MP	Mathematical Programming
MSBM	Modified Slack-Based Measure
MV	Majority Voting
NED	Non-Executive Director
NN	Neural Networks
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
OR	Outranking Relation
PNN	Probabilistic Neural Networks
PPS	Productivity Possibility Set
PTE	Pure Technical Efficiency
RDM	Range Directional Measure
ROC	Receiver Operation Curve
RPA	Recursive Partitioning Algorithm
RSF	Random Similarity Functions
RTS	Returns to Scale
SBM	Slacks-Based-Measures
SE	Scale Efficiency
SEC	Securities and Exchanges Commission
SFA	Stochastic Frontier Analysis
SME	Small and Medium sized Enterprise
SOE	State-Owned Enterprise
SOM	Self-organising feature map
ST	Special Treatment
SVM	Support Vector Machines
TC	Technology Change
TE	Technical Efficiency
TVC	Time-Varying Covariate
UEBS	University of Edinburgh Business School
VIF	Variance Inflation Factor
VRM	Variant of Radial Measure
VRS	Variable Returns to Scale

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I never thought that I would pursue a Doctor of Philosophy until I discovered the amazing art of credit scoring. I think I am destined to come across it and I am sure this is my future. I thank all the people who helped me to get here and make it come true.

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Abstract

Credit models are essential to control credit risk and accurately predicting bankruptcy and financial distress is even more necessary after the recent global financial crisis. Although accounting and financial information have been the main variables in corporate credit models for decades, academics continue searching for new attributes to model the probability of default. This thesis investigates the use of corporate efficiency and corporate governance measures in standard statistical credit models using cross-sectional and hazard models.

Relative efficiency as calculated by Data Envelopment Analysis (DEA) can be used in prediction but most previous literature that has used such variables has failed to follow the assumptions of Variable Returns to Scale and sample homogeneity and hence the efficiency may not be correctly measured. This research has built industry specific models to successfully incorporate DEA efficiency scores for different industries and it is the first to decompose overall Technical Efficiency into Pure Technical Efficiency and Scale Efficiency in the context of modelling financial distress. It has been found that efficiency measures can improve the predictive accuracy and Scale Efficiency is a more important measure of efficiency than others. Furthermore, as no literature has attempted a panel analysis of DEA scores to predict distress, this research has extended the cross sectional analysis to a survival analysis by using Malmquist DEA and discrete hazard models. Results show that dynamic efficiency scores calculated with reference to the global efficiency frontier have the best discriminant power to classify distressed and non-distressed companies.

Four groups of corporate governance measures, board composition, ownership structure, management compensation and director and manager characteristics, are incorporated in the hazard models to predict financial distress. It has been found that state control, institutional ownership, salaries to independent directors, the Chair’s age, the CEO’s education, the work location of independent directors and the concurrent position of the CEO have significant associations with the risk of financial distress. The best predictive accuracy is made from the model of governance measures, financial ratios and macroeconomic variables. Policy implications are advised to the regulatory commission.

Chapter One
Introduction

1.1 Preamble

The recent financial crisis highlighted the importance of credit risk management and the necessity of recognising early indicators of corporate financial distress in order to prevent potential losses. Credit scoring models used to generate early signals of corporate bankruptcy have received academic attention since at least the 1950s, and are still widely used.

One of the main problems in failure prediction models is variable selection. Financial ratios which are the quotient of two items taken from financial statements are the most popular variables that have been considered in the literature. Beaver (1966) was the first author to introduce financial ratios into bankruptcy prediction. In recent decades there have been a large number of bankruptcy prediction studies based on financial ratios using various statistical and machine-learning techniques. They were reviewed by Altman (1993), Balcaen and Ooghe (2006), Kumar and Ravi (2007), Bahrammirzaee (2010) and Verikas *et al* (2010). Recent papers (*e.g.* Sun and Li, 2013) also demonstrated that financial ratios are still dominating the variable selection.

At the same time, changes in financial ratios often become visible after the causes of failure have begun. Market-based information can produce a more timely prediction under the assumption of efficient markets (Merton, 1974; Bharath and Shumway, 2008) but recently this has also been criticised for a lack of adequate statistical power (Campbell *et al*, 2008).

Therefore besides financial variables, researchers are constantly looking for other information to improve the predictive accuracy of corporate credit models or to explain the causes of business failure. Those efforts include incorporation of macroeconomic factors (Duffie *et al*, 2007; Hernandez Tinoco and Wilson, 2013), external resource factors (Hu and Ansell, 2007), legal actions from creditors, audit opinions, board characteristics for Small and Medium-sized Enterprises (SMEs) (Altman *et al*, 2010; Wilson and Altanlar, 2014).

In recent years, academics have paid attention to the role of corporate efficiency (Paradi *et al*, 2004) and corporate governance (Platt and Platt, 2012) and have begun to study their relationships to financial distress. Corporate efficiency is the productivity to turn resources into preferable outputs and is the outcome of management and exogenous factors, whilst corporate governance is the system of management by which companies are directed and controlled, which can be argued to be one of the underlying reasons why a company will fail or succeed (Eisenhardt, 1989). Therefore, measures of both corporate efficiency and corporate governance are of importance in the assessment of credit risk.

Corporate credit risk, more specifically, is present in every company and is borne by all creditors in the activities of lending and trading. By credit default, we generally refer to failure, bankruptcy, financial distress, etc. – though strictly speaking they have their own definitions practically, legally, or financially. Our interest is in the credit risk behind them (see discussions in Section 2.2).

In summary, the aim of this research is to use corporate efficiency and governance measures in association with conventional financial ratios to create corporate credit risk prediction models, and to analyse predictive accuracy improvements when those new measures are added to the model.

1.2 Motivation

Previous studies have tried to investigate the relationship between corporate efficiency measures, corporate governance measures and credit risk. For example, relative efficiency calculated by Data Envelopment Analysis (DEA) is used as either a classifier (Cielen *et al*, 2004) of failed and non-failed companies or as a variable in other analysing methods (Premachandra *et al*, 2009). Some researchers find corporate efficiency can successfully classify the good from the bad or explain a part of the risk of default. Information about corporate governance such as directors on the board and shareholding has also been found to be associated with corporate credit risk (Chaganti *et al*, 1985; Daily and Dalton, 1994a).

Most applications of DEA efficiency measures in corporate default prediction models do not observe some important assumptions of this approach. Firstly, few of them has considered Variable Returns to Scale (term defined in Section 4.3.1) but instead assume Constant Returns to Scale, which is not reflected in reality. Secondly, using the mathematical programming method DEA to calculate relative efficiency requires samples to be homogeneous in terms of their industry. Otherwise, relative efficiency scores computed in comparison to a company's peers become meaningless. Most studies using mixed industry samples ignore this important assumption in DEA methodology, or studies using a single industry have only a limited sample size, which potentially suffers statistical criticism. No study has ever tried to decompose Technical Efficiency into Pure Technical Efficiency and Scale Efficiency in this context, which can provide more information for analysis. Also, no study has ever conducted analysis of an efficiency score on dynamic prediction models.

In the applications of corporate governance measures, most studies are from the perspective of corporate governance and its relationship with corporate performance. They either lack the specification of prediction models – model training and validation – and instead stop at hypothesis testing, or they do not cover many aspects of corporate governance, if they are in the form of credit risk prediction. Also, few studies has tried a dynamic analysis on governance measures in this field.

Inspired by previous literature, it is necessary to bridge these gaps, investigate the DEA application whilst following its assumptions and build a stable and robust model to predict the probability of financial distress using these additional nonfinancial variables.

1.3 Aims

By understanding the gaps in the literature above, this thesis has three major aims and objectives to achieve. These are:

1) To estimate cross-sectional models that incorporate corporate efficiency measures and its components to predict financial distress

The objective is to use relative efficiency calculated by Data Envelopment Analysis in prediction models. Three different efficiency measures and an indicator of the level of Returns to Scale are incorporated into logistic regression models, to predict financial distress alone or with financial ratios.

2) To estimate panel survival models that incorporate *dynamic* efficiency to predict financial distress

The objective is to find an appropriate DEA model to calculate dynamic efficiency scores to conduct panel analysis on the risk of financial distress. Dynamic efficiency scores are used as a classifier directly and as variables in a second stage of regression analysis. Both out-of-sample and out-of-time validations are employed to ensure the robustness of predictions.

3) To estimate panel survival models that incorporate corporate governance measures to predict financial distress

The objective is to employ a large selection of corporate governance measures in survival models to predict the probability of financial distress in a chosen time period. The available variables cover four aspects of corporate governance: board composition, ownership structure, management compensation and characteristics of the CEO and the Chair. Unlike cross sectional models, panel models given more reliable estimates of parameters and allow one to track changes over time in covariates on the probability of financial distress.

1.4 Contributions

This thesis makes several contributions to knowledge. First, it presents the first model to use the components of overall efficiency into Pure Technical Efficiency and Scale Efficiency. Pure Technical Efficiency indicates the ability to improve efficiency by wisely allocating resources and applying new technology. Scale Efficiency measures the ability to achieve better efficiency by adjusting the organisation to its optimal scale into a prediction model. Second, in contrast to most applications of DEA in financial distress prediction which assume Constant Returns to Scale and ignore the issue of homogeneity, our industry-specific modified models allow for Variable Returns to Scale and use relatively homogenous industry samples and so this work is the first to be methodologically correct in the context of mixed-industry bankruptcy prediction. Third, the results in this thesis are the first time that DEA efficiency scores have been calculated dynamically and analysed in survival models to make a robust prediction of financial distress. Fourth, the model including corporate governance measures is the most comprehensive and thorough study to date to use such variables in a panel data structure to predict the probability of financial distress in China. Fifth, the analysis relates to large Chinese corporations and is the first to address the influences of both scale and government ownership on the probability of financial distress in the largest emerging market in the world. Sixth, the data covers the period of the recent global financial crisis and by incorporating macroeconomic variables we believe we have established statistical relationships that are robust over very different macroeconomic conditions.

1.5 Importance

This research is important to the following stakeholders.

Creditors

Prediction models are important credit risk management tools for creditors. Accurate prediction models can provide early signals to prevent possible future losses. Banks and other financial institutions can benefit by properly implementing risk management tools and efficiently allocating their funds to low risk customers.

Owners and managers

Companies are owned by directors and shareholders, not creditors, and as such should care more their companies' thrive. They want their companies to grow and succeed, not fail. This growth and success is the role of the companies' managers. Information given by explanatory variables is helpful for them to identify problems and implement changes in management.

Policy makers and regulators

Governments obviously do not want to see any scale of financial crisis damage the country's economy. Corporate governance is particularly closely linked to government policies and legal enforcement. Our models can clearly give insights into the influences of policies and regulations on corporate governance of individual companies. Sound governance mechanism can prevent unnecessary risks in their decisions.

Researchers

Other researchers who are in the field of credit scoring and corporate credit risk management can consider the methods and results of this research and possibly extend it in various directions.

1.6 Main findings

The empirical results of the cross sectional models show that lower efficiency is associated with higher probability of financial distress. Either the overall Technical Efficiency or its components Pure Technical Efficiency and Scale Efficiency have similar effects on the probability of financial distress. We also find that among these types of efficiency Scale Efficiency is more important than Pure Technical Efficiency so if a firm wants to reduce the probability of financial distress, it needs to optimise its scale of business rather than optimising resources or applying new technology. However, decomposition of efficiency is of little help to improve the predictive accuracy, neither is the allowance for levels of Returns to Scale. To gain greatest predictive accuracy, financial ratios and efficiency variables should both be included. The proposed industry specific logistic regression is capable of modelling DEA efficiency for different industries.

In the panel analysis of corporate efficiency, dynamic efficiency scores are calculated by Malmquist DEA models with fixed reference, global reference, super efficiency and mixed efficiency. Firstly, the Malmquist DEA efficiency over ten years compared to the first year was directly used to classify distressed and non-distressed companies. Its classification accuracy is generally better than when DEA efficiency is used to predict financial distress alone in the cross sectional models. But their discriminant power is lower than that in the cross sectional models. Secondly, various efficiency scores were combined with financial ratios to make predictions in hazard models. It is found that dynamic efficiency with global reference gives the best discriminant power in terms of AUC and Gini measures in both out-of-time and out-of-sample validations.

In the panel analysis of corporate governance measures, each of the predefined groups of corporate governance has been found to be useful in detecting financial distress. More specifically, the significant variables include the size of the board, the number of senior managers and supervisors, the work location of independent director, the state ownership and institutional ownership, the salary paid to independent directors, the Chair’s age, the CEO’s education and the CEO’s concurrent position in other organisation. The best predictive model comes from the combination of corporate governance measures, financial ratios and macroeconomic variables.

1.7 Outline of structure

This chapter is an evaluative chapter giving an overview of this thesis and the contributions it makes. This thesis is generally made up of three separate projects which each employs different data samples. These are discussed in details in Chapter Four, Five and Six. The remaining parts are outlined below.

Chapter Two is a general literature review on corporate credit models. It begins with a brief discussion of the definitions of default. Methods and algorithms in corporate credit models are introduced. They include two main streams - statistical methods and artificial intelligence methods and in addition operational research methods and hybrid models which have become particularly popular in recent years. An understanding of credit prediction techniques can inform the establishment of a new and accurate model which can take advantage of previous studies and eliminate their limitations. Chapter Two also discusses the variables and information used as predictions in those models. We find that although financial ratios still dominate, and in recent times academics pay more attention to non-financial information. Other studies of SMEs as special cases of corporations and development in consumer credit scoring techniques are briefly introduced.

Chapter Three describes the data used in this research. As this research focuses on Chinese listed companies, the data source, variables, general description and software packages are introduced. Each research project has its own observation windows, therefore, their samples are different and are described in each chapter. The measurement of model performance is also introduced.

Chapter Four presents the cross-sectional models on corporate efficiency measures. It starts by reviewing the findings of previous studies using DEA efficiency scores in financial distress prediction and identifies some of their limitations. A new model is then proposed, which is a two-stage industry-specific model, where in the first stage, DEA scores are calculated under Variable Returns to Scale and in the second stage, overall Technical Efficiency and its decomposed elements serve as inputs into logistic regression. Comparisons of results are made across thirteen different models. Data comes from three industries and the training sample consists of the years 2001-2003 and the test sample consists of the years 2005-2007.

Chapter Five presents a survival analysis of time to financial distress using corporate efficiency measures as covariates. Firstly, it discusses the advantages of dynamic models compared to traditional static models. We also review many dynamic models to capture the time effect in prediction, including dynamic discrete and continuous time models. Dynamic DEA models are the focus of the second project. The methodology of Malmquist DEA models, global reference DEA models and super efficiency models are given and justified. The estimation of the simple hazard model is specified. Dynamic DEA scores are used as the classifier directly and as variables in the second stage, similar to the cross-sectional model. Data also comes from three industries and the observation window is the period of 2001 to 2010, ten years in total. Results of six models are compared and discussed.

Chapter Six presents a survival analysis of corporate governance measures. It starts by evaluating findings from previous empirical studies by summarising various variables into four groups: board composition, ownership structure, management compensation and director characteristics. A background of corporate governance in China is then introduced because some features are different from those found in Western countries. The methodology chosen is the discrete time hazard model. Due to data availability, the observation window is restricted to be the period of 2003-2010. Four groups of governance measures are selected and tested separately. Macroeconomic variables are also added in.

Chapter Seven is the concluding part of this thesis. The objectives of the whole thesis are reviewed and the findings summarised. Some conclusions are given with policy implications. The limitations in this research are also mentioned and future work is suggested.

Chapter Two
Review of the Literature

2.1 Introduction

This chapter will comprehensively review the literature covering the development of corporate credit models. It includes the definition of default, the evolution of algorithms, and the information used to make predictions. It briefly discusses other studies on SMEs and consumer credit scoring which is another important field of credit models.

2.2 Definition of default in credit risk models

The first thing in studying credit risk is to get a clear understanding of what exactly is meant by 'default' as it is the object about which we try to make predictions. Most generally, as the Basel Committee on Banking Supervision (BCBS) stated, default in credit risk refers to a bank borrower or counterparty failing to 'meet its obligations in accordance with agreed terms' (BCBS, 2000, p.1). In corporate credit, these obligations include fixed term corporate bonds, trade invoices, employee's salaries, stock dividends and loans from lenders when they become due. Hence Beaver (1966) used bankruptcy, bond defaults, overdrawn bank accounts and non-payments as events of business failure. But such an occurrence does not necessarily imply the end of a business: only in a serious situation does credit default lead to the failure of a business. So we find that in most studies on credit risk, bankruptcy is the most direct indictor of business failure. Various examples can be found in Altman (1968), Wilcox (1973), Ohlson (1980), Wilson and Sharda (1994), Shumway (2001), Hillegeist *et al* (2004), Aziz and Dar (2006) and Olson *et al* (2012). In the US, bankruptcy of a business is commonly filed under Chapter 7 or Chapter 11 of the Bankruptcy Code while in the UK, because there is no singular law of bankruptcy, it is usually liquidation, administration or receivership that is often used when predicting business failure (Altman *et al*, 2010; Agarwal and Taffler, 2008; Wilson and Altanlar, 2014).

However, as bankruptcy only occurs rarely in normal times and thus presents difficulties in collecting data, in order to study business failure and credit default, researchers sometimes relax the definition and use various proxies for bankruptcy default in prediction. For example, Campbell *et al* (2008) added financial driven delisting and credit rating of D to increase the sample of bankrupt firms.

More often, other than US studies focusing on bankruptcy prediction, scholars have tried to predict financial distress because distressed companies are more likely to violate financial obligations. Obviously definitions of financial distress are more flexible due to their background of studies and availability of data. For instance, Elloumi and Gueyie (2001) defined financial distress as negative earnings per share for listed companies. Bhattacharjee and Han (2010) regarded financial distress as occurring when a company’s interest cover is less than 0.7 and there is a decline in fixed assets or a decrease in share capital. Chen (2008) defined it as when the net worth of a company falls below half of its share capital. Lee and Yen (2004) even took renegotiations with repayment schedules and discount in interest into account. For financial distress in SMEs, Lin *et al* (2012) specifically used stock-based insolvency and flow-based insolvency as in Altman (1983) and Ross *et al* (1999) when interest coverage is less than one and the insolvency ratio is negative. They furthermore compared their differences in model parameters. More specifically, Pindado *et al* (2008) discussed the finance-based definition of financial distress and argued that its definition should be consistent with an *ex ante* prediction method, i.e. independent of its outcome. So they defined financial distress to be that EBITDA are lower than the financial expenses or a decline in its market value for two consecutive years.

A broader definition of corporate default or financial distress makes modelling easier by increasing the sample size of the Bad, but at the same time it brings difficulties in interpreting the results of different dependent variables. A more formal and universal concept of financial distress is preferred. Therefore in this research, the definition of financial distress is chosen to be the official one, ‘Special Treatment’ (details of the definition given in Section 3.4.1) in Chinese securities markets. This is in line with other Chinese studies: Wang and Deng (2006), Li *et al* (2008), Sun and Li (2008) and Altman *et al* (2007), which used ST as the indicator of default.

2.3 Review of algorithms in corporate credit models

2.3.1 Statistical methods

The essential goal of bankruptcy or financial distress prediction is to separate those companies that do not have the ability to fulfil their financial obligations in future from those companies that can fulfil their obligations. In other words, it is to distinguish bad companies from good companies. As obviously no model can perfectly separate the Good from the Bad or one hundred per cent accurately predict how a company will behave in the future, researchers have made great efforts to try various algorithms to improve the predictive accuracy of the models. Since the pioneering work of Beaver (1966) and Altman (1968), the techniques of credit risk modelling have evolved over 40 years.

Beaver's (1966) dichotomous classification test was actually a simplified univariate discriminant analysis which directly applied a cut-off to a financial ratio. More generally, Altman (1968) employed a Multiple Discriminant Analysis (MDA or DA for short) model which is referred to as the famous Z-score model because the dependent variable is letter 'Z' in the discriminant function. The five explanatory financial ratios are Working Capital to Total Assets, Retained Earnings to Total Assets, EBIT to Total Assets, Market Value Equity to Book Value of Total Debts and Total Sales to Total Assets. The success of Altman's Z-score model sheds light on the development of corporate credit models. Many people have followed his lead, (Deakin, 1972; Abidali and Harris, 1995; Grice and Ingram, 2001), including Altman himself who extended it to a quadratic discriminant analysis (Altman and Loris, 1976) and a more accurate ZETA model with seven ratios (Altman *et al*, 1977). Also, in recent decades, the Z-score model is often used as the base model in comparison with new proposed models (Altman *et al*, 1994).

However, in practice, MDA has some big weaknesses. These include the violation of the assumption of a multivariate normal distribution of the variables, unequal dispersion matrices in linear equations and difficulties in interpreting the role of independent variables (Eisenbeis, 1977). More importantly, MDA does not give a prediction on the probability of default of a company but only a dichotomous classification whether it is good or bad (Dimitras *et al*, 1996). After the 1980s, MDA has become less used in predicting bankruptcy or business failure and conditional probability models which are conditional on a vector of predictive variables to explain bankruptcy have become popular instead.

At first, Linear Probability Models (LPM) using Ordinary Least Squares (OLS) regression were introduced to predict bankruptcy by Meyer and Pifer (1970) but this method is methodologically flawed because its predicted probabilities can go beyond the range of 0 to 1. Later Logistic Regression (LR) or logit analysis was used by Martin (1977) to give earning warnings for bank failure. In 1980, Ohlson introduced his LR model (called O-score model) for predicting bankruptcy and because of its less requirement concerning variables than MDA, it soon dominates the corporate credit models. LR is inherently advantageous because its predicted probabilities are bounded between 0 and 1. After that LR was widely examined by Zavgren (1985), Tennyson *et al* (1990) and Gilbert *et al* (1990). It has been discussed in comparison with other algorithms by BarNiv and Hershbarger (1990), Mossman *et al* (1998), Lin and McClean (2001) and Kim (2011). It has also been used as a benchmark model as alongside the Z-score model (Ting *et al*, 2008). Similarly with LR, probit regression introduced by Zmijewski (1984) is much less used but it still is occasionally seen in some literature (Gentry *et al*, 1985; Lennox, 1999; Grunert *et al*, 2005).

These classical statistical algorithms (MDA, LR, probit etc.) have been used widely but at the same time they have been criticised. For example, they may have problems in defining a dichotomous dependent variable, non-stationarity and instability of data, sensitivity to selection of samples, variables and optimisation criteria (Balcaen and Ooghe, 2006), but these are generally true for all prediction models. More importantly, these classical statistical methods neglect the time dimension and sometimes even pool together data from different years (*e.g.* Altman, 1968; Zmijewski, 1984). Thus there is a bias in selecting the sample (Shumway, 2001). More details of the time effect will be discussed in Chapter Five. They may also suffer from multicollinearity, which possibly makes explanatory variables uninterpretable or misleading in the results (Edmister, 1972; Joy and Tollefson, 1975; 1978). Assuming an equal cost of misclassification (*e.g.* Zavgren, 1985) is unrealistic in real business but Koh (1992) argued that it is not a big problem and the optimal cut-off is robust to different misclassification costs. Taffler (1982) is one of the few studies that considered different misclassification costs.

To overcome the difficulty of dichotomy of the dependent variable in predicting financial distress, Lau (1987) used multinomial logit (MNL) to model five states of bankruptcy and Johnsen and Melicher (1994) followed it by claiming that multinomial outcomes add more information in modelling. However, Jones and Hensher (2004) found Lau's (1987) definition of dependent variables violated the independent and identically distributed (i.i.d.) assumption. Therefore they used an ordered LR to consider different degrees of financial distress. They applied it on three levels of states: healthy, insolvent and bankrupt companies and concluded that the ordinal logit is consistently superior to the binary or rudimentary MNL approach. Jones and Hensher (2007) later introduced a more advanced LR called nested logit in corporate failure prediction and they have listed a group of strengths and weaknesses of it compared to standard logit analysis.

Survival analysis is another statistical method which was initially used in medical science to study the time to death in biological organisms. By adding the time dimension into the regression model, parameters, covariates and predicted probabilities are all made dynamically so it is more suitable for prediction. The Cox proportional hazard model proposed by Cox (1972) and Cox and Oakes (1984) is a continuous time hazard model and Lane *et al* (1986) used it to predict bank failure. The discrete time hazard model proposed by Shumway (2001) has advantages in computation and the nature of covariates because most financial ratios and macroeconomic variables are only observed periodically. The discrete hazard model was followed by Chava and Jarrow (2004) and many others and is discussed in details in Section 5.2.2 of Chapter Five.

A further sample splitting algorithm in credit scoring is a named classification tree or Recursive Partitioning Algorithm (RPA). This applies a group of rules on the characteristics and splits the answers into different sets. Based on the actual classification, the prior probability and the misclassification costs, a binary classification tree is built and the risk of the final nodes and the entire tree is calculated (Breiman, 1993). Marais *et al* (1984) used RPA with bootstrapping to classify bank loans. Frydman *et al* (1985) was the first to introduce the classification tree into bankruptcy prediction and compared it with DA in their sample of 200 firms. However Dimitras *et al* (1996) commented that RPA does not review the classification rules once the tree is set up and can suffer the problem of overfitting.

2.3.2 Operational Research

Beside statistical methods, mathematical programming (MP) can also be used in classification problems (Mangasarian, 1965). The optimising target can be set to minimise the sum of the absolute deviations (Freed and Glover, 1981a), the maximum deviation (Freed and Glover, 1981b) or the number of misclassifications (Bajgier and Hill, 1982) rather like a discriminant analysis. Mahmood and Lawrence (1987) used MP in a bankruptcy prediction model but their results show linear programming models were more successful in classifying non-bankrupt firms than in classifying bankrupt firms. MP is a type of nonparametric approach because it does not specify the structure of parameters but only focuses on the goal.

Similarly Data Envelopment Analysis (DEA) is also a nonparametric approach with mathematical programming features, though its optimising target is totally different. DEA can be used directly to predict bankruptcy or financial distress (*e.g.* Paradi *et al*, 2004; Cielen *et al*, 2004; Emel *et al*, 2003).

Sueyoshi (1999) combined the characteristics of DA, DEA and MP and proposed a new method called DEA-DA which can be used in bankruptcy assessments. Because DEA models are some of the major aims in this research, a comprehensive collection of literature of DEA, including Sueyoshi's DEA-DA model, will be discussed in Section 4.2.1, Chapter Four.

2.3.3 Artificial Intelligence Expert Systems (AIES) methods

Since the 1970s, the development of computer science has made it possible for computer programmes to mimic human attributes and learn skills in dealing new information (Thomas *et al*, 2002). Therefore they are also called machine learning algorithms. Ever increasing learning capabilities have resulted in much more efficient processing in many different streams. Here a selection of successful applications to corporate credit models are reviewed.

An Expert System (ES) is a process of imitating the decision-making behaviour of an expert. When an expert decides whether or not to give credit to an applicant, he relies on his knowledge which consists of a series of rules. This makes the approach of expert systems very similar to RPA, except that expert systems can update their knowledge from the results (Thomas *et al*, 2002). A typical expert system tries to describe two classes (bankrupt/non-bankrupt) by a set of characteristics (financial ratios) and generate a system using variables and cut-off scores to classify all firms (Dimitras *et al*, 1996). When the best classification is formed, a decision tree (DT) can be extracted from the system. Messier and Hansen (1988) used ES to predict business failure based on Quinlan's (1983) data-driven method. The expert's opinion is helpful with the setting of initial rules. Kattan *et al* (1993) added human judgment into the machine learning process and compared recursive partitioning, Quilan's ID3 and a neural network. They found strategies with human judgement are more accurate but large decision trees were no better than smaller ones. Based on Frydman *et al* (1985), Gepp *et al* (2010) included decision trees in comparison and also found less complex and smaller trees were better than more complex ones. Decision trees were recently developed into a survival model called survival trees and forest by Bou-Hamad *et al* (2009) and Bou-Hamad *et al* (2011).

Artificial Neural Networks (ANN or NN) were developed to model the communication and information processing mechanism in the human brain. In the structure of NN, there are a number of inputs (variables) to be multiplied by weights (dendrites), and the sum of them are transformed in neurons and become an input for another neuron (Thomas *et al*, 2002). There are several types of NN in terms of the topology employed: Back Propagation NN (BPNN), Self-organising feature map (SOM), Probabilistic NN (PNN), Auto Associative NN (AANN) and Cascade Correlation NN (CCNN). There are some examples where NN is used in predicting corporate credit risks. Tam (1991) was one of the earliest to use BPNN to predict the failure of banks in Texas and concluded it was more accurate than other methods DA and K-Nearest Neighbour (K-NN). Lacher *et al* (1995) assessed future corporate health by CCNN. Kaski *et al* (2001) used SOM in predicting bankruptcy where the local displacement in the primary data space was measured using the Fisher information matrix. Yang *et al* (1999) compared PNN with and without pattern normalisation in bankruptcy problems. More examples of the applications of NN come from Wilson and Sharda (1994), Leshno and Spector (1996), Salchenberger *et al* (1992) and Tsai and Wu (2008) and a more detailed review of NN in bankruptcy prediction can be found in Atiya (2001).

The Genetic Algorithm (GA) is ‘a procedure for systematically searching through a population of potential solutions to a problem so that candidate solutions that come closer to solving the problem have a greater chance of being retained in the candidate solution than others’ (Thomas *et al*, 2002, p. 29). By this global search procedure and the mechanics of natural selection and natural genetics, Back *et al* (1996) made an attempt to use GA to predict the failure of 37 Finnish companies based on 31 financial ratios. They claimed that the best results were achieved by GA compared to DA and logit analysis. Following them, Shin and Lee (2002) also applied GA in predicting bankruptcy and they commented that compared to NN, which gives the final rules of classification that are exceptionally difficult to identify the results, GA are easier to understand.

Rough Sets Theory was proposed by Pawlak (1982) to use the lower and the upper approximations to replace the original set in which its information and objects are indistinguishable or indiscernible. Rough sets integrated with decision trees can be applied in the prediction of business failure where a group of attributes linked to financial distress can be discovered (Dimitras *et al*, 1999). In a set of 80 Greek firms, Dimitras *et al* (1999) trained rough sets and found it was generally better than DA and logit analysis. They also commented that rough sets models can only reflect the experience of a certain set of samples. When it is applied to other sets, the procedure of identifying the decision rule should be repeated. Additionally, Tay and Shen (2002) discussed some issues of the rough sets theory in indicator selection, discretisation and validation and thought it was a good alternative in economic and financial prediction.

Case-based reasoning (CBR) follows the idea that when people solve a problem, they search in their past experiences for similar cases and reuse or modify these experiences to generate a possible answer for the current problem. So when a company is identified as failing, CBR can provide additional cases of companies that failed in the past with similar characteristics as a justification for this prediction (Kumar and Ravi, 2007). Bryant (1997) designed a CBR model and applied it to a sample of 85 bankrupt and 2,000 non-bankrupt firms. However his CBR model was outperformed by LR. Most CBR algorithms use the methodology of k-NN in matching similar cases, so Park and Han (2002) have tested the analytic hierarchy process (AHP) weighted k-NN algorithm in CBR in bankruptcy prediction. Their model can handle both quantitative (financial ratios) and qualitative variables (non-financial variables) at the same time. Furthermore, Li and Sun (2009a) used multiple CBR by majority voting (Multi-CBR-MV) in a Chinese case and compared it with standard CBR and statistical models, and they found their Multi-CBR-MV to be superior to the other in making prediction. They further attempted forward ranking-order CBR (Li and Sun, 2011) and random similarity functions (RSF) based CBR (Li and Sun, 2013) .

The last artificial intelligence model we want to discuss is Support Vector Machines (SVM) introduced by Vanpnik (1998), who used a linear model to create a hyperplane in a multi-dimensional space by taking input vectors nonlinearly and predicting their class. The hyperplane is formed when the maximum margin between two classes is found and those samples that are closest to the hyperplane are called support vectors. Min and Lee (2005) used the kernel function in SVM to find the optimal parameters and classify a paired sample of 1,888 Korean firms. They concluded that their SVM model outperformed MDA, logit and three-layer BPNN in predictive accuracy. Similarly, Shin *et al* (2005) also found SVM to be better than BPNN in corporate bankruptcy prediction.

There are also some other artificial intelligence methods such as Bayesian Networks (BN) (Sarkar and Sriram, 2001; Sun and Shenoy, 2007), Multinorm analysis (De Andrés *et al*, 2012) and Automatic clustering and feature selection (Wu, 2010). Examples of some other comparative studies of intelligent methods with statistical methods are by Tseng and Hu (2010) and Zhou *et al* (2012). Artificial intelligence expert systems due to their various modifications have many derivatives in those main streams discussed above. A detailed discussion on intelligent techniques comes from Kumar and Ravi (2007) and Aziz and Dar (2004). Their methodologies are not as ‘standard’ as statistical methods so sometimes it may be difficult interpreting and comparing results with each other, but their self-learning skills are particularly helpful in improving the model itself. Therefore, in recent years, these are usually combined together to take advantage of both. The next section will review some hybrid models in corporate credit modelling.

2.3.4 Hybrid models

As we discussed previously, some machine learning techniques such as decision trees and rough sets can develop an explanatory structure identifying a number of attributes or variables which contribute to the risk of financial distress. Therefore, in recent years as new methods are proposed by scholars, many others try to build hybrid models to combine different AI models with others or with other classical statistical models. They also achieve great success in prediction. Thus hybrid models are also reviewed in this section.

MaKee and Lensberg (2002) argued that researchers often look for a causal basis for bankruptcy prediction but functional methods or statistical selection methods require an *a priori* structure. They therefore proposed a two-stage model: rough sets to identify subsets of important explanatory variables in stage one and a genetic algorithm to develop a structural model in stage two. Their model produced efficient and robust prediction results and offered insightful information. Li and Sun (2009b) combine ELECTRE, a chief outranking relation (OR) developed by Roy and Vincke (1984) and Roy and Slowinski (2008) and case-based reasoning to create a ELECTRE -CBR model, which is similar to the OR-CBR model (Li *et al* 2009). Li and Sun (2010) also combined CBR with case representation. Ahn *et al* (2000) integrated rough set theory into a neural network for business failure prediction. Much earlier, Back *et al* (1994) tried using the combination of NN and GA. Lin *et al* (2009) even combined three expert systems RST, Grey Relational Analysis (GRA) and CBR together and made a more accurate model. Kiviluoto (1998) compared three different SOM-based classifiers which are hybrid with linear DA, K-NN and learning vector quantisation (LVQ). More examples can be found in GA and SVM (Min *et al*, 2006; Wu *et al*, 2007) and Bayesian inference SVM (Gestel et al, 2006).

In the practice of integration of machine learning techniques and statistical methods, Hua *et al* (2007) modified the outputs of the SVM classifiers according to the result of logistic regression and improved the accuracy of SVM in financial distress prediction. Jo and Han (1996) in an early case integrated CBR, NN into DA for bankruptcy prediction. More recently, Cao (2012) put the fuzzy measure of choquet integral into MDA, logit and decision trees. More innovatively, De Andrés *et al* (2011) proposed a hybrid approach using Fuzzy c-means clustering and Multivariate Adaptive Regression Splines (MARS) and found it to be not only more accurate in terms of correct classification but also more effective in terms profit generation by wise lending decisions. MARS is an extension of the linear model but is a nonparametric regression proposed by Friedman (1991). Sánchez-Lasheras (2012) used SOM-NN and MARS together to predict bankruptcy. Yang *et al* (2011) used partial least squares and SVM in bankruptcy prediction, and Cho *et al* (2009) used subject weight to integrate MDA, logit, NN and decision trees together.

In the applications of DEA efficiency scores in financial distress prediction, one popular method is a two-stage procedure which uses DEA models to calculate relative efficiency scores in the first stage and input them into other classifying methods as a variable in the second stage (*e.g.* Xu and Wang, 2009; Yeh *et al,* 2010; Psillaki *et al,* 2010). Because this research on DEA efficiency measures is to take them into a logistic regression, it is actually a hybrid model and in line with the trend in recent corporate credit models.

2.4 Review of variables in corporate credit models

2.4.1 Accounting information

From the 1930s, many formal studies began to use financial ratios to detect company distress and financial difficulties. It was believed there should be some significant ratios which could reveal advance signs of default.

Beaver (1966) was the first to introduce financial ratios into bankruptcy prediction. His univariate DA included six groups of ratios: cash flow, net income, liability, liquid assets to total assets, liquid assets to liabilities and turnover. Since then, various financial ratios have been used in corporate credit models in many studies (Altman, 1968; Meyer and Pifer, 1970; Edmister, 1972; Ohlson, 1980; Zmijewski, 1984; Wilson and Sharda, 1994; Shumway, 2001; Jones and Hensher, 2004; Campbell *et al*, 2008; Gepp *et al*, 2010). As a matter of fact, financial ratios so dominate corporate credit models that nearly all studies using statistical methods or artificial intelligence models have to take more or less ratios into their prediction (except a very few, *e.g.* Wilson and Altanlar, 2014). Financial ratios are calculated using items in a company's accounting reports. There are many items available in the report, as financial ratios can cover many aspects of the condition of a company. Although there is no clear classification of financial ratios, generally they can be grouped in to profitability, liability, liquidity, leverage, operational efficiency, and others ratios. As Beaver (1966) commented at the end of his paper, he rather preferred that it is 'accounting data' but not 'financial ratios' to be the predictors of failure. Therefore, Beaver's (1966) successors in various studies can be called accounting-based models in terms of the type of information they used.

The overwhelming position of financial ratios in corporate credit models sometimes calls on the introspection of scholars to rethink their values. Whilst Barnes (1987) gave two reasons for the use of financial ratios: to control for the effect of size and to control industry-wide factors, he also commented that in using ratios in bankruptcy prediction, there was the matter of ratio selections. The decision model would either 'contain repetitive-redundant data' or lose the information content of the semi-independent ratios and therefore 'to identify those ratios which contain complete information about a firm whilst minimising duplication cannot be achieved purely by logic' (Barnes, 1987, p.456). A group of financial ratios calculated by each other can easily suffer the problem of multicollinearity (Mensah, 1984). More critically, Argenti (1976) commented that the use of financial ratios only as symptoms of business failure cannot provide insights into the causes of business failure. Dambolena and Khoury (1980) questioned the stability of financial ratios over time. Gilbert *et al* (1990) argued financial ratio-based bankruptcy models perform poorly and nonfinancial factors are needed.

Despite the questions raised historically, forty years after Beaver (1966) brought financial ratios into corporate credit models, he revisited their predictive power in a simple hazard model (Beaver *et al*, 2005) and concluded their performance remains strong in prediction though with slight changes, but more accuracy can be added by market-based variables. In fact, market-based variables have also received academic attention for a long time.

2.4.2 Market-related information

The Merton-typed model proposed by Merton (1974) was a pure market-driven model which was an extension of the Black-Scholes option price theory (Black and Scholes, 1973). Default happens when the market value of a company's assets falls below a certain level relative to its total liabilities. Thus, if a shareholder has an option to default on the firm's liabilities, he will exercise it when its assets are not worth as much as the amount to cover its total liabilities. In an efficient market where all information is reflected on the option price, Merton-typed models can give timely predictions on the probability of default, which is called the Distance to Default (DD). Merton-typed models are also structural models because they evolve directly from an economic model of an optimising equation. Merton-typed models are incorporated into Moody's KMV model later.

While Duffie *et al* (2007) and Hillegeist *et al* (2004) found Merton DD models can produce acceptable predictions on business default, Campbell *et al* (2007) and Bharath and Shumway (2008) argue Merton's DD is not statistically significant as a variable in the default prediction model. More interestingly, Agarwal and Taffler (2008) found accounting-based models and Merton-typed market-based models are equally good in their predictive ability and they just capture different aspects of bankruptcy risk.

Nevertheless, market variables are still occasionally tested in other forms. For example, Shumway (2001) has three similar market-driven variables as in Beaver *et al* (2005), regarding market capitalisation, excess return from the previous year, and standard deviation of the return. The variance of return has also been used in an early study from Aharony *et al* (1980) who found the deterioration of return of bankrupt companies occurred faster and earlier than for healthy companies. Distinguin *et al* (2006) tried various market indicators including cumulative market excess return and the change in Beta. Hernandez Tinoco and Wilson (2013) included four market variables which are share price, lagged cumulative return, the company size relative to the total size of the FTSE index and the ratio market capitalisation to total debts along with accounting and macroeconomic variables in their panel logit model. They found those market variables are all related to the probability of financial distress.

2.4.3 Nonfinancial information

Beside accounting and financial variables and market related variables, researchers also look for other information which can either explain corporate credit risk or improve the accuracy of prediction of the probability of financial distress. Sometimes, accounting information or financial ratios are difficult to obtain, especially for SMEs (Edmister, 1972). It therefore becomes more necessary to employ alternative or extra information to assist prediction. Keasey and Watson (1987) tested a series of nonfinancial variables including the age of the company, information regarding the directors and auditors. Both Altman *et al* (2008) and Altman *et al* (2010) found nonfinancial information such as legal action by creditors, company filing histories and audit opinions can improve the predictive power in SME credit risk models. More specifically, before newly incorporated SMEs disclose their first accounting reports (for example in the first year) and considering that the initial period is more critical to their survival, Wilson and Altanlar (2014) used no financial information but only legal actions and some board characteristics (corporate, female, local, or family directors, etc.) as well as macroeconomic variables to capture the risk of failure.

Whitaker (1999) investigated the chances of distressed companies going bankrupt and found management actions are essential for them to avoid bankruptcy but can do little to avoid distress caused by macroeconomic conditions. Aziz and Dar (2006) also suggested corporate governance structures and management practices help with the understanding of corporate failure.

Hu and Ansell (2007) investigated the retail industry from view of the Resource-Advantage theory of competition and included political, economic, technological and social-cultural factors in the model. Nwogugu (2007) suggested bankruptcy prediction models should use a mix of situation-specific dynamic, quantitative and qualitative factors and take into account psychological, legal, liquidity, knowledge and price factors in the capital market.

Grunert *et al* (2005) highlighted the relationship between nonfinancial factors and default risk. They identified two nonfinancial factors: management quality and market position, which were directly sourced from credit files. However they failed to provide methods to measure these two factors and only management quality was significant in their probit regression.

Additional management-related variables can be found in Sun and Cui (2013), Bryan *et al* (2013) and Perry (2001) who looked for relationships between corporate social responsibility, business strategy and written business plans and default risk respectively.

This research also follows this trend and mainly use nonfinancial information to predict the probability of financial distress. Corporate efficiency and corporate governance measures provide soft information in looking into the causes of distress.

2.5 Other relevant literature

2.5.1 Studies on SME

Considering the fact that SMEs contribute a large part to the economy in many countries in terms of number, employment and GDP they produce, SMEs are more important than large companies in the credit loan market and they are more sensitive in response to changes of economic conditions (Altman and Sabato, 2007). Therefore in recent years, SMEs have received much attention from academics in terms of their credit worthiness.

One of the early studies came from Edmister (1971) who used MDA and 19 financial ratios to predict small business defaults from 1954 to 1969. Since the Basel II Accord stressed the importance of SMEs in bank capital adequacy, many researchers started to investigate the SME segment. Jacobson *et al* (2005) found that SME loans are more like retail credit and they are riskier than credit for large corporations. But Altman and Sabato (2007) argued that loans for SMEs are actually more profitable for banks and banks should build special credit models for SMEs. Their logistic model applied on 120 defaults and 1,890 non-default over the period 1994 to 2002 performed much better than generic corporate models. After that, Altman *et al* (2008) considered qualitative information and Altman *et al* (2010) considered nonfinancial information in SME risk models. Kim and Sohn (2010) investigated SMEs in Korea using an SVM model. They focused on technology SEMs so in their model they include five measures to measure the level of technology in a company. Chen *et al* (2010) employed KMV Merton models on Chinese SMEs. However, considering the much larger scale of Chinese corporations, the threshold for Chinese SMEs is that the number of employees is less than 2,000 (compared to 250 in the EU), turnover less than 37 million EUR and total assets less than 50 million EUR. Besides, there are a Russian case using DA (Lugovskaya, 2010), a Turkish case using data mining application (Koyuncugil and Ozgulbas, 2012), a Slovakian case using a probit model (Fidrmuc and Hainz, 2010) and a UK case using a logit model (Lin *et al*, 2012) and so on.

2.5.2 Credit scoring in consumer credit

Consumer credit models are implementing credit scoring techniques rather than simply correctly classifying the Good and Bad in corporate credit, because the credits consumers may get largely depend on the score they obtained. Credit scoring is ‘the set of decision models and their underlying techniques that aid lenders in the granting of consumer credit’ (Thomas *et al*, 2002, p.1). But essentially they share the same techniques, i.e. most of prediction models we discussed in Section 2.3 are applicable to consumer credit scoring, or in many cases, these models are developed by scholars in both fields. For their applications on consumer credit, see reviews in Rosenberg and Gleit (1994), Hand and Henley (1997) and Crook *et al* (2007). There are also other applications of consumer credit models, such as behaviour and profit scoring, reviewed in Thomas (2000). And for a more systematic and complete introduction, the books by Thomas, Edelman and Crook (2002) and Thomas (2009) are comprehensive.

More recently, development in consumer credit scoring is led by research such as a survival model incorporating macroeconomic variables (Bellotti and Crook, 2008), an SVM model (Bellotti and Crook, 2009) and a dynamic model (Crook and Bellotti, 2010) and an ensemble model of multiple classifiers (Finlay, 2011) .

Consumer credit and corporate credit are generally applied in different areas, although sometimes they are linked together. It is argued that credits for SMEs and consumers share some common features in terms of the small amount of credits, credit information and the correlation of personal (the owner's) and business success (Berger *et al* 2007; Berger *et al* 2011). Therefore the fundamentals of default in SMEs and consumers may be the same.

From the perspective of this research, as we are looking at corporate governance measures, some of the important variables come from the characteristics of the Chair and the CEO. It is expected that, their personality and demographic information may affect the probability of financial distress, though maybe not as much as that in SMEs.

2.6 Conclusion

This chapter has reviewed the definitions of corporate default, algorithms in corporate credit models, variables of explanatory information to make predictions. It has found that various definitions of financial distress have been used in previous studies but not the legal term – bankruptcy which is a more formal form of corporate default. However in China, there is an official definition of financial distress for listed companies – ‘Special Treatment’ which brings convenience to research.

Generally corporate credit models originated from statistical methods such as MDA and logit, but in recent decades, various AI algorithms have been developed. They are of machine learning and nonparametric features but still statistical and dynamic models such as hazard models are also popular in this field. An even more powerful solution is to build hybrid models which combine the advantages of different algorithms and make more accurate predictions than when they perform separately. In this research, two-stage models with DEA and logistic regression also follow this trend.

Accounting information and market-related information has generally dominated all corporate credit models but researchers always keep looking for other information to bring additional predictive power to the models. In all kinds of non-financial information that has been tried, the information about the management of a company, its corporate governance and the board of directors attracted some attention from modellers. However their attempts were rather limited to a small range of measures. This research mainly incorporates two groups of important measures, corporate efficiency and corporate governance into the model and expect they can improve the predictive accuracy and provide insightful information as to why a company becomes financially distressed.

Other studies on SMEs and consumer credits are also reviewed and their concurrence with this research is that the characteristics of the owner is of great impact on the performance of the company, which is exactly what consumer credit scoring models try to capture.

Chapter Three
Data and Variables

3.1 Introduction

This chapter will introduce the data and variables for the research. Methods and samples for each project are different so they are introduced in corresponding sections in Chapter Four, Chapter Five and Chapter Six. The common methods to calculate multicollinearity and predictive accuracy are followed. Finally the analytical software packages used for estimation and calculation are also presented.

3.2 Data source

The data used in this research originates from two Chinese security markets, the Shanghai Stock Exchange and the Shenzhen Stock exchange. Until recently a total of 2,550 companies have listed on these Stock Exchanges. Delisting is rare for Chinese securities markets. Until the end of 2012, only 74 companies delisted from the markets. Thus the size of the two exchanges has grown very fast, increasing at a rate of about 30% annually.

Figure 3.2.1 Number of active listed companies in China

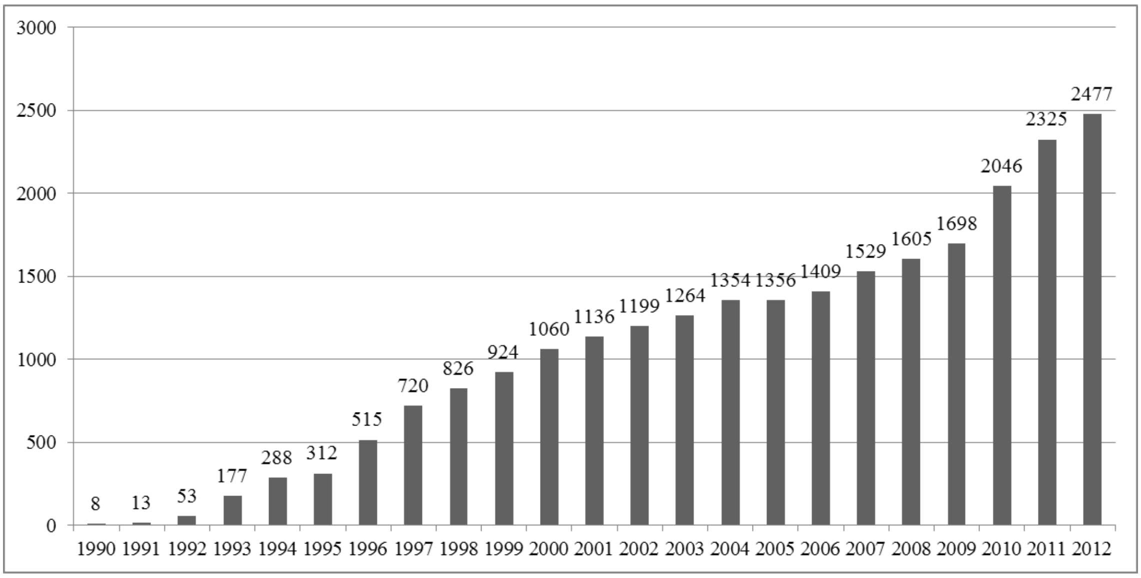


Figure 3.2.1 displays the number of active listed companies in the two markets for the period 1990-2012. Indeed in the last three years (2010-2012), when the influence of the financial crisis was mitigated, there was a wave of new Initial Public Offerings (IPOs).

We focus on Chinese listed companies because normally only listed companies are obligated to disclose their financial reports to the public under the supervision of the China Securities Regulatory Commission (thereafter CSRC) and only listed companies are required to disclose corporate governance information (the variables in Chapter Six) in their reports. So the active listed companies in Figure 3.2.1 compose the population for this research.

However certain facts have reduced the size of the sample. Firstly, Cash Flow statements only began to be published after the *Disclosure of Information of Listed Companies* (CSRC, 2007) in 1998. The cash flow theory of Aziz *et al* (1988) implies that cash flow is an important variable in corporate credit models and cash flow related ratios should be included. Secondly, the indicator of financial distress (introduced in Section 3.4.1) only became available after 1998. Therefore we can only focus on the sample from 1998 afterwards. The actual data collection stops at the year 2010. The observation period in this research is therefore 1998 to 2010.

All data is sourced from the Wind database[1]. The database provides information for those companies listed in both markets (note that no cross listing is allowed) and covers the historic records from 1991. For panel analysis, companies are observed periodically but it has been found that only data on the annual reports of Chinese listed companies are reliable and complete enough for analysis, though a considerable number of companies have disclosed their quarterly reports.

[1] Wind Database is one of the leading integrated service providers of financial data, information, and software in China. The Credit Research Centre, UEBS subscribed to it for the purpose of this research. For more information, please refer to website: http://www.wind.com.cn/En/Default.aspx

3.3 Sampling

In the early days, particularly when DA was popular in corporate credit models, the aim of models was to correctly classify failed and non-failed companies. A pairing method of sampling was suggested by Beaver (1966) and after that most literature has followed this (Altman *et al*, 1977; Takahashi *et al*, 1984). Failed ones are usually paired with non-failed ones according to their size, industry or time period on the basis of a 1:1 or 1:2 ratio. This pairing method can also be found in studies of corporate governance in credit risk too. For example, Hambrick and D'Aveni (1992), Donoher (2004), Polsiri and Sookhanaphibarn, (2009) all have an equal number of Goods and Bads in their samples. In the samples of Chen (2008), Lee and Yeh (2004), the good/bad ratios are 2:1.

This pairing method could be called “matched sampling” or “choice-based sampling”. Cram *et al* (2009) particularly studied the sampling method in accounting research and found three possible errors in matched samples. The first is the use of unconditional analysis for matched samples. The second is the failure to emplace control for effects of imperfectly matched variables. The third is the failure to reweight observations according to different sampling rates.

Obviously, matched sampling disobeys the nature of business bankruptcy which happens rarely. Non-random samples are not recommended (Cram *et al*, 2009). In our cross-sectional analysis (Chapter Four), excluding the unusable cases, all cases left in the population were selected to be in the sample (introduced in Section 4.4.1) so it is out-of-time prediction. Industries are controlled by three dummies in the model (referring to equation (4.20)). The distressed rates in the training and test samples are similar so there is no bias in sampling.

In the panel analysis in Chapter Five and Chapter Six, out-of-sample validation is employed. Stratified sampling is used. Stratification has advantages when subpopulations are independent. In our study, the healthy group and the distressed group, and industries sectors are independent. Random sampling is applied on each company separately within each subgroup. For example, if there are six subgroups in three industries for both healthy and distressed groups given in Table 3.3.1, six random numbers are applied to six subgroups to split the sample into the training set and the test set proportionally at a 2:1 ratio. The results of sampling in three projects are given in the corresponding sections.

Table 3.3.1 Sampling method

	Sector 1	Sector 2	Sector 3
Healthy	Subgroup 1 (Training/Test=2:1)	Subgroup 3 (Training/Test=2:1)	Subgroup 5 (Training/Test=2:1)
Distressed	Subgroup 2 (Training/Test=2:1)	Subgroup 4 (Training/Test=2:1)	Subgroup 6 (Training/Test=2:1)

3.4 Variables

3.4.1 Dependent variable

In China, the latest bankruptcy law was implemented in 2007. Between 2007 and the end of 2011, there were about only 30 listed companies that had applied for bankruptcy. These are too few to be used as the dependent variable for credit modelling. Therefore the dependent variable – the indicator of financial distress is chosen to be ‘Special Treatment’ (ST).

‘Special Treatment’ is the status imposed by the government since 1998 to give notice of bad performance to investors and so it is an indicator of financial distress. A company is ascribed ST status if any of the following conditions holds (Shanghai Stock Exchange, 2008):

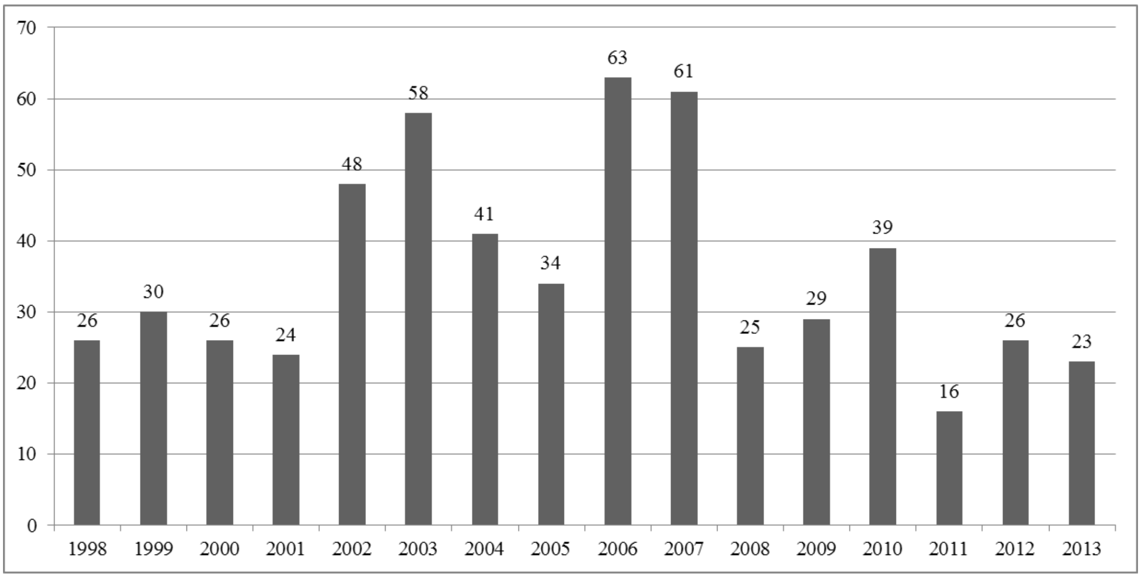
- negative net profit in the most recent two consecutive years or if the correction of errors yields this result;
- failure to disclose its annual interim report;
- likelihood of being dissolved;
- reorganisation, settlement or bankruptcy liquidation;
- other characteristics determined by the Stock Exchange.

Our data shows that the majority of companies (85.9%) received ST because of losses in two successive fiscal years. When a company received ‘Special Treatment’, its stock symbol is marked with ST and the daily up and down limit of its stock is restricted within 5% of its stock price. Apart from these conditions, such a stock is traded similarly to other stocks. Therefore ST is a status of listed companies. An ST company can recover from ST to normality if its financial condition improves and a company can experience ST status multiple times. It is noted that there are around 50 companies which have multiple ST experiences. In this research, the event of interest was only their first time ST.

Historically, from 1998 to the end of 2013, there were 569 case years of ST. The annual frequency of ST occurrences is displayed in Figure 3.4.1.

To set up the out-of-time prediction in Chapter Five and Six, additional two years of ST are recorded though the observation window for the sample is 2001-2010.

Figure 3.4.1 Number of distressed companies over 1998-2010



3.4.2 Independent variables

The independent variables differ between the research projects because it is obviously subject to the model specification, the sample, the observation period and the data availability. In Chapter Four and Chapter Five with corporate efficiency measures, there are DEA inputs and outputs and financial ratios. In Chapter Six with corporate governance measures, there are various governance information and financial ratios, as well as macroeconomic variables. The relevant variables will be introduced in detail in each chapter.

The common independent variables to predict bankruptcy, widely used in the past literature, are financial ratios. The initial list of financial ratios as independent variables were selected in the following way. Referring to financial ratio analysis, only classical and informative ones were kept and grouped into six categories: profitability, liabilities and liquidity, capital and asset composition, cash flow, operation and growth rate. Some ratios with too many missing values (>10%) were left out. In fact, most ratios have valid values for over 98% of company years as they are standard items. For those variables where only a small portion (<5% or 10% for important ones) of values were missing, the missing values were replaced by the arithmetic means for that year (Carling *et al*, 2007).

Financial ratios in the same group are often correlated, which may cause problems in estimation. The VIF (Variance Inflation Factor) is a measure to describe the severity of multicollinearity in a linear regression. If there are k variables $x_1, x_2, \cdots, x_k$ and we want to determine the collinearity of x_i with other variables, linear regression can be conducted:

$$x_i = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{i-1} x_{i-1} + \beta_{i+1} x_{i+1} + \cdots + \beta_k x_k + \varepsilon$$

R_i^2 is the coefficient of regression. Then the VIF for x_i is

$$VIF = \frac{1}{1 - R_i^2} \tag{3.1}$$

Tolerance also is defined as $1 - R_i^2$. There is no universally accepted rule on the VIF and collinearity but usually when $VIF > 5$, it indicates a problem of collinearity (O'Brien, 2007).

Collinearity diagnostics were regularly conducted in the variable selection process not only between financial ratios but also between ratios and other interested variables because correlated variables may present unstable or reversed coefficient signs. The diagnostics for major variables in each chapter is attached in Appendix C.

A list of ratios and their definitions are given in Table 3.4.1.

Table 3.4.1 List of financial ratios

Group	Ratio	Definition
Profitability	Operating Revenue per Share	Operating Revenue / Average Common Share
	Return on Equity (ROE)	Net Income / Shareholder Equity
	Return on Assets (ROA)	Net Income / Total Assets
	Return on Invested Capital (ROIC)	(Net Income – Adjusted Tax) / Invested Capital
	Gross Margin / Total Sales	(Total Sales – Cost Of Goods Sold) / Total Sales
	Operating Profit / Total Sales	Net Income / Total Sales
	Operating Expenses / Total Sales	Operating Expenses / Total Sales
	Financial Expenses / Total Sales	Financial Expenses / Total Sales
	Undistributed Profits per Share	Undistributed Profits / Average Common Share
	EBIT per Share (EBITPS)	EBIT / Average Common Share
Liquidity and liability	Current Liabilities / Total Liabilities	Current Liabilities / Total Liabilities
	Current Ratio	Current Assets / Current Liabilities
	Quick Ratio	(Current Assets – Inventory) / Current Liabilities
	Cash Ratio	Cash and Cash Equivalents / Current Liabilities
	EBITDA / Total Liabilities	EBITDA / Total Liabilities
	Surplus Capital per Share	Capital Surplus / Average Common Share
	Surplus Reserve per Share	Reserve Surplus / Average Common Share
Capital composition	Book Value per Share (BPS)	Shareholder Equity / Average Common Share
	Equity Multiplier	Total Assets / Shareholder Equity
	Current Assets / Total Assets	Current Assets / Total Assets
	Tangible Assets / Total Assets	Tangible Assets / Total Assets

Table continued

Cash flow	Net Cash Flow From Operating per Share	Net Cash Flow From Operating / Average Common Share
	Net Cash Flow per Share	Net Cash Flow per Share / Average Common Share
	Net Cash Flow from Operating / Operating Revenue	Net Cash Flow from Operating / Operating Revenue
	Net Cash Flow from Operating / Total Liabilities	Net Cash Flow from Operating / Total Liabilities
	Net Cash Flow from Operating / Interest Bearing Liabilities	Net Cash Flow from Operating / Interest Bearing Liabilities
	Net Cash Flow from Operating / Current Liabilities	Net Cash Flow from Operating / Current Liabilities
Operation capacity	Inventory Turnover	Operating Costs / Average Inventory
	Receivables Turnover	Operating Revenue / Average Receivables
	Current Assets Turnover	Operating Revenue / Average Current Assets
	Total Assets Turnover	Operating Revenue / Average Total Assets
Growth rates	Operating Revenue Growth	Operating Revenue (current year) / Operating Revenue (last year) - 1
	Total Profit Growth	Total Profit (current year) / Total Profit (last year) - 1
	Net Profit Growth	Net Profit (current year) / Net Profit (last year) - 1
	Total Assets Growth	Total Assets (current year) / Total Assets (last year) - 1

3.5 Measurement of model performance

The performance of a model can be interpreted in many ways, but generally we can evaluate a model by its classification accuracy and discriminant power.

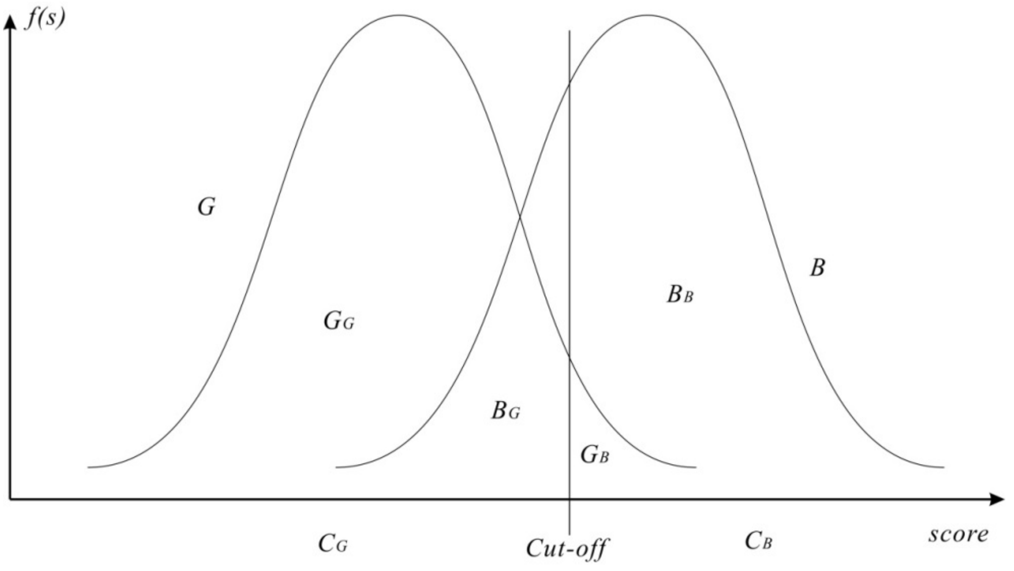
In terms of classification accuracy, when a probability of default is predicted by a model, usually a cut-off is assigned to the series of probabilities. Companies with probabilities above the cut-off point are classified as ‘bad’ and those with probabilities below the cut-off point as ‘good’ ones with lower chance of default. Then the cut-off point becomes critical for the assessor to decide on an acceptable default rate, which would absolutely determine the profitability of the loan business and credibility of the underlying portfolio. In modelling, however, it is assumed that the influence of variables in one year remains the same in the next year.

As one may focus on the good classification and one may care about whether all defaults are detected, Type I and Type II errors were calculated based on the classification of Goods and Bads. The Type I error occurs when the null hypothesis (H_0) is true but is rejected and the Type II error occurs when the null hypothesis (H_0) is accepted when it is actually false (Sheskin, 2003). Therefore Type I and Type II errors are usually called false positive and false negative respectively. In this study, the Type I error occurs when a distressed company is wrongly classified as a non-distressed company and the Type II error occurs when a non-distressed is wrongly classified as a distressed company. Their relationship can be described in Table 3.5.1.

Table 3.5.1 A confusion matrix

		Observation		
		Null hypothesis False (1)	Null hypothesis True (0)	Total
Prediction	Reject null hypothesis (1)	Correct Goods True positive	Type I error False positive	Bads predicted
	Fail to reject null hypothesis (0)	Type II error False negative	Correct Bads True negative	Goods predicted
	Total	Bads in sample	Goods in sample	Sample size

Figure 3.5.1 Type I and Type II errors



More clearly, in Figure 3.5.1, if curves G and B denote the distributions of Goods and Bads and the x axis is the predicted score, the areas under the curve overlap in the middle. When the cut-off is given, the classification of Goods and Bads can be determined, as C_G and C_B. Furthermore the cut-off line divides the areas into four parts: true Goods (G_G), false Goods (B_G), true Bads (B_B) and false Bads (G_B). Then,

$$\text{Type I error rate} = \frac{G_B}{G_B + B_B} \times 100\% \tag{3.2}$$

$$\text{Type II error rate} = \frac{B_G}{G_G + B_G} \times 100\% \tag{3.3}$$

And

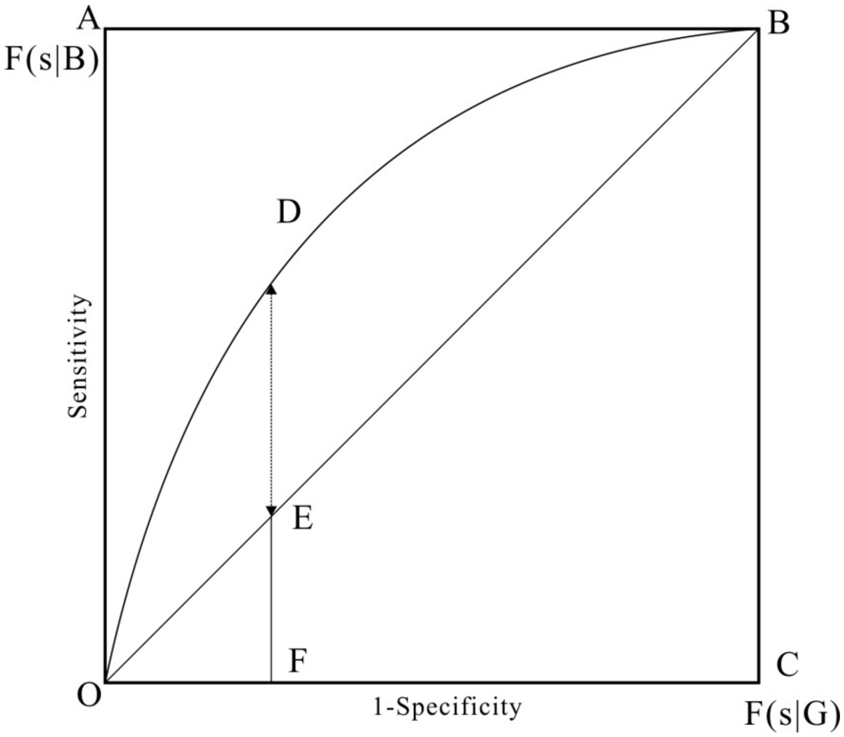
$$\text{Overall accuracy rate} = \frac{G_G + B_B}{G_G + G_B + B_G + B_B} \times 100\% \tag{3.4}$$

We would prefer a low Type I error rate and Type II error rate and a high overall accuracy rate for good predictive performance.

Type I error and Type II errors are only measures for a single cut-off point. More specifically, measuring the discriminant power of a model does not only distinguish the groups of cases but also describe the distance of how good a non-default case is and how bad a default case is. Some other measures are needed. The Receiver Operation Curve (ROC) could give a good measure for the overall performance of all possible cut-offs (Crook *et al*, 2007). The ROC curve is a graph of the true positive rate against the false positive rate at all values of cut-offs. The true positive rate is also called sensitivity and the false positive rate is called 1-specificity, where specificity is the true negative rate. A typical ROC curve is described by curve ODB in Figure 3.5.2.

If two groups of cases can be totally separated by a model, the ROC curve would go along the edges of the square, OAB. If a model performs just as well as a random guess, the curve would be the diagonal line OEB (Crook *et al*, 2007). The measure of the overall performance in the ROC graph is the Area Under ROC (AUC), which is the area of ODBC. By an integral on the standardised x value, the area of ODBC could be found within the range of 0 to 1. Considering the curve below OEB could be used in the opposite way, the absolute value of AUC is between 0.5 and 1.

Figure 3.5.2 ROC, Gini and KS



Another popular measure of performance is the Gini coefficient introduced by Gini in 1909. It is defined on the Lorenz curve diagram ODB (L). The Gini coefficient is defined as the proportion of the area between the Lorenz curve and the diagonal line in the half square, then

$$\text{Gini} = \frac{A_{ODB}}{A_{OAB}} = \frac{0.5 - A_{OABD}}{0.5} = \frac{0.5-(1-A_{ODBC})}{0.5} = \frac{A_{ODBC}-0.5}{0.5} = 2A_{ODBC}-1 \qquad (3.5)$$

where $A_{ODBC} = \int_0^1 L(x)dx$

Then we can have the relationship between AUC and Gini that

$$\text{Gini} = 2\text{AUC} - 1 \qquad (3.6)$$

Another related measure in Figure 3.5.2 is the Kolmogorov-Smirnov (KS) statistic, which is the maximum difference between the bad and good cumulative score distribution. It takes all values from 0 to 1, where the value 0 indicates it is a random model and the value 1 indicates it is a perfect model. If we use $F(s \mid G)$ to denote the probability that a good has a score less than s and correspondingly for a Bad, it is $F(s \mid B)$. Then if two groups of cases can be totally separated by a model, the ROC curve would go along the edges of the square, OAB. If a model performs just as well as a random guess, the curve would be the diagonal line OEB (Crook et al, 2007). The measure of the overall performance in the ROC graph is the Area Under ROC (AUC), which is the area of ODBC. By an integral on the standardised value, the area of ODBC could be found within the range of 0 to 1. Considering the curve below OEB could be used in the opposite way, the absolute value of AUC is between 0.5 and 1.

Figure 3.5.2 is the plot of $F(s \mid B)$ (x axis) against $F(s \mid G)$ (y axis). The KS is the maximum distance between $F(s \mid B)$ and $F(s \mid G)$:

$$KS = \max_s \left| F(s \mid B) - F(s \mid G) \right|$$

Because on the plot $OF = EF$, then

$$\begin{aligned} KS &= \max_s \left| F(s \mid B) - F(s \mid G) \right| \\ &= \max_s \left| DF - OF \right| \\ &= \max_s \left| DE + EF - OF \right| \\ &= \max_s \left| DE \right| \end{aligned} \tag{3.7}$$

KS becomes the largest vertical distance from the curve to the diagonal.

In practice, the lender has different views on the classification of Goods and Bads, especially when considering the cost of misclassification. A misclassification of a Good to be a Bad only means a little loss in profit but a misclassification of a Bad to a Good may bring a default and large losses to the lender. Hand (2005) argues that the common limitation of AUC, Gini and KS is that they only take the number of cases into account but not the cost of misclassification. He also added that the AUC uses different misclassification cost distributions for different classifiers, which brings misleading results in algorithm comparison. He suggests the H measure named after him be reported if cost distributions are known (Hand, 2009). If they are unknown, it is still preferred to compare H measures of models because it is assumed the cost weight function is the same in its estimation which makes them comparable. Similar to other performance measures, the discriminative power is better when the H value is larger.

Therefore, in this research, AUC, Gini, KS and H measures are all used at the same time to evaluate the performance of the models.

3.6 Software

The raw data was stored in and processed by Microsoft Office Excel 2010[2] and preliminary analysis including frequency distribution, missing data and basic graphs are assisted by IBM SPSS Statistics 20[3].

The DEA programming models were calculated using MaxDEA Pro 6.1[4].

The regression models were estimated and predicted using integrated statistical software package Stata 12 MP 64bit[5].

The four measures of predictive accuracy were calculated using R code provided by Hand and Anagnostopoulos (2013) in R environment version 3.0.2[6]. The R codes for the H measure as well as AUC, Gini, KS were integrated together[7] (See Appendix A).

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[2] Microsoft Office Excel 2010 is licenced to the University of Edinburgh. For more information, please refer to webpage: http://office.microsoft.com/en-gb/excel/

[3] IBM SPSS Statistics 20 is licenced to the University of Edinburgh Business School. For more information, please refer to webpage: http://www-01.ibm.com/software/uk/analytics/spss/

[4] MaxDEA Pro is permanently licenced to the author. It offers most powerful and professional DEA solutions without limitation on the number of DMUs. It includes twenty-two groups of DEA models such as Malmquist models, Dynamic models and Cluster models and all their possible combinations. The programmers are Dr CHENG Gang and Dr QIAN Zhenhua. For more information, please refer to the webpage: http://www.maxdea.cn/

[5] Stata 12 MP 64bit is licenced to the University of Edinburgh Business School. For more information, please refer to webpage: http://www.stata.com/

[6] R is a free software environment for statistical computing and graphics. For more information, please refer to webpage: http://www.r-project.org/

[7] David Hand and Christoforos Anagnostopoulos are the authors of the codes. For more information, please refer to webpage: http://www.hmeasure.net/

3.7 Conclusion

This chapter has given introduction to the data, dependent and independent variables, sampling methods and software used in this research. We used Chinese listed companies from two stock exchanges as the sample to study. After the year 2000, there were constantly over 1000 companies in the sample. Data prior to 1998 was censored due to availability and policy implementation. The indicator of financial distress was chosen to be 'Special Treatment' and there are 504 ST observed between 1998 and 2010. The VIF is the indictor to measure the level of multicollinearity which possibly existed between covariates. Type I, Type II errors, overall accuracy, AUC, Gini, KS and H were used to evaluate the performance of prediction models.

Chapter Four
Cross-sectional Modelling Using Corporate Efficiency Measures

4.1 Introduction

One way to assess the efficiency of an organisation relative to the most efficient one is to use Data Envelopment Analysis (DEA). A number of papers have used DEA efficiencies in corporate bankruptcy modelling (see next section). In this chapter we use DEA to compute various measures of corporate efficiency that we then input as a variables in a standard classifier to see how well this enables one to predict financial distress.

This research makes a number of contributions. Firstly, unlike previous papers on corporate failure modelling that simply use a single efficiency measure, we decompose this measure, Technical Efficiency (TE), into Pure Technical Efficiency (PTE) which indicates the ability to improve efficiency by wisely allocating resources and applying new technology, and Scale Efficiency (SE) which measures the ability to achieve better efficiency by adjusting the organisation to its optimal scale. We examine how each of these separately contributes to predicting financial distress. Secondly, in contrast to most applications of DEA in financial distress prediction, we assume variable rather than Constant Returns to Scale (RTS). Thirdly, DEA can only meaningfully be carried out for a sample of firms that use the same or similar technology (Dyson *et al*, 2001) and our study is the first to meet this requirement in the context of mixed-industry bankruptcy prediction. Whilst this reduces our sample size, by modifying the second stage logistic regression we are able to determine the effects of variables that are common across industries. Fourthly, we add corroboratory evidence to the very few studies that, regardless of country, have explored corporate efficiency as a predictive variable in a financial distress model.

This chapter is organised as follows. The next section provides a comprehensive review of the application of DEA in corporate distress prediction models. In the third section the methodology adopted in this research is presented. This is followed by a description of the data used in the empirical analysis and the subsequent section reports the results. This chapter finishes with conclusions and recommendations.

4.2 Literature review

4.2.1 DEA in bankruptcy prediction

Data Envelopment Analysis is an optimising technique which measures the relative efficiencies of a group of companies or Decision Making Units (DMUs) that use multiple inputs and produce multiple outputs. An efficient company uses less inputs to produce more outputs. Such efficiency is evaluated by the distance of a particular DMU to the efficient frontier (ideal position) which is based on its peers (other DMUs in the sample). The main idea and notation will be introduced in the next section; for more comprehensive explanation of DEA see Cooper *et al* (2000).

DEA has been incorporated into the prediction of corporate distress (or bankruptcy) in two different ways. Firstly, DEA has been used to derive a classification algorithm to separate distressed firms from non-distressed firms (Paradi *et al*, 2004; Cielen *et al*, 2004; Emel *et al*, 2003). Secondly, the relative efficiency of firms has been computed using DEA and this relative efficiency has been used as a feature of each firm in a subsequently developed classification rule (Xu and Wang, 2009; Yeh *et al*, 2010; Psillaki *et al*, 2010). We consider the former first.

As a classifier DEA has a number of advantages compared with statistical methods. For example, it is non-parametric and so does not require any distributional assumptions about error terms or covariance matrices. Yeh (1996) states the idea of standard classifiers such as discriminant analysis, logistic regression and probit regression is to develop meaningful peer group analysis between two or more groups, such as failed and non-failed, problematic and non-problematic cases. Thus DEA can properly fulfil the task as a natural peer comparison algorithm. Yeh (1996) also added that DEA requires no *a priori* information about input and output variables, which is very helpful in the estimation procedure. DEA is like a ‘black box’, where variables are entered, it generate results comparing the relatively more efficient ones to the others.

However, this also could be an inherent disadvantage of DEA. Whilst it requires no *a priori* information about inputs and outputs, it does not give an evaluation of their importance either, which is unlike other statistical methods that report variable significance or standard errors. Other shortcomings of DEA are sensitivity to the selection of inputs and outputs and issues when dealing with negative values. When the number of variables is close to or larger than the number of companies, efficiency scores tend to be 1, so discriminative power is lost.

It is logical to assume that corporate efficiency is associated with the probability of failure as Psillaki et al (2010) argued that in a competitive environment, efficient firms can generate more cash flows to repay their debts. Barr *et al* (1993) found there were significant differences in the scores in a sample of banks between those surviving and those failing and the difference increases as the date of failure approaches. Paradi *et al* (2004) used an additive DEA model to compute a worst performance boundary. Output variables were those that reflected poor financial performance such as bad debt, warranty claims etc. and input variables represent the opposite, for example profits, sales etc. For each DMU, an inefficiency score was computed. Paradi *et al* (2004) then used the layer technique (or tiered DEA, Barr *et al*, 2000) of removing inefficient companies to find a new boundary, each lower boundary indicating a lower chance of bankruptcy. A similar method was followed by Cielen *et al* (2004) who applied a cut-off to the estimated efficiency of each DMU (rather than the layer technique). They found, in a comparison of classification accuracy, that the DEA method outperformed decision trees and a linear programming method (Freed and Glover, 1981a). However they used the ratio form of the DEA model which is problematic when negative financial ratios are incorporated. Min and Lee (2008) estimated a Charnes, Cooper and Rhodes (CCR) model (defined in the next section) with Constant Returns to Scale (CRS) and applied a cut-off to the efficiency score for each firm. The DEA score method performed less well than a linear discriminant function. Premachandra *et al* (2009) estimated an additive DEA, which is invariant to data translation (and so can deal with negative data) with varying RTS. In the training sample, DEA had an inferior predictive performance whereas out of sample it was superior compared with logistic regression. Unfortunately they could not compare the performance of the two techniques using the same test dataset. More recently Premachandra *et al* (2011) estimated an additive DEA model to produce efficiency and a bankruptcy frontier and derived a prediction index for each firm from these two. They found the use of a two frontier method improved predictive performance compared to a single bankruptcy frontier.

As the second method of incorporating DEA into distress prediction, many researchers have carried out experiments to incorporate a DEA efficiency score (or Technical Efficiency - TE) as a predictor into other classification models. Xu and Wang (2009) put efficiency scores obtained by DEA into Support Vector Machines (SVMs), logistic regression and linear discriminant analysis (MDA). Yeh *et al* (2010) also used efficiency scores into SVMs and neural networks. Both studies found that the inclusion of efficiency scores increased the predictive performance of failed companies.

Sueyoshi (1999) proposed a two stage method labelled 'DEA-DA' (Data Envelopment Analysis – Discriminant Analysis). He contributes to both DEA and DA in the application of distinguishing two groups of units. However his DEA-DA methodology is not the combination of two algorithms but is inspired by the non-parametric advantages of DEA. Because generally a DA model would either be a statistical model or goal programming which aims to minimise the number of misclassifications or the sum of deviations. To reach an optimal goal, a hyperplane needs to be built by a linear function. However, in order to make the cut-off more precise, a nonlinear piecewise hyperplane is preferred, though in practice it is difficult to fit it to real data. For a VRS DEA model, the frontier is such a piecewise hyperplane. So Sueyoshi's (1999) DEA-DA model has two stages in its computation. In the first stage linear programing is used to predict class membership of each case and to identify cases where the predicted class is ambiguous by two discriminating functions which are class A, class B or class unclear. In the second stage a model that classifies cases that could fit into either group is estimated. Subsequent work has compared the performance of the two stage classifier with that of other standard methods. For example, Sueyoshi (2001) applied it to a dataset of 100 Japanese banks and compared it to linear and nonlinear DA. Sueyoshi (2006) compared DEA-DA with another eight algorithms. Later, Sueyoshi and Goto (2009) used it in bankruptcy assessment. They concluded that DEA-DA performs at least as well as other techniques in corporate bankruptcy prediction. Tsai *et al* (2009) followed their work and extended it to loan default prediction and found it was better in the case of consumer loans.

4.2.2 DEA assumptions and limitations in previous application

Though as a non-parametric method, DEA has many inherent advantages, it still has its shortcomings especially when applied in practice. Dyson *et al* (2001) summarised some of these issues which limit the applications of DEA most in practice: the requirement for homogeneity of units, the selection of inputs and outputs, the measurement of variables and weights attributed to variables. One of the most crucial assumptions of DEA is the homogeneity across all DMUs in the comparison of their relative efficiency. Dyson *et al* (2001) explain it in three ways. Firstly, all DMUs should be engaged in similar activities and produce similar outputs - similar products and services in businesses. It is not wise to calculate the relative efficiencies between a group of supermarkets and banks because the retailers sell consumable goods and banks provide financial services with different technologies. Secondly, all DMUs shall employ a range of similar resources in production. There is a difference between labour intensive industries and capital intensive industries. Thirdly, as sometimes neglected in many studies, all DMUs are supposed to act in a similar market environment. This is particularly important in international comparative studies where external environments such as political, social and legal factors are different. The assumption of homogeneity requires to be carefully considered continuously in DEA. Otherwise the relative efficiency scores are fairly meaningless.

A limitation of many studies that have used DEA efficiency in bankruptcy prediction is that they have estimated TE across a range of industries that use heterogeneous technologies (*e.g.* Cielen *et al,* 2004; Premachandra *et al*, 2009; Premachandra *et al,* 2011). Basically they simply randomly sampled a list of companies from a database but did not take their industries into account. If the technology used by the DMUs in the sample is different, then the weights on the inputs and outputs will be different and the concept of relative efficiency will be miscalculated. Otherwise, studies which use a single industry obviously limit the sample size (*e.g.* Paradi *et al*, 2004; Shetty *et al,* 2012). A possible solution was also suggested by Dyson *et al* (2001) that clustering units into homogeneous subsets would be helpful. In this research we use industrial clusters to realise this assumption.

The use of a DEA classifier or an efficiency score computes the relative efficiency of firms in a sample and can be used for in-sample prediction. However, if we wish to predict the failure probability for a case out of the sample, difficulties arise because the addition of a new case may alter the relative efficiencies of all of the firms currently included in the model, possibly changing the optimal weights on the inputs and the outputs and so altering the efficiency frontier. In principle the addition of a new case would necessitate the re-estimation of the DEA model. Both Emel *et al* (2003) and Min and Lee (2008) estimated a statistical model to predict DEA efficiency using the input and output financial ratios that could be used to classify out-of-sample cases. Arguably efficiency scores are not generated by a DEA model. They cannot be called efficiency and lose their peer comparable discrimination.

Inspired by Emel *et al* (2003), Bruni *et al* (2014) integrated DEA and Stochastic Processes together and built a new stochastic DEA model. They took the uncertainty of outputs into account and generated scenarios to run DEA programmes repeatedly. They thought that, in this way, the average credit scores could be more reliable. However the application of their stochastic DEA model was rather limited because they only considered the uncertainty of outputs of the next year but not the uncertainty of inputs which they believed to be certain at the point of time of making decision and budgets (one year in advance). In practice, it is preferable to gain a warning of credit risk as early as possible, of course with an acceptable level of accuracy. When the time of decision making is two years or more in advance, both inputs and outputs are uncertain and therefore their stochastic DEA model would become extremely complicated.

Stiglitz (1972) emphasised that RTS impacted on the probability of bankruptcy. In practice RTS are typically increasing or decreasing so it is surprising to see that most applications of DEA in corporate failure prediction have an assumption of CRS. Examples of papers that assume CRS are Xu and Wang (2009) and Yeh *et al* (2010). The paper of Psillaki *et al* (2010) is one of the few cases which assumed VRS to evaluate credit risk. They used the Banker, Charnes and Cooper (BCC) model named by Banker *et al* (1984) but with only one output and two inputs.

In this research, we firstly assume a VRS technology rather than CRS which is not common in reality, and secondly, under the assumption of VRS, include four additional variables in a model to predict financial distress. These variables are the Technical Efficiency (CRS efficiency), Pure Technical Efficiency (VRS efficiency), Scale Efficiency and a RTS parameter (defined in the next section). By incorporating these four variables, our prediction models include variables that are economically directly related to the probability of distress. Unlike most European companies which are relatively small in size, Chinese companies are often much larger and their employees can exceed 100,000 and total revenue exceed £20 billion. Therefore, cases of decreasing are often observed and it is expected to have some causality for financial difficulty.

Whilst a large number of papers have estimated models to predict financial distress for Chinese listed companies using financial ratios (for example see Ding *et al*, 2008; Sun *et al*, 2011 and Xiao *et al*, 2012), as far as we are aware only one paper (Xu and Wang, 2009) considered DEA efficiency as an explanatory variable in SVM, LR and MDA.

4.3 Methodology

4.3.1 Data Envelopment Analysis

DEA is an optimising technique which measures the relative efficiencies of a group of DMUs that use multiple inputs and produce multiple outputs. Performance is evaluated by the distance of a DMU to the efficiency frontier which is formed by a group of efficient DMUs. In traditional DEA, models can be divided into input-oriented and output-oriented models, where in the former, one aims to minimise inputs when satisfying at least the given output levels while output-oriented tries to maximise output given a certain level of inputs. There could be no orientation in the model but here input-oriented is used for illustration.

Consider a set of DMUs, each denoted as DMU$_j$ ($j=1,\ldots,n$), each producing several outputs $y_r(r=1,\ldots,s)$ by using several inputs $x_i(i=1,\ldots,m)$. $v_i(i=1,\ldots,m)$ is the weight for input x_i and $u_r(r=1,\ldots,s)$ is the weight for output y_r . They are denoted in a matrix (4.1).

$$
\begin{array}{cc}
\begin{array}{cc|cccccc|}
 & & 1 & 2 & \cdots & j & \cdots & n \\
v_1 & 1 & x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\
v_2 & 2 & x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\
v_i & \vdots & \vdots & \vdots & \cdots & x_{ij} & \cdots & \vdots \\
\vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\
v_m & m & x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn}
\end{array} & \\
\begin{array}{|cccccc|cc}
y_{11} & y_{12} & \cdots & y_{1j} & \cdots & y_{1n} & 1 & u_1 \\
y_{21} & y_{22} & \cdots & y_{2j} & \cdots & y_{2n} & 2 & u_2 \\
\vdots & \vdots & \ddots & \vdots & \cdots & \vdots & \vdots & \vdots \\
\vdots & \vdots & \cdots & y_{rj} & \cdots & \vdots & \vdots & u_r \\
\vdots & \vdots & \cdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
y_{s1} & y_{s2} & \cdots & y_{sj} & \cdots & y_{sn} & s & u_s
\end{array} &
\end{array}
\tag{4.1}
$$

Efficiency or productivity is defined as weighted outputs over weighted inputs. So for each DMU$_j$, the efficiency is measured by:

$$\theta_j = \frac{u^T y_i}{v^T x_i} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}, \; j = 1, 2, \ldots, n \tag{4.2}$$

For any DMU_0 being the unit to be evaluated, we wish to find the weights on each output and on each input that maximises efficiency defined as the ratio of weighted outputs to weighted inputs, subject to the ratio being not greater than 1 for any DMU. We have the Fractional Programming (FP) problem (equation (4.3)) to solve the weights of inputs and outputs.

$$\begin{aligned} &(FP) \quad \max \quad \theta = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_r x_{i0}} \\ &\text{s.t.} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1; \; j = 1, \ldots, n \\ &\qquad v_i, u_r \ge 0; \; r = 1, \ldots, s; \; i = 1, \ldots, m. \end{aligned} \tag{4.3}$$

This Fractional Programming problem can be converted into a Linear Program (LP) (equation (4.4)) (Cooper *et al,* 2000) and for convenience the Dual Program (DLP) (equation (4.5)) is usually considered.

$$\begin{aligned} &(LP) \quad \max \quad \mu y_0 \\ &\text{s.t.} \quad -\nu \mathrm{X} + \mathrm{uY} \le 0 \\ &\qquad \nu x_0 = 1 \\ &\qquad \nu \ge 0, \mathrm{u} \ge 0 \end{aligned} \tag{4.4}$$

$$\begin{aligned} &(DLP) \quad \min \quad \theta \\ &\text{s.t.} \quad \theta x_0 - X\lambda \ge 0 \\ &\qquad Y\lambda \ge y_0 \\ &\qquad \lambda \ge 0 \end{aligned} \tag{4.5}$$

The production technology may be characterised by either CRS or VRS. Simply speaking, RTS is the term used to describe the proportional change in output as the scale of production increases when all inputs and outputs increase by the same proportion. When the relative change in output equals the relative change in input, we have Constant RTS. If the proportional increase in outputs is larger than the proportional increase in inputs, increasing RTS exist and if the proportional increase in outputs is smaller than the proportional increase in inputs, we have decreasing RTS.

Whilst many DEA models have been proposed, the CCR model proposed by Charnes *et al* (1978) is a typical CRS model. Define X to be an $m \times n$ data matrix of inputs and Y to be an $s \times n$ data matrix of outputs, $\mathbf{e}$ to be a column vector of ones, $\boldsymbol{\lambda}$ to be a $n \times 1$ column vector of variables, and $\mathbf{s}^+$ and $\mathbf{s}^-$ to be a $m \times 1$ column vector of s^+ values and a $s \times 1$ column vector of s^- values, respectively. The term $\varepsilon, \varepsilon > 0$, is a non-Archimedean infinitesimal, which is a number smaller than any positive real number. Then the CCR model can be represented in envelopment form as:

$$
\begin{aligned}
&\min \quad \theta_{\mathrm{C}} - \varepsilon[\mathbf{e}^T(\mathbf{s}^- + \mathbf{s}^+)] \\
&s.t. \\
&X\boldsymbol{\lambda} + \mathbf{s}^- = \theta \mathbf{x}_0 \\
&Y\boldsymbol{\lambda} - \mathbf{s}^+ = \mathbf{y}_0 \\
&\boldsymbol{\lambda} \geq 0, \mathbf{s}^+ \geq 0, \mathbf{s}^- \geq 0
\end{aligned}
\tag{4.6}
$$

The elements in the $\mathbf{s}^+$ and $\mathbf{s}^-$ vectors are slack variables that convert the two constraints from inequalities to equalities. The solution is found in two stages: the first stage objective is to minimise θ_C without the slack terms and with equations in (4.6) as inequalities to give θ_C^*, and the second stage objective is to minimise $-\mathbf{e}^T(\mathbf{s}^- + \mathbf{s}^+)$ given $\theta_C = \theta_C^*$ and the constraints of equations (4.6). A DMU is said to be CCR efficient when $\theta_C^* = 1$ and the slack values are all zero. If $\theta_C^* = 1$ the DMU is globally technically efficient. If $\theta_C^* < 1$ then all of the inputs could be reduced without reducing output.

An example of a VRS DEA model is that by Banker *et al* (1984) labelled the BCC model and is the model consisting of equations (4.6) above with the additional constraint

$$
\mathbf{e}^T \boldsymbol{\lambda} = \mathbf{1} \tag{4.7}
$$

and θ_C replaced by θ_B. Again the solution is found in the same two stages as for the CCR model. In a one input one output context, non-constant RTS are represented by a line joining two points each representing a DMU on the efficiency frontier that does *not* project through the origin.

If we take the dual of the first stage model represented by equations (4.6) and (4.7) (i.e. omitting the slack terms) we gain

$$\begin{aligned}
&\max \quad v = \mathbf{u}^T \mathbf{y}_0 - u_0 \\
&s.t. \\
&\mathbf{v}^T \mathbf{x}_0 = 1 \\
&-\mathbf{v}^T X + \mathbf{u}^T Y - u_0 \mathbf{e}^T \leq 0 \\
&\mathbf{v} \geq 0, \mathbf{u} \geq 0,
\end{aligned} \tag{4.8}$$

where **u** and **v** are column vectors of weights to be estimated.

If U^*, V^*, u_0^* is the optimal solution to (4.8), and (X_0, Y_0) is the reference point on the efficiency frontier, then $U^* Y_0 - u_0^* = V^* X_0 = 1$. Further if (X, Y) is another point on the frontier, the supporting hyperplane through (X_0, Y_0) is $U^* Y = V^* X + u_0^*$, then

$$Y = \frac{V^*}{U^*} X + \frac{u_0^*}{U^*} \tag{4.9}$$

At this point, $u_0^* > 0, u_0^* = 0,$ and $u_0^* < 0$ implies and is implied by increasing, constant and decreasing RTS respectively (Banker and Thrall, 1992). In Figure 4.3.1, they are marked as hyperplanes BC, OB and AB respectively. In a one input one output context the u_0 term would be the intercept for the line referred to above.

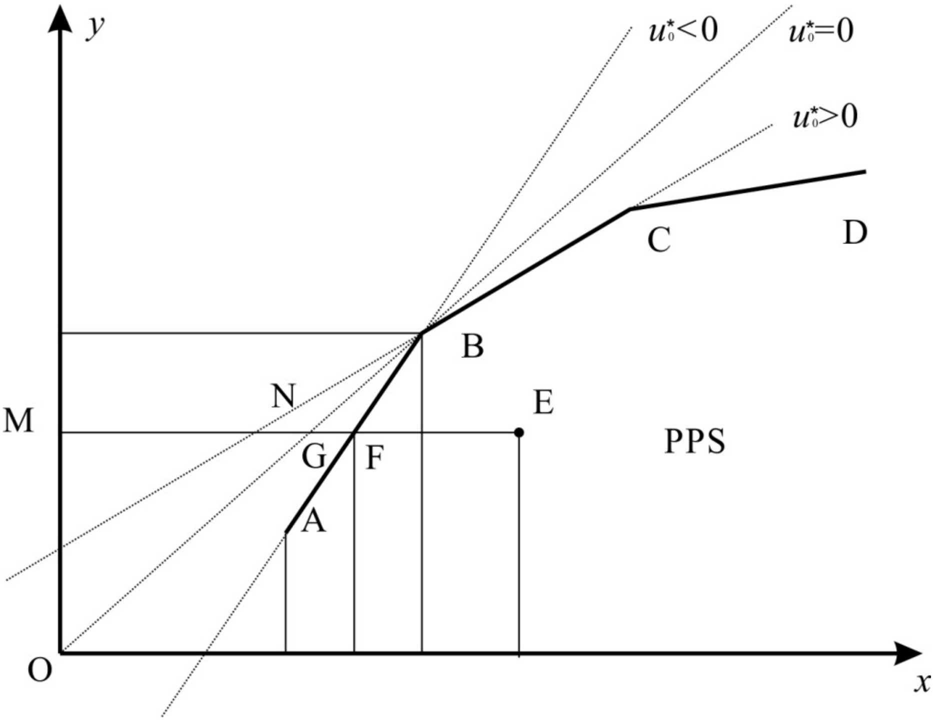
Furthermore, if θ_C^* and θ_B^* denote CCR and BCC efficiency scores of a particular DMU then Scale Efficiency is defined as (Charnes *et al*, 1978)

$$SE = \frac{\theta_C^*}{\theta_B^*} \tag{4.10}$$

Intuitively, the BCC model finds the optimal efficiency for a DMU when RTS are not necessarily constant. Dividing the efficiency of a DMU when estimated with CRS by the efficiency when VRS are assumed isolates the Scale Efficiency of the DMU. Thus we can write:

Technical efficiency (TE) = Pure Technical Efficiency (PTE) × Scale Efficiency (SE)

Figure 4.3.1 A two dimension DEA problem



More clearly, in a two dimension DEA problem (Figure 4.3.1), the Productivity Possibility Set (PPS) consists of a group of DMUs and there are four units lying on the efficiency frontier, A, B, C and D. Unit E is the point to be evaluated. Point F is the technically efficient reference point with the same Scale Efficiency. Unit B is the reference point with the most productive scale size. Then the relative efficiency for Unit E is

$$\begin{aligned}
\text{(Overall) Technical efficiency} &= \frac{MG}{ME} = \frac{y_E}{x_E}\bigg/\frac{y_G}{x_G} = \frac{x_B}{x_E}\cdot\frac{y_E}{y_B} \\
\text{Pure Technical Efficiency} &= \frac{MF}{ME} = \frac{y_E}{x_E}\bigg/\frac{y_F}{x_F} = \frac{x_F}{x_E} \\
\text{Scale efficiency} &= \frac{MG}{MF} = \frac{y_F}{x_F}\bigg/\frac{y_G}{x_G} = \frac{x_B}{x_F}\cdot\frac{y_F}{y_B}
\end{aligned} \tag{4.11}$$

4.3.2 Selecting inputs and outputs

Choosing the most appropriate inputs and outputs is of crucial importance when conducting all DEA studies, but so far, there is no generally agreed method for selection. Different DEA studies have used different inputs and outputs, which is a shortcoming of DEA (Premachandra *et al*, 2009). First of all, inputs and outputs have to be meaningful within the framework of the competitive environment (Oral and Yolalan, 1990). One disadvantage of DEA is that it computes relative efficiency with more discrimination between DMUs when the number of variables is significantly smaller than the number of DMUs (Parkan, 1987). This is normally the case in recent research. It is desirable that the number of input variables is larger than or equal to the number of output variables (Yeh, 1996). Dyson *et al* (2001) list four criteria for input and output selection: full coverage of resources, full measurement of activities and performance, common factors for all units, and environmental factors if relevant. They also suggest a 'rule of thumb' that the number of units is more than double the number of inputs and outputs, which can then keep the discrimination of efficiency score at an acceptable level. In this research, the sample size is much larger than the number of inputs and outputs and there are more inputs than outputs selected.

In the few studies that use DEA to model default risk, input variables are selected from, for example, Capital, Liability, Human Resources, Technology and Real Estate etc. and the output variables are profits and sales. Psillaki *et al* (2010) used one output (Value Added) and two inputs: Capital Shares and Number of Fulltime Employees. Similarly, Yeh *et al* (2010) selected R&D expenses, R&D designers and the number of patents and trademarks as input variables and the output variables included Gross Profit and Market Share.

When empirically modelling bankruptcy, to eliminate scale or size and unit effects in the values, it is common to use financial ratios rather than physical or monetary items. Min and Lee (2008) included three input ratios (Financial Expenses to Sales, Current Liabilities Ratio, Bonds Payable to Total Assets), an ordinal variable (Total Borrowings) and three output ratios: Capital Adequacy Ratio, Current Ratio and Interest Coverage Ratio. Cielen *et al* (2004) argued that financial ratios with a positive correlation can be used as inputs while those with a negative correlation are outputs. Premachandra *et al* (2009) proposed that the smaller (inferior) values in the financial ratios, which could possibly cause financial distress, are considered to be inputs, whereas the larger (superior) values in those ratios, which could cause financial distress, are considered as outputs. This is also called 'isotonic' which means increased input reduces efficiency and increased output reduces efficiency (Dyson *et al*, 2001). Xu and Wang (2009) in a Chinese case study went back to the original definition of efficiency for variable selection. They used Total Assets, Total Liabilities and Costs of Sales as the inputs, with Income from Sales as the sole output.

Furthermore Banker *et al* (1984) indicated for all inputs and outputs, a meaningful zero shall be assigned. Then no index variable should be used. Our choice of variables has been influenced by the following considerations: since financial ratios are going to be used in a second stage logistic regression we do not employ them in the first stage so as to reduce possible collinearity. We follow the original idea of DEA that inputs and outputs are measured as absolute amounts rather than as ratios. Thus we have chosen five inputs (Number of Employees, Share Capital, Total Cost, Total Assets and Total Liabilities) and three outputs (Total Sales, Total Profit and Cash Accrued) which are main items in all financial reports.

One may argue that in the selection of inputs and outputs, it is obvious that Total Sales - Total Costs = Total Profits. And that would bring correlation into DEA. However having correlated variables in DEA does not lead to a problem because their weights can automatically adjust without a significant impact on the efficiency score (Dyson *et al*, 2001). On the contrary, 'omission of a highly correlated variable can on occasion lead to significant changes in efficiencies' (Dyson *et al*, 2001, p.249). Therefore in the basic understanding, companies pay for labour and raw materials in operation (measured by Total Costs), turn them into products and services, and sell for revenue (measured by total sales) and aim for a large earning (measured by total profit). The reason for keeping both Total Sales and Total Profits is that a large revenue does not definitely imply a large profit.

A key issue regarding DEA is how to deal with negative values in inputs and outputs. In the early days, DEA models could only process non-negative values. As applications develop, negative values such as growth or profits sometimes exist, and negative values cannot be used before transformation. Inputs and outputs with pure negative values are the easiest to be tackled by simply switching their positions of inputs or outputs. For mixed value inputs and outputs, traditional methods of value transformation (such as adding a large number to the variable) is problematic since their relative efficiency is changed. It is preferred that in the solution to negative values, translation invariant (the same optimal efficiency frontier) and unit invariant (independent of scale of measurement of the variables) should be kept (Lovell and Pastor, 1995). The model of Portela *et al* (2004) is the first to keep both translation invariant and unit invariant at the same time without any transformation, by using range values, which is the distance between the original value and the best observed value. This is called the Range Directional Measure (RDM). But Cheng *et al* (2013) argued the efficiency calculation process was different from the radial model and so results were different. Later Sharp *et al* (2006) on the basis of RDM, developed it into the Modified Slack-Based Measure (MSBM) which gave a more precise evaluation of efficiency. Then Emrouznejad *et al* (2010) proposed the Semi-Oriented Radial Measure (SORM), which used two other variables for one mixed value variable, one to represent negative values and the other to represent positive values. Cheng *et al* (2013) pointed out that this introduces more artificial inputs and outputs and therefore a new method, the Variant of Radial Measure (VRM) was introduced by them. VRM replaces the original values by the absolute values of the proportion of improvements to reach the frontier and it gives the exact same results as the traditional radial model.

Our data output matrix, Y has negative values and we wish to assume VRS, which is both unit invariant and translation invariant and can handle positive and negative mixed data. A suitable model is the slacks based efficiency model where input orientation can be expressed as (from Cooper *et al*, 2000):

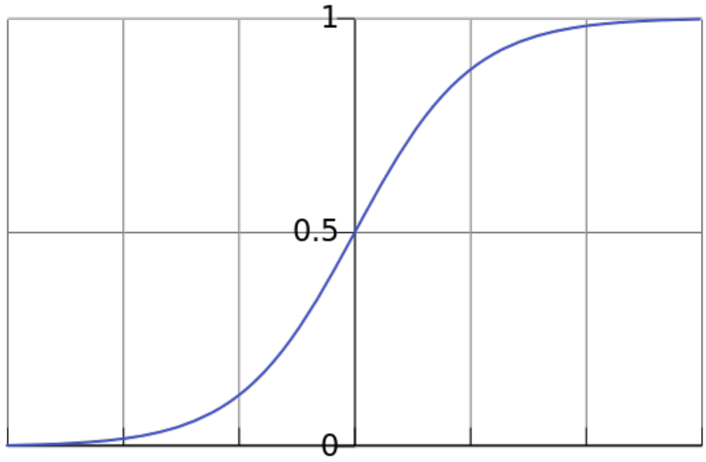
$$\begin{aligned} \min \quad & \rho = 1 - \frac{1}{\mathrm{m}} \sum_{i=1}^{m} \frac{s_i^-}{x_{i0}} \\ s.t. \quad & \mathbf{x}_0 - X\boldsymbol{\lambda} - \mathbf{s}^- = \mathbf{0} \\ & \mathbf{y}_0 - Y\boldsymbol{\lambda} + \mathbf{s}^+ = \mathbf{0} \\ & \boldsymbol{\lambda} \geq \mathbf{0}, \mathbf{s}^- \geq \mathbf{0}, \mathbf{s}^+ \geq \mathbf{0} \end{aligned} \tag{4.12}$$

MaxDEA Pro is used to solve the programs for each industry separately.

4.3.3 Logistic regression

In credit scoring, Logistic Regression is a very classic model which is inherently capable of dealing binary outcomes such as Goods and Bads, default and non-default. Compared to linear regression where the value of the dependent variable can go from $-\infty$ to $+\infty$, the dependent variable is limited in the range of $(0,1)$. A standard logistic distribution function is $f(x) = \dfrac{1}{1+e^{-x}}$ which has a sigmoid shape on the coordinate (Figure 4.3.2).

Figure 4.3.2 Distribution of logistic regression



A binary logistic regression does not require independent variables to be normally distributed and they could be continuous or categorical variables. In credit scoring, the probability of default depends on a group of explanatory variables and it can be expressed as

$$p(D=1 \mid x_1, x_2, \ldots, x_k) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k)}} \tag{4.13}$$

Where $p(D=1)$ is the probability of event of interest, i.e. default.

If using p_i to denote the probability of default for individual i (company i in this study) , equation (4.13) could be transformed to

$$\frac{1-p_i}{p_i} = e^{-(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik})} \tag{4.14}$$

Then take logarithm for both sides, we have

$$\log(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \tag{4.15}$$

If we use a notation $\text{logit}(t)$ short for $\log(\frac{t}{1-t})$ and vectors $\boldsymbol{\beta}, \mathbf{x}$ to denote $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ and $x_{i1}, x_{i2}, \ldots, x_{ik}$, we have

$$\text{logit}(p_i)=\boldsymbol{\beta}\mathbf{x}^T \tag{4.16}$$

Probability p_i take values from 0 to 1, $\frac{p_i}{1-p_i}$ take values from 0 to ∞ and $\text{logit}(p_i)$ values from $-\infty$ to $+\infty$, as linear regression.

However the estimation of parameters in equation (4.16) is not Ordinary Least Squares (OLS) for linear regression but a Maximum Likelihood (ML) method. The maximum likelihood method finds a set of values, called the maximum likelihood estimates, at which the log-likelihood function attains its local maximum.

For each training data-point, we have a vector of characteristics x_i and an observed class y_i. The probability of the class is either p , if $y_i = 1$ or $1-p$, if $y_i = 0$ the likelihood function is defined as

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{n} p(x_i)^{y_i} [1 - p(x_i)]^{1-y_i} \tag{4.17}$$

where $\boldsymbol{\beta}$ is the vector of parameters.

Then the log-likelihood function is

$$\begin{aligned} l(\boldsymbol{\beta}) &= \sum_{i=1}^{n} [y_i \log p(x_i) + (1 - y_i) \log(1 - p(x_i))] \\ &= \sum_{i=1}^{n} \log(1 - p(x_i)) + \sum_{i=1}^{n} y_i \log \frac{p(x_i)}{1 - p(x_i)} \end{aligned} \tag{4.18}$$

If we put equations (4.13) and (4.15) in (4.18), we can get,

$$l(\boldsymbol{\beta}) = \sum_{i=1}^{n} -\log(1 + e^{\beta x}) + \sum_{i=1}^{n} y_i (\beta x) \tag{4.19}$$

The estimators are the fixed-effects parameters, the variance components, and the residual variance. The maximum likelihood estimates are obtained by an iterative procedure that uses the Newton-Raphson method.

We deduce a score for each DMU for each type of efficiency and relate these to the probability of distress using logistic regression. However, DEA scores assume a common technology across the DMUs, which is the assumption of homogeneity discussed in the literature review. When we include the four types of efficiency variables we ensure that only DMUs within the same industry sector are accorded the same parameters whilst the financial ratios are assumed to have the same parameters across all sectors. In this way, it is assured that efficiency scores calculated in a sector are specific to this sector only. They are named as 'industry specific' models (details of them are introduced in Table 4.5.4). Therefore the specification of the logistic regression is amended to be

$$\text{logit}(p_i) = \alpha + \sum_{r=1}^{R} \sum_{s=1}^{S} \delta_{rs} D_s e_{irs} + \beta_1 w_{1i} + \beta_2 w_{2i} + \cdots + \beta_K w_{Ki} \tag{4.20}$$

where p_i denotes the probability of suffering distress for company *i;*

e_{irs} denotes efficiency score type *r* for sector *s* for company *i;*

w_{1i} denotes financial variable 1 for company *i* and so on;

$D_s = 1$ if company *i* is a member of sector *s*, 0 otherwise;

δ_{rs} denotes a parameter for efficiency score type r for sector s to be estimated;

β_1 denotes a parameter for covariate 1 to be estimated;

K denotes the number of covariates.

We compared three alternative specifications of equation (4.20): with only efficiency variables, with only financial variables and with combinations of both.

4.4 Sample

4.4.1 Training and test samples

The sample contains the annual data of 2,104 listed companies in China between 1998 and 2010. Since one of the important input variables in the DEA models is Number of Employees and it was not until 2001 that the companies started to report this information in their statements, the reports prior to 2001 are excluded from the sample. A few companies with extreme outlying values of input or output variables (mainly caused by unusual or abnormal value changes and rare events) were also excluded because the efficiency frontier is very sensitive to outlying values and so their inclusion may have resulted in inaccurate estimates of relative efficiencies. Besides, all companies that experienced ST prior to 2003 are excluded because companies being distressed cannot be distressed again.

Since DEA models are estimated for homogeneous production processes (Dyson *et al*, 2001), we solve DEA programs to compute efficiency scores for separate industry sectors and within the same year to ensure that the companies in the sample share the same productivity process and a similar business environment. To keep as many distressed companies as possible in the sample for modelling, all industries were examined and the second level industrial sectors Raw Materials (code 1510 in Wind database), Industrial Equipment (code 2010) and Real Estate (code 4040) were found to have the highest frequency of ST cases. In 2002, 2003, 2006 and 2007, there were more ST cases than in other years (Figure 3.4.1). Therefore, the STs in 2002 or 2003 are grouped together as the training sample and the STs in 2006 or 2007 are grouped into the hold-out sample to test the predictive performance of the logistic regression. Thus efficiency scores and financial covariate data for 2001 with ST/non-ST status taken from 2002 and 2003 were used to train the model, which then was then applied to the data in 2005 to predict the probability of becoming ST in 2006 and 2007.

The numbers of ST and non-ST companies are displayed in Table 4.4.1. Some companies were delisted and some new companies entered the sample during the study period. There are 429 cases common to both samples. The predictive accuracy is tested by an out-of-time rather than an out-of-sample validation, which is in line with the literature (*e.g.* Shumway, 2001).

Table 4.4.1 Sample 1

	Training sample (2001 to 2003)				Test sample (2005 to 2007)			
Sector Code	1510	2010	4040	Total	1510	2010	4040	Total
non-ST	181	144	95	420	218	185	92	495
ST	17	14	19	50	18	20	22	60
Total	198	158	114	470	236	205	114	555
ST/Non-ST	9.40%	9.70%	20.00%	11.90%	8.30%	10.80%	23.90%	12.10%
ST rate	8.59%	8.86%	16.67%	10.64%	7.63%	9.76%	19.30%	10.81%

4.4.2 DEA variables

Descriptive statistics for financial variables used in the DEA analysis are shown in Table 4.4.2. The occasional negative values for profits and cash flows are apparent and our model can deal with them.

Table 4.4.2 Statistics of DEA variables

			2001					2005				
		Sector	*N*	*Mean*	*SD*	*Min*	*Max*	*N*	*Mean*	*SD*	*Min*	*Max*
Inputs	Employees	1510	198	3925	5388.8	104	45943	236	4240.6	5622.1	140	44421
		2010	158	2498.2	2353	102	15000	205	2281.4	2312.9	129	19676
		4040	114	1252.9	1594.5	56	13319	114	1038.9	1742.2	34	12568
	Capitals (mCNY)	1510	198	524.5	1182.4	51	12512	236	604.1	1434.3	60.4	17512
		2010	158	291.7	224.7	80.2	1884.4	205	323.7	296.7	57.6	2689.6
		4040	114	298.3	234.3	66	1867.7	114	369.7	410.9	53.5	3722.7
	Costs (mCNY)	1510	198	1410.6	2935	37.6	25497.9	236	3620.3	9098.1	49.3	108422.4
		2010	158	995.1	1820.5	50	19358.6	205	1656.7	2563.9	110.4	19459.7
		4040	114	506.5	607.9	48	4157.4	114	774.4	964.3	12.2	8528.6
	Assets (mCNY)	1510	198	2478.9	4881.2	154.6	58042.1	236	4269.4	10471.3	164.4	142024.2
		2010	158	1671.7	1436.8	198.1	9907.9	205	2273.6	2330.4	172.9	18033.6
		4040	114	1659.2	1507	287	9690.3	114	2428.5	2747.5	27.3	21992.4
	Debts (mCNY)	1510	198	1120.2	2561.6	43	31752	236	2248.9	4926	22.6	63097.3
		2010	158	805.8	810.5	45.9	4810	205	1318	1491.5	55.6	9517.7
		4040	114	834.4	978.2	6.5	7380.5	114	1459.5	1675.6	7	13411.2
Outputs	Profits (mCNY)	1510	198	88.5	355.4	-1797.4	3709.6	236	281.4	1334.9	-997.2	18310.8
		2010	158	54.9	160.9	-1009.8	1011.8	205	60.4	238.2	-696	2057.1
		4040	114	44.1	126.1	-537.6	501.9	114	40.9	293.6	-1142.2	1976.2
	Cash (mCNY)	1510	198	16.7	336.9	-3686.2	872.5	236	-6.6	334.4	-2664.6	1784.3
		2010	158	50.1	208.1	-686.4	882.7	205	-15.6	160.9	-953.8	661.3
		4040	114	45.9	150.8	-329.9	585.2	114	-22.9	216.3	-1100.2	597.9
	Sales (mCNY)	1510	198	1499.3	3142.1	20.1	29170.8	236	3895.2	10297.5	17.9	126608.4
		2010	158	1037.8	1858.1	51.6	19565.1	205	1706.5	2657.2	0.9	19474.2
		4040	114	536.1	663.6	12.2	4455.1	114	825.4	1154.4	3.5	10558.9

The list of financial ratios selected for inclusion in the logistic regression and represented by w_q in equation (4.20) is described in Table 3.4.1.

4.5 Results

4.5.1 DEA

There are four types of efficiency scores of importance to this paper: Technical Efficiency, Pure Technical Efficiency, Scale Efficiency and RTS levels. The first three are all continuous scores, whereas is a categorical ordinal variable with three levels: decreasing, constant and increasing.

Table 4.5.1 Means and standard deviations of efficiency scores

			Training Sample							Test Sample					
			TE		PTE		SE			TE		PTE		SE	
Sector code	ST	N	Mean	SD	Mean	SD	Mean	SD	N	Mean	SD	Mean	SD	Mean	SD
1510	0	181	.557	.209	.628	.214	.886	.117	218	.493	.219	.597	.214	.824	.163
	1	17	.323	.180	.533	.277	.647	.247	18	.237	.086	.439	.199	.614	.233
	All	198	.537	.216	.620	.221	.866	.148	236	.474	.222	.585	.216	.808	.178
2010	0	144	.556	.239	.694	.214	.792	.171	185	.493	.242	.615	.227	.796	.198
	1	14	.231	.082	.473	.243	.545	.188	20	.201	.084	.439	.182	.497	.194
	All	158	.527	.248	.675	.225	.770	.186	205	.465	.247	.598	.229	.767	.216
4040	0	95	.632	.251	.728	.232	.864	.154	92	.578	.285	.706	.269	.824	.221
	1	19	.368	.271	.574	.264	.665	.300	22	.207	.092	.394	.218	.610	.278
	All	114	.588	.272	.702	.244	.831	.199	114	.506	.298	.646	.287	.782	.247
Total	0	420	.574	.231	.673	.222	.849	.151	495	.509	.243	.624	.233	.813	.188
	1	50	.314	.206	.532	.261	.625	.255	60	.214	.087	.422	.199	.574	.241
	All	470	.546	.242	.658	.230	.825	.179	555	.477	.249	.602	.238	.788	.208

First, we consider aggregate results. One of the objectives of this research is to test whether the probability of distress is associated with low efficiency. We consider various efficiency measures where following previous literature (Xu and Wang, 2009) we do not treat each sector separately. Secondly when we treat each sector separately by assumption. Descriptive statistics of efficiency scores are shown in Table 4.5.1. As a preliminary analysis we computed two-way ANOVA (Table 4.5.2) and found that for each of the three types of efficiency score, there is a significant difference between the mean score for the ST group and the mean score for the non-ST group. But there is a significant difference in the mean efficiency scores between the industry sectors in 2001 only in terms of Technical Efficiency and Scale Efficiency, and for 2005 only in Scale Efficiency.

Table 4.5.2 Two-way ANOVA for TE, PTE and SE

	Training Sample						Test Sample					
	TE		PTE		SE		TE		PTE		SE	
Source	*F*	*Sig.*	*F*	*Sig.*	*F*	*Sig.*	*F*	*Sig.*	*F*	*Sig.*	*F*	*Sig.*
Sector	3.18	.042	1.95	.143	6.67	.001	0.69	.502	0.36	.698	3.20	.041
ST	63.84	.000	21.67	.000	88.72	.000	93.04	.000	47.21	.000	80.70	.000
Interaction	0.56	.569	1.11	.331	0.39	.679	1.12	.326	2.42	.090	1.19	.305

Table 4.5.3 Levels of RTS

	RTS 2001				RTS 2005			
	Decreasing	Constant	Increasing	Total	Decreasing	Constant	Increasing	Total
ST	69	69	282	420	58	66	371	495
Non-ST	5	0	**45**	50	0	0	**60**	60
Total	74	69	327	470	58	66	431	55

As the level of RTS is a categorical variable, we can only pursue a cross table on it. From Table 4.5.3 we can see that both in 2001 and 2005 there are relatively low numbers of companies with decreasing or constant RTS. We therefore classified the RTS values into two values: decreasing or constant on the one hand and increasing (IRS) on the other and included a dummy variable to represent the existence of IRS in the logistic regressions.

4.5.2 Logistic regression

We have two objectives. Firstly, to investigate the statistical significance of efficiency measures in explaining the probability of suffering financial distress and secondly, to evaluate the predictive performance of including efficiency variables in such posterior probability models.

Pre-analysis showed that if efficiency variables and financial ratios are entered together into a stepwise logistic regression, nearly all of the efficiency variables are excluded. However, we are interested in the role specifically of efficiency variables and so we adopted the following procedure. Since values of the efficiency variables were derived from a DEA model where the objective function consisted of financial variables, collinearity is possible between some financial ratios and some efficiency scores. Conscious of this potential collinearity we considered three model specifications. Firstly we have models with only efficiency variables (Models 1-6). Models 1-4 contain only industry specific efficiency variables to try to reduce the heterogeneity in technologies that would otherwise be present. Models 5 and 6 are included simply to show the parameter estimates if, as in previous literature, in the DEA analysis all industrial sectors were assumed to be homogeneous.

Secondly, we estimated models that included combinations of the industry specific efficiency variables and subsequently uncorrelated financial ratios were entered using a stepwise routine (Models 7-9). Thirdly, we estimated models that included significant financial variables selected from all those available using a forward stepwise routine together with combinations of efficiency scores. Thus the efficiency score was ‘force’ entered in each model, except Model 10. All of the models were parameterised across all industries with industry specific dummies interacted with each efficiency variable to yield industry specific parameters and the efficiency scores. We therefore assume the marginal effects of the efficiency variables are specific to each industry sector but the marginal effects are the same for each financial variable for all industries. The models are specified in Table 4.5.4.

Table 4.5.4 Model comparison 1

A Efficiency Variables Only	
Model 1	Industry specific TE only
Model 2	Industry specific PTE and SE
Model 3	Industry specific TE and RTS
Model 4	Industry specific PTE, SE and RTS
Model 5	Pooled TE
Model 6	Pooled PTE and SE
B Efficiency Variables forced entry, financial ratio variables selected by stepwise routine	
Model 7	Industry specific TE forced entry, financial ratios selected by forward stepwise routine.
Model 8	Industry specific PTE and SE forced entry, financial ratios selected by forward stepwise routine
Model 9	Industry specific PTE, SE and RTS forced entry, financial ratios selected by forward stepwise routine
C Financial variables selected by stepwise and then forced entry with efficiency variables	
Model 10	Financial variables selected by forward stepwise routine.
Model 11	Industry specific TE, financial ratios from Model 10
Model 12	Industry specific PTE and SE, financial ratios from Model 10
Model 13	Industry specific PTE, SE and RTS, financial ratios from Model 10

DEA allows one to compute the efficiency of an organisation relative to the most efficient organisations in the dataset. To compute the relative efficiency scores for a new case requires us to solve the program for a different set of DMUs and so could alter the efficiency boundary and thus the efficiencies of the original cases relative to the new efficiency boundary. To assess the discriminatory power of including efficiency variables we computed the relative efficiency for each member of the holdout sample in 2005. We assume that the marginal effects of relative TE, PTE and SE, and so the logistic regression parameters that were estimated for 2001-3, remained constant over time. We argue that in competitive markets it is relative efficiency rather than absolute efficiency that determines the chance of financial success or, as in our case, financial distress. This is consistent with the approach used in the literature (see Xu and Wang, 2009). We then predicted the probability of a new case becoming distressed in 2006-7 using the 2005 efficiencies and 2001-3 parameters.

4.5.3 Parameters and significance levels

Table 4.5.5 shows that when included alone, each of the efficiency variables had the expected sign: an increase in efficiency is associated with a decrease in the probability of distress. This is true when we consider TE alone or PTE and SE together. The effect of a marginal change in relative TE score for Real Estate has a smaller effect on the probability of distress than in the Industrial Equipment industry. Generally, an increase in relative PTE has a smaller marginal effect on distress likelihood that does an increase in relative SE. RTS (either constant-decreasing or increasing) have no detectable effect of the probability of distress. A failure to compute relative efficiency for each industry sector separately and so to assume homogeneity of technology across all three sectors not only yields incorrect efficiency scores but also masks considerable differences in the effects of each type of efficiency between industry sectors if such scores are used.

Table 4.5.6 shows that when we force the efficiency scores into each logistic regression, and then select financial variables in a stepwise fashion, the Scale Efficiency variables remain significant with the expected signs, whilst the RTS variables are never significant. In all sectors, improving relative PTE has a smaller effect on the chance of distress than an improvement in relative scale.

The parameters of most of the financial ratios have the expected signs. For example, higher net cash flow per share or higher return on equity or return on assets is associated with a lower chance of distress. In Table 4.5.7 we see that if we include the efficiency variables and the financial ratios that would be included if the efficiency variables were not, then only the Scale Efficiency scores remain significant. Again their parameters have the expected signs.

Table 4.5.5 Coefficient estimates from efficiency only logistic regressions A

Variable	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
TE Score					-10.52**	
Raw materials	-11.89**		-12.34**			
Industrial Equipment	-14.23**		-24.41**			
Real Estate	-9.40**		-8.56**			
PTE Score						-4.95**
Raw materials		-3.82**		-4.39**		
Industrial Equipment		-6.93**		-9.53**		
Real Estate		-5.89**		-5.77**		
SE Score						-7.33**
Raw materials		-9.79**		-10.16**		
Industrial Equipment		-9.02**		-12.27**		
Real Estate		-7.26**		-6.90**		
RTS indicator						
Raw materials			-0.97	-5.77		
Industrial Equipment			2.08	3.32		
Real Estate			1.39	-1.54		
Constant	2.58**	7.56**	3.47**	8.59**	2.13**	6.20**

** indicates the figures are significant at 5% level of significance.

Table 4.5.6 Coefficient estimates from logistic regressions B

Variable	*Model 7*	*Model 8*	*Model 9*
Technical Efficiency Score			
Raw materials	-8.35**		
Industrial Equipment	-10.67**		
Real Estate	-7.12**		
Pure Technical Efficiency Score			
Raw materials		-2.81	-1.82
Industrial Equipment		-6.19**	-9.75
Real Estate		-6.24**	-5.25*
Scale Efficiency Score			
Raw materials		-10.82**	-11.08**
Industrial Equipment		-9.66**	-16.17**
Real Estate		-8.21**	-7.93**
RTS indicator			
Raw materials			-1.68
Industrial Equipment			5.24
Real Estate			-2.09
Net cash flow from operating per share	-5.43**	-6.12**	-4.82**
Return on equity	-0.09*	-0.20**	-0.25**
Return on assets	-0.18**		
Undistributed profit per share			
Gross margin / total sales	-0.07**		
Operating profit / total sales	0.03*		
Financial expenses / total sales	0.13*	0.12*	0.15*
Tangible assets / total assets	-0.04*	-0.05**	-0.06**
Current ratio		3.22**	
Quick ratio			3.31**
Cash ratio		-6.37**	-7.77**
Net cash flow / current liabilities			-5.53*
Inventory turnover	0.36**	0.66**	0.72**
Total profit growth			
Total assets growth	-0.08**	-0.09**	-0.09**
Constant	3.47**	10.16**	11.74**

Models 7, 8 and 9: Efficiency variables forced entry, financial variables selected by forward stepwise routine.
* and ** indicate the figures are significant at 10% and 5% levels of significance respectively.

Table 4.5.7 Coefficient estimates from logistic regressions C

Variable	*Model 10*	*Model 11*	*Model 12*	*Model 13*
Technical Efficiency Score				
Raw materials		-3.39*		
Industrial Equipment		-4.43		
Real Estate		-2.26		
Pure Technical Efficiency Score				
Raw materials			-1.12	-1.85
Industrial Equipment			-1.16	-2.74
Real Estate			-1.72	-2.45
Scale Efficiency Score				
Raw materials			-4.28**	-4.56*
Industrial Equipment			-4.89**	-6.89*
Real Estate			-2.9*	-3.59*
RTS indicator				
Raw materials				-1.52
Industrial Equipment				0.4
Real Estate				-0.95
Net cash flow from operating per share	-4.32**	-4.03**	-3.85**	-4.32**
Return on equity	-0.11**	-0.11**	-0.12**	-0.12**
Return on assets				
Undistributed profit per share	-1.58**	-1.41**	-1.17**	-1.19**
Gross margin / total sales	-0.06**	-0.07**	-0.08**	-0.07**
Operating profit / total sales				
Financial expenses / total sales	0.12**	0.09**	0.11**	0.12**
Tangible assets / total assets				
Current ratio	-0.71*	-0.54**	-0.75*	-0.81*
Quick ratio				
Cash ratio				
Net cash flow / current liabilities				
Inventory turnover				
Total profit growth	-0.006**	-0.005**	-0.004**	-0.004*
Total assets growth	-0.05**	-0.04**	-0.04**	-0.04**
Constant	0.07	1.39	4.11*	5.84**

Model 10: All variables selected by forward stepwise routine.

Model 11, 12 and 13: Efficiency variables forced entry, financial variables from Model 10.

* and ** indicate the figures are significant respectively at 10% and 5% levels of significance.

4.5.4 Predictive performance

The statistical significance of a covariate does not necessarily imply that predictive performance is increased if the variable is included in a model. We now examine the predictive performance of all of our models. Firstly we compare the predictive performance of using overall efficiency (TE) versus decomposed efficiency (PTE and SE); secondly we compare models with RTS levels versus models without RTS levels, and thirdly we compare models with and without financial ratios. The classification accuracy is presented in Table 4.5.8. For Error Rate calculation the proportion of STs that are predicted to be STs is the proportion of the observed STs in the training sample. The AUC, Gini coefficient, KS and H measure are presented in Table 4.5.9.

Table 4.5.8 Classification accuracy

	Training sample			Test sample		
	Type I error	Type II error	Overall accuracy	Type I error	Type II error	Overall accuracy
Model 1	40.00%	4.80%	91.50%	41.70%	4.80%	91.20%
Model 2	52.00%	6.20%	88.90%	46.70%	5.50%	90.10%
Model 3	42.00%	5.00%	91.10%	46.70%	5.50%	90.10%
Model 4	52.00%	6.20%	88.90%	45.00%	5.30%	90.50%
Model 5	42.00%	5.00%	91.10%	43.30%	5.10%	90.80%
Model 6	50.00%	6.00%	89.40%	46.70%	5.50%	90.10%
Model 7	20.00%	2.40%	**95.70%**	36.70%	4.20%	92.30%
Model 8	30.00%	3.60%	93.60%	40.00%	4.60%	91.50%
Model 9	24.00%	2.90%	94.90%	40.00%	4.60%	91.50%
Model 10	22.00%	2.70%	95.40%	30.60%	3.90%	93.40%
Model 11	22.00%	2.70%	95.40%	30.60%	3.90%	**93.40%**
Model 12	22.00%	2.70%	95.40%	32.30%	4.10%	93.00%
Model 13	24.00%	2.90%	94.90%	32.30%	4.10%	93.00%

Table 4.5.9 Discriminative power

	Training sample				Test sample			
	AUROC	GINI	KS	H	AUROC	GINI	KS	H
Model 1	0.869	0.738	0.612	0.382	0.921	0.841	0.737	0.369
Model 2	0.881	0.761	0.590	0.356	0.898	0.797	0.670	0.293
Model 3	0.882	0.765	0.660	0.404	0.915	0.829	0.746	0.357
Model 4	0.887	0.775	0.616	0.348	0.895	0.791	0.665	0.303
Model 5	0.844	0.687	0.616	0.387	0.917	0.833	0.691	0.347
Model 6	0.843	0.686	0.548	0.313	0.891	0.781	0.613	0.313
Model 7	0.970	0.940	0.850	0.683	0.952	0.904	0.796	0.451
Model 8	0.979	0.957	**0.887**	0.650	0.935	0.869	0.765	0.384
Model 9	**0.983**	**0.965**	0.881	**0.695**	0.935	0.870	0.798	0.382
Model 10	0.964	0.927	0.856	0.627	0.952	0.903	**0.804**	0.518
Model 11	0.967	0.933	0.849	0.626	**0.955**	**0.909**	0.803	**0.520**
Model 12	0.968	0.936	0.832	0.632	0.955	0.909	0.801	0.502
Model 13	0.971	0.941	0.837	0.637	0.955	0.909	0.788	0.497

In the first comparison (Model 1 vs 2 and Model 5 vs 6) both pairs show that decomposition of efficiency scores reduces the classification accuracy in the test samples by a noticeable amount. The Gini decreases from 0.841 to 0.797 and from 0.833 to 0.781 if TE is decomposed into PTE and SE. In the second comparison (Models 1 vs 3 and Model 2 vs 4) we see that inclusion of RTS decreases predictive performance slightly. For example, without RTS, Model 1 has a Gini of 0.841 whilst with RTS this is 0.829 in the test set and the corresponding figures for Models 2 and 4 are 0.797 and 0.791 respectively.

One might notice that for Models 1-6 (with only efficiency variables) the Gini for the test set exceeds that for the training set. We explain this unusual observation with reference to a particular model. Consider Table 4.5.1 and industry 4040 (Real Estate). Model 1 consists only of the TE variable. Notice that the difference in the mean TE between the ST and not-ST groups in the training set (0.632 - 0.368 = 0.264) is less than that in the test set (0.578 - 0.207 = 0.371). In a Kolmogorov-Smirnov diagram (Figure 4.5.1) the increase in the difference in the mean TE between the two groups will move the $P_{non\text{-}ST}$ (s) line further from the P_{ST} (s) line in the test set than in the training set, where $P_{non\text{-}ST}$ (s) and P_{ST} (s) denote the cumulative proportions at and below each score, s, of non-STs and STs respectively. Therefore plotting $P_{non\text{-}ST}(s)$ against $P_{ST}(s)$ in a ROC curve graph will result in a more accentuated curve and so the greater difference in the means will result in a larger Gini (see Thomas *et al*, 2002).

Figure 4.5.1 Kolmogorov-Smirnov plot for Model 1 Sector 4040

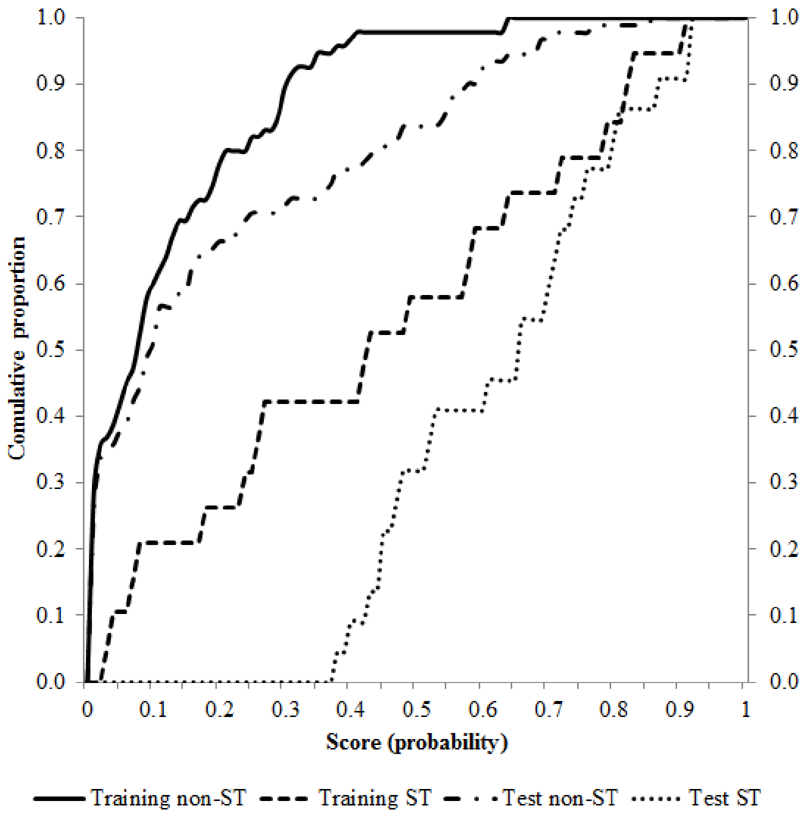


Figure 4.5.3 also shows the KS plots for other models. For Model 1 to 6, they have larger maximum distance between the cumulative Goods score and the Bads score, so they lead to larger Gini coefficients in the test sample than the training sample (Figure 4.5.2).

Figure 4.5.2 Gini plots for all models

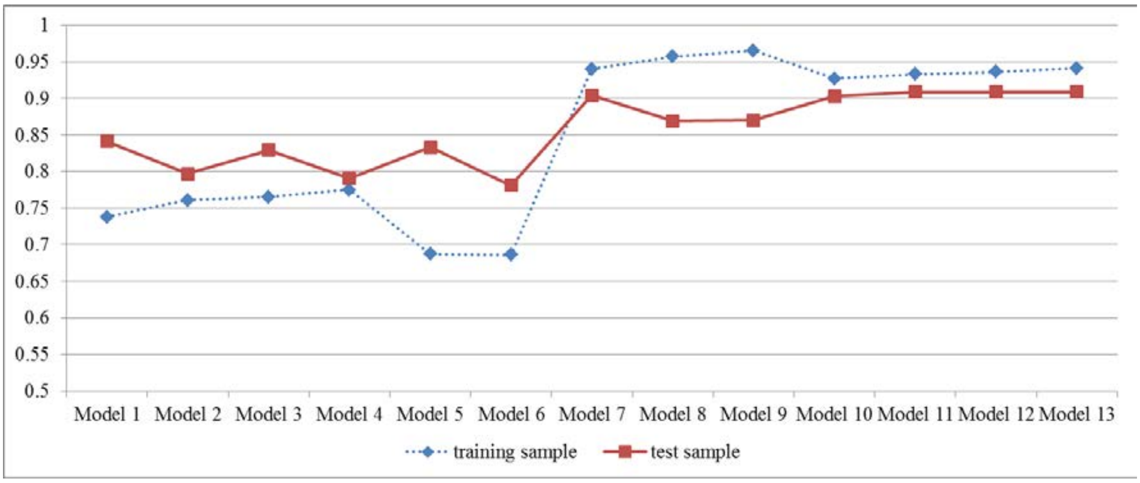


Figure 4.5.3 KS plots for all models

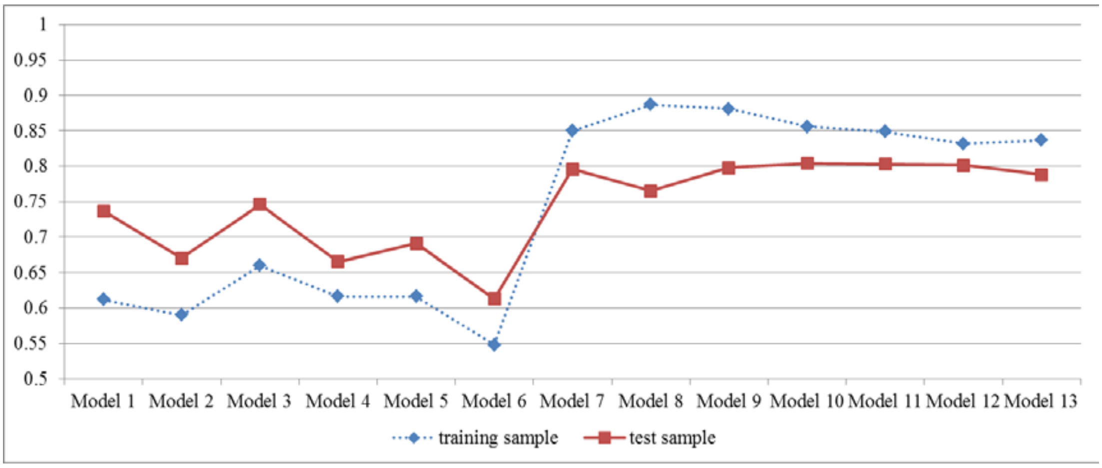
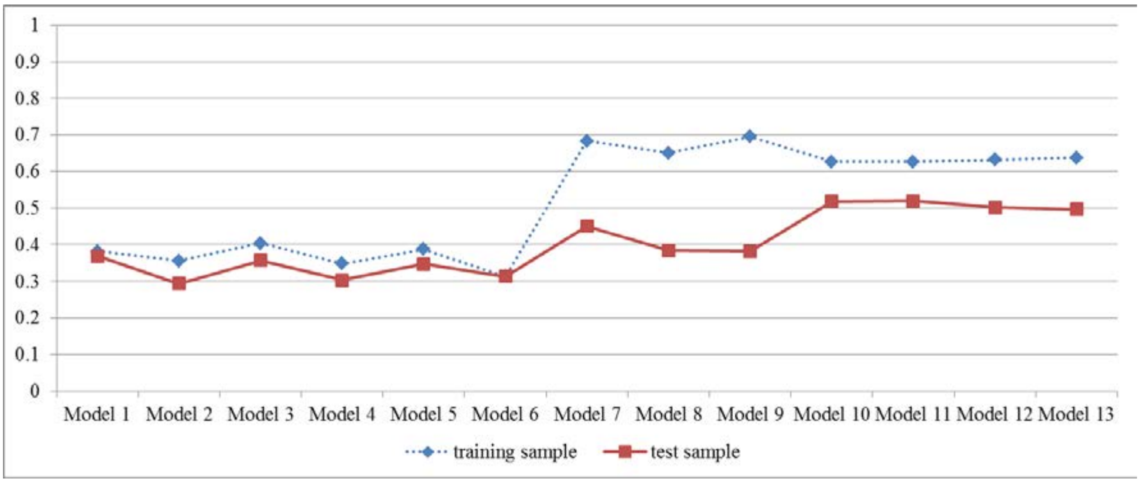


Figure 4.5.4 H plots for all models



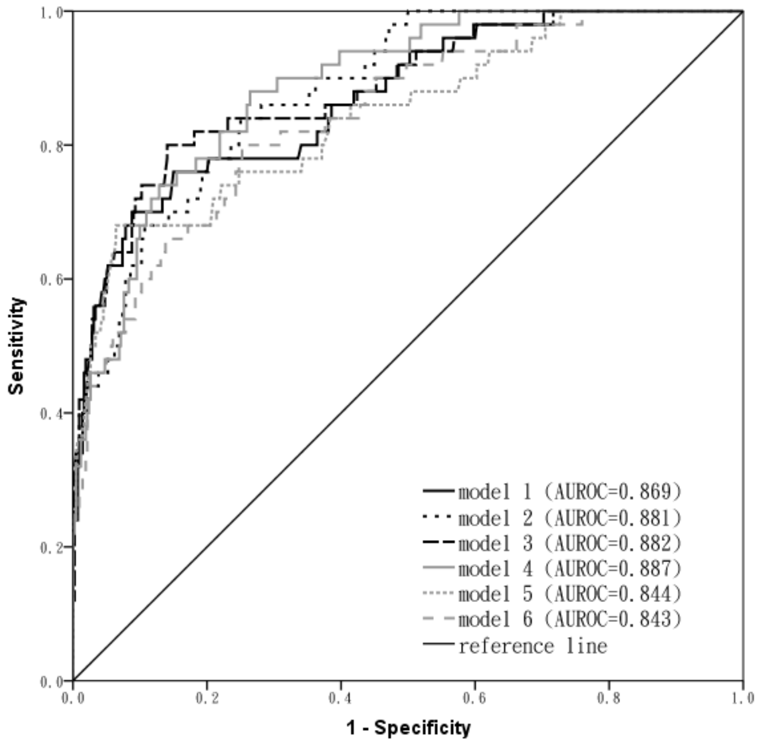
But if looking at the H plots (Figure 4.5.4), when assuming the same H cost distribution, the performance of the test sample is consistently worse than that of the training sample, which would be expected. In terms of H measure, once again, decomposition of efficiency scores reduces the discriminative power (Model 1 vs 2 and Model 5 vs 6). But the effect of RTS is mixed (Models 1 vs 3 and Model 2 vs 4). Model 1, which incorporates the technical efficiency score only, is the best one in testing (0.369).

Turning to the inclusion of financial ratios, we see that they outperform the first six models that contain only efficiency variables. In Table 4.5.8 and Table 4.5.9, for each performance measure we highlight the model with the greatest predictive power. By observing Figure 4.5.2, Figure 4.5.3 and Figure 4.5.4, it can be seen that generally, in the training sample the models of efficiency variables assisted by ratios (Models 7, 8 and 9) are better in predictive accuracy than the models of ratios assisted by efficiency variables (Models 10, 11, 12 and 13). But in the test sample, it is the other way round. In the test sample the highest classification accuracy and the highest discriminatory power based on AUC, Gini and H is gained by Model 11, which includes industry specific TE together with the most significant of all financial ratios. The KS values of Model 10 and Model 11 are very close. However, the difference between the performance of this model and models 12 and 13 that have the same financial ratios but decompose TE and include RTS (Model 13), is inconsequential by AUC and Gini but decreases in H measures.

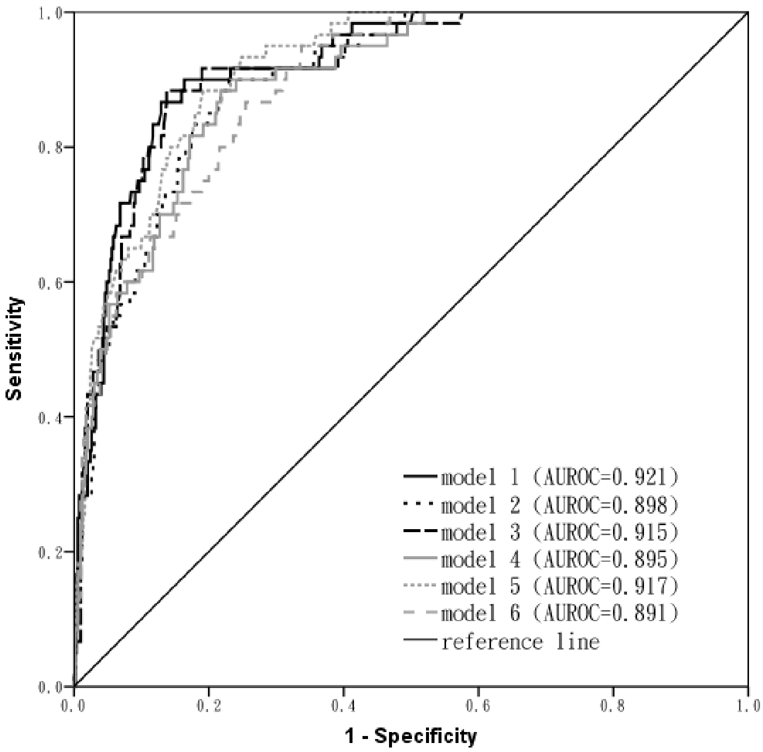
Figure 4.5.5 shows the ROC curves across three groups of regression: Models 1-6, Models 7-9 and Models 10-13. It can be observed that in regression A, curves of six models are dispersed though they cross each other in places. But when financial ratios are added to the model (Models 7 to 9, and Models 11 to 13), they become closer particularly in the last four models. When the best predictive variables are selected from a range of financial ratios, the influence of efficiency scores becomes less, though generally they improve the discriminative power.

Figure 4.5.5 ROC curves

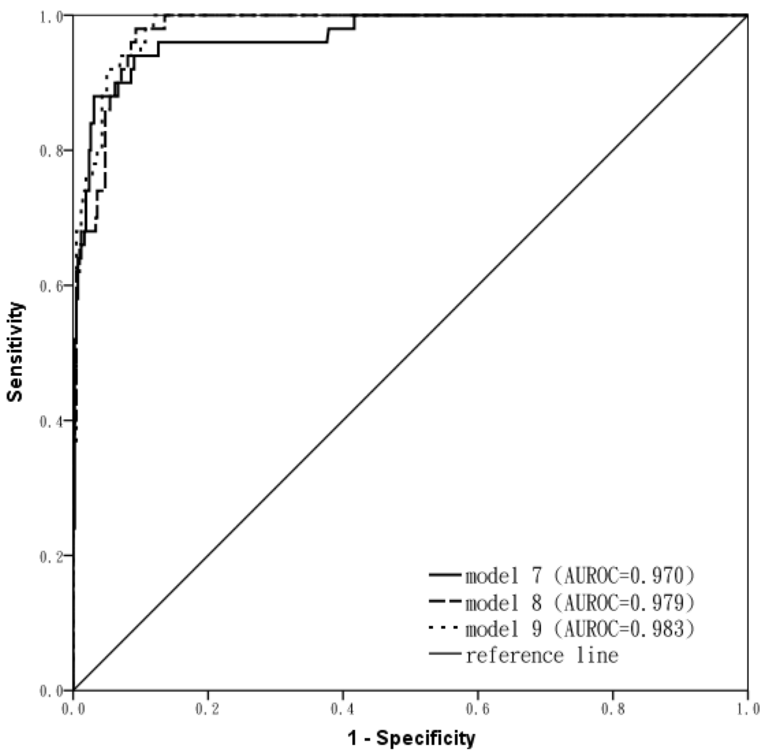
Model 1 to 6 Training Set



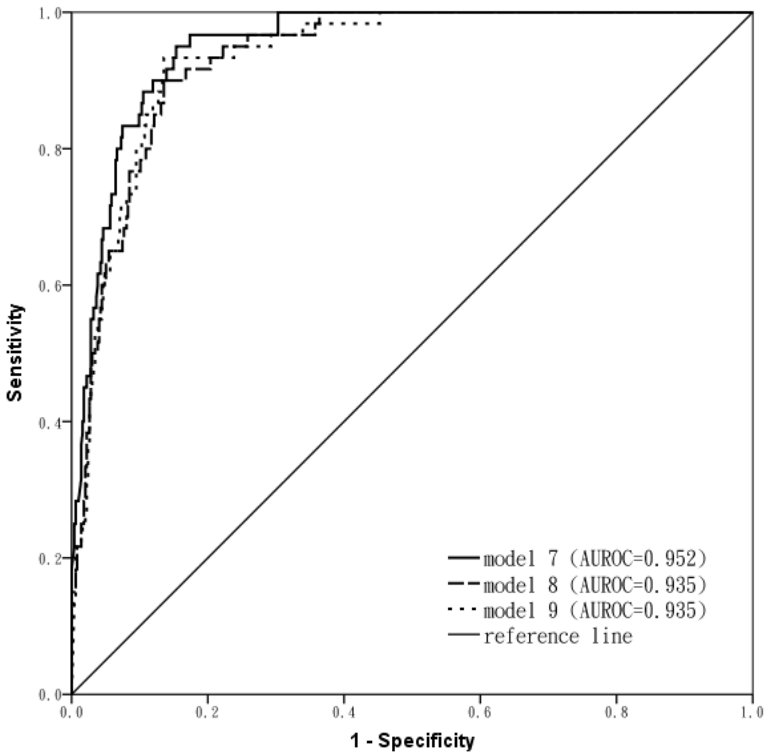
Model 1 to 6 Test Set



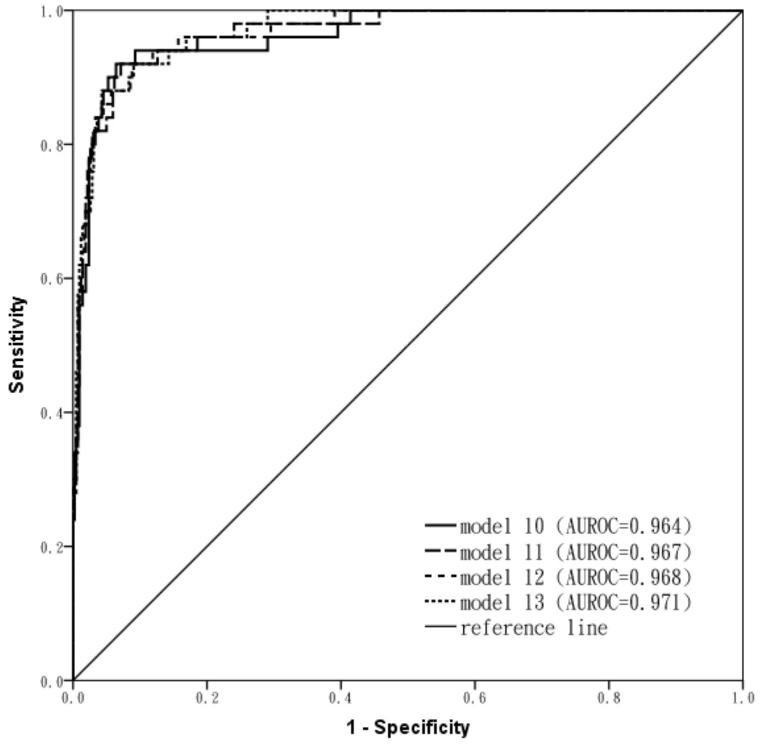
Model 7 to 9 Training Set



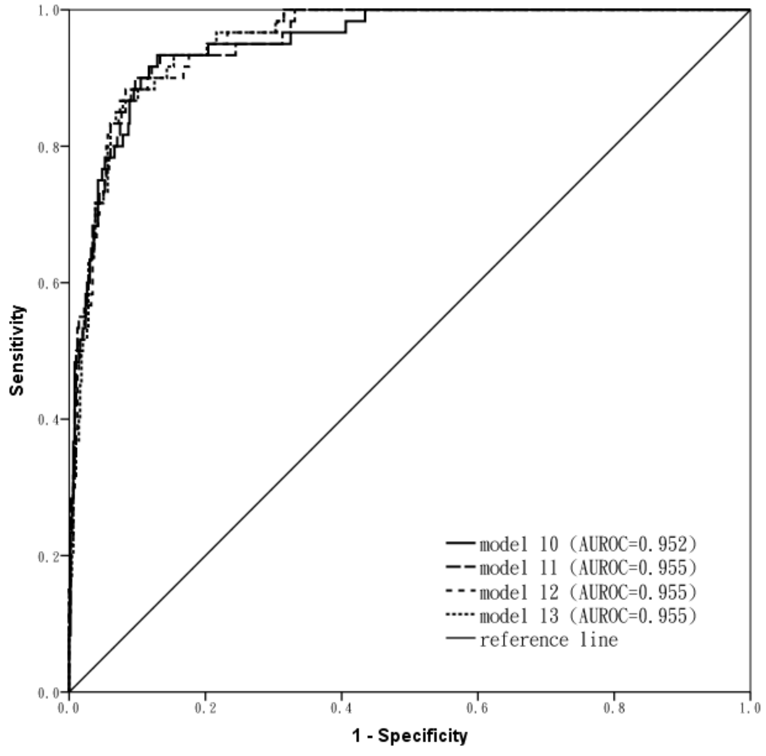
Model 7 to 9 Test Set



Model 10 to 13 Training Set



Model 10 to 13 Test Set



4.6 Conclusion

Data Envelopment Analysis is a useful method to measure relative corporate efficiency and corporate efficiency is found to be helpful in credit scoring in previous literature and in this research as well. Rather than assuming Constant Returns to Scale, this research adopts a more realistic assumption, Variable Returns to Scale. It allows the model to decompose overall technical efficiency into Pure Technical Efficiency and Scale Efficiency which actually provides more information for analysis. Practically, these measures indicate that an inefficient company should improve its efficiency of use of inputs or adjust its operating scale to the optimum level to achieve better performance. The results show that not only are those less technically efficient firms at greater risk of becoming financially distressed than more technically efficient firms but that improvements in both pure technical and Scale Efficiency would reduce the risk. Of these two what really matters is how relatively scale efficient, rather than how pure technically efficient, firms are. This indicates that a firm which wants to perform better, in practice, should pay more attention to optimising its scale of business rather than optimising resources or applying new technology. Increasing scale of operation is likely to have a great effect on reducing risk of distress than moving on an efficiency frontier.

These results are consistent with those of Psillaki *et al* (2010) who found that technical efficiency was significantly negatively related to the probability of business failure for a sample of French firms in each of three industries. But because no study that models financial distress has decomposed technical efficiency no further comparison can be made.

However, in the prediction of financial distress, decomposition of efficiency variables is of little help for predictive accuracy. A simpler model using Technical Efficiency only to assist financial ratios in logistic regression is just as effective as including Pure Technical Efficiency and Scale Efficiency as separate variables as found in the out-of-time validation. We also found that the inclusion of RTS levels had no detectable effect on the predictive accuracy of the model.

In terms of using efficiency as the only predictor, these results show that a group of financial ratios does outperform efficiency scores as they can cover many aspects of business, while a DEA score is only based on a limited number on inputs and outputs. That is also the reason why financial ratios have dominated corporate credit models for decades. However, to gain greatest predictive accuracy, financial ratios and efficiency variables should both be included. This is consistent with the findings of Yeh *et al* (2010) and Xu and Wang (2009).

Nevertheless, although predictive accuracy is the main concern in credit risk management, there is also the necessity to understand risk drivers that may give early indications of potential problems. In this respect decomposed efficiency measures, in particular Scale Efficiency, can provide useful information to a credit analyst interested in relative performance of companies in a credit portfolio.

This research has also introduced a modified logistic regression model, particularly for DEA variables. This is the first application of DEA in credit scoring to use the dummy variables for different industries to overcome the dilemma that a large sample size and homogeneity of DMUs cannot be achieved at the same time. Industry specification slightly improves prediction accuracy and remarkably increases discriminative power. More importantly, the proposed logistic regression properly handles the assumption of DEA methodology which should be kept all the time when applying it. Such methodology allows employing a large dataset with a mixture of industries, but it needs to be noted that as more industries are included, more dummy variables are required, and the number of companies in each category should still be sufficiently large.

Finally, it has to be mentioned that the data analysed in this chapter covers two time periods. It would be beneficial if more years of data are found to be supportive with the above conclusion in the cross sectional analysis. Moreover, recent developments of DEA actually can give estimation of time serial efficiency scores which allow panel analysis across a period of time. Then as an extension of these cross-sectional models developed in this chapter, the next chapter will build panel regression models to incorporate both dynamic DEA scores and financial ratios on a large panel dataset of over 10,000 company years.

Chapter Five
Panel Modelling on Corporate Efficiency Measures

5.1 Introduction

The preceding chapter carried out a cross-sectional analysis including efficiency measures to predict financial distress. Cross-sectional models are estimated for single periods and make forecasts for single periods as well. In practice, cross-sectional models are trained using information from the past and applied to data of the present to make predictions into the future. This would necessarily assume that the influences of variables and parameters of the model remain unchanged from time to time. Because of this assumption of stability of the underlying relationships and parameters, Shumway (2001) preferred to call them 'static' models. Alternatively Altman and Eisenbeis (1978) argued that cross-sectional models are only valid for the sample period and so can only make within time out-of-sample predictions. The inference for a subsequent period (out-of-time prediction) is that it may not be valid. For example, Dombolena and Khoury (1980) investigated the stability of financial ratios in predicting business failures and found inconsistency in their performance over time. Shumway (2001) even claimed that half of financial ratios that were found to be successful in the predictive models of Altman (1968) and Zmijewski (1984) turned out to be unrelated to bankruptcy probability in later periods. Grice and Dugan (2001) also found that Zmijewski's ratios had worse predictive power when transferred to another period. Nevertheless, in practice, Altman and Eisenbeis (1978) indicated that the bias decreases with the increase of the sample size. They agreed that inferences should be made based on the expected error rates, the predictive content and the role of individual variables.

'Dynamic' models, in contrast to 'static' models, are preferred because of the nature of business failure (Shumway, 2001). Bankruptcy or corporate default takes a longer time to observe and it is rarer in term of incidence compared to consumer credit default, which is commonly defined as payment three months late. The internal and external conditions of companies change over time. Static models can only forecast the probability of default at a given time (usually during the year before failure) but ignore the fact that at this given time, some ‘healthy’ companies will eventually fail. To overcome some of these problems, hazard models such as proposed by Shumway (2001) have become popular in the field of credit risk prediction. This chapter, and also the next chapter, on corporate governance measures, will use panel datasets and follow Shumway’s (2001) simple hazard model to present more robust results.

This chapter will continue assessing corporate efficiency measures. Literature on both dynamic models of corporate credit risk modelling and DEA is discussed. The algorithms of the discrete hazard model and Malmquist DEA are presented in the methodology section. A sample of 742 companies over 10 years, in total 5,490 company years, is employed in the analysis. Results and discussions follow.

The proposed models combining both dynamic DEA and survival analysis are the first to incorporate corporate efficiency in financial distress prediction. The DEA models assuming VRS and homogeneity in samples calculate various efficiency measures according to different options.

5.2 Literature review

5.2.1 Advantages of hazard models

There are mainly three advantages of hazard models as described by Shumway (2001). Firstly, hazard models can adjust for periods at risk automatically using a function of time of being financially healthy. That time, sometimes referring to the age of a company, is called survival time or duration time. A company, just like a human being or other creature, has its own life cycle where at each stage of life, there are different natural risks of death. A hazard model can capture that risk by incorporating duration dependence.

Secondly, hazard models can also naturally incorporate Time-Varying Covariates (TVCs) which are defined as explanatory variables changing over time. The financial ratios and certain other predictive variables in static models, are typically TVCs.

Macroeconomic variables are another group of TVCs which have been found to be associated with business failure (*e.g.* Wilson and Altanlar, 2014). The Basel II Accord from the Bank of International Settlements (BIS) has addressed the influence of the macroeconomy on financial risks since 2004. Major macroeconomic indicators are reported regularly (quarterly or annually), and discrete hazard models (DHM) can handle them well. Furthermore, other firm-specific variables, such as corporate governance variables (discussed in detail in Chapter Six) are TVCs as well. For example, the CEO could be sacked for bad company performance and replaced by a more capable one. Also shareholding of investors are often variable from year to year. Hazard models are capable in dealing with TVCs.

Thirdly, hazard models can make better predictions because they take advantage of utilising more data. Typically, cross-sectional models (except multi-periods models) can only employ single period data such as the information for year 2001 in the training sample in Chapter Four. But by observing data over a period of time, for instance, ten years in this chapter, the training sample is much larger than that in cross-sectional models. Estimates of parameters are then more robust over time as predictions.

Apart from the above, additionally, hazard models take into account censoring (a failure event occurs but is not observed in the observation time window) (Cleves *et al*, 2008). Details of this are discussed in Section 5.3.4. Hazard models allow one to make a prediction in different time periods not just the predefined observation window time interval (Lane *et al*, 1986).

However, hazard models are not the only models that researchers have tried in credit risk modelling. The next section will review various efforts that have been made in modelling corporate credit risk dynamically by taking the effect of time into account.

5.2.2 Dynamic models in corporate credit

In the early days, researchers proposed many methods to capture the time effect or the time to default. Peel and Peel (1988) and Keasey *et al* (1990) employed multinomial logistic regression to discriminate between healthy and failed companies. They simply stacked lagged independent variables with the dependent variable of different classes to indicate the number of years to default. Compared to binary LR, the multinomial logit is suitable when alternative choices are offered, and these choices should be independent of irrelevant alternatives (IIA). Their choices of the dependent variable, marked as 1, 2 and 3 years to default are obviously not irrelevant. Laitinen (1993) defined the typical process of failure into starting, intervening and final phases. His model can possibly identify the phase in which a firm is, and the trend of ratios measured by a naive estimation is used to capture the change over time. Besides, both survival statuses (failed or non-failed) and survival time are used as the dependent variables in two separate models. Sometimes, the trend and stability of ratios are measured and added to the model (Dombolena and Khoury, 1980; Betts and Belhoul, 1987).

Multi-period LR may be more suitable than multinomial LR in handling panel data. In multi-period LR, the dependent variable is usually defined as $\Pr(y_{it}=1)$ where y_{it} is a binary outcome whether the event of interest is observed for company i at time t. The probability is conditional on a function of covariates which are explanatory variables x_{it} in making predictions. A number of examples exist in studies such as Charitou *et al* (2004) and Campbell *et al* (2008). This kind of dataset was regarded as time-series-cross-sectional data with a binary dependent variable (BTSCS data) by Beck *et al* (1998). When it is modelled by ordinary logit and probit regression, problems arise as the temporal dependence of the dependent variable violates the assumption of independent observations. Researchers tend to ignore this flaw as the estimate of the parameters was simple (Beck *et al*, 1998).

Whilst static models imply a consistent hazard rate over time, survival models do not and so are more appropriate in modelling. The Cox (1972) proportional hazard model is a classic survival model which assumes that a default can happen any time during the interval $[T, T+t)$ where T is the time of default. Therefore the Cox proportional model is a continuous time hazard model. Applications of it were used by Bonfim (2009) to Portuguese data of 113,119 observations over the period from 1996 to 2002, and Pederzoli and Torricelli (2005) to US data over the period from 1971 to 2002. The former study tried five distributions of the baseline hazard: exponential, Weibull, Gompertz, lognormal and log-logistic distributions. More complicated, Duffie *et al* (2007) applied it to 390,000 firm-months data from 1980 to 2004 with respect to variables of Merton's DD and Markov stochastic covariates. They found the conditional probability of default depends on the stock return, distance to default, S&P 500 returns and US interest rates. Much earlier work could be found in bank default prediction from Lane *et al* (1986).

Sometimes when covariates are only observed at given points of time, it is more convenient to use Shumway's (2001) simple hazard model which is a discrete time survival model. For example, abundant financial and accounting information is disclosed in annual reports and popular TVCs, such as macroeconomic indicators are also calculated by the Office of National Statistics on a regular basis, where the yearly data receives much attention and is of great importance. Therefore, in credit risk models, the default event is usually defined in a specific period of time, commonly one year (Carling *et al*, 2007). As recommended by Beck *et al* (1998), binary time series cross sectional (BTSCS) data could be used in hazard models because they allow corrections for censoring, heterogeneity and duration dependence (Bennett, 1997). BTSCS data should be grouped to duration data because the continuous process of the event of interest can only be observed at discrete intervals. Shumway (2001) stated that a DHM is equivalent to a multi-period logistic model in terms of computation but with an additional term $h_0(t)$ which is the baseline hazard function. This function, as Shumway (2001) comments, could be of any form regarding the duration time, though he used the time since listing. His simple hazard model, by incorporating market driven variables, market size, stock returns and volatility of returns, outperforms Altman's (1968) and Zmijewski's (1984) selections of ratios in predicting bankruptcy.

Shumway's (2001) model has been followed by many studies on corporate credit risk such as Carling *et al* (2007), Nam *et al* (2008), De Leonardis and Rocci (2013) and Wilson and Altanlar (2014). One of their common features is that they all take macroeconomic variables into the model and find they indeed bring influences on the probabilities of business failure. More specifically, Nam *et al* (2008) implied that the baseline hazard to be two macroeconomic variables: volatility of foreign exchange rate and change in interest rates. This is similar to De Leonardis and Rocci (2013), but they employed separate analysis for the two dimensions of the default risk: whether the default happens and when given that it can happen. They call this a cure rate model. Basically they split the population into healthy ones modelled by a binary logit regression and unhealthy ones modelled by the discrete time hazard model. They conclude their cure model is better than traditional survival analysis at predicting defaults. However, their validation procedure was not an out-of-sample test but a subsample test. So the real predictive power is in question. Besides accounting and macroeconomic data, Carling *et al* (2007) also employed credit bureau opinions and the type of loan specific and payment behaviour variables. Wilson and Altanlar (2014) particularly focused on new incorporated companies where accounting data is not available before their first disclosure. They set the baseline hazard to be related to the macro-economy. Furthermore their macroeconomic data is regionally based on postcode in the UK as new start-up SMEs are more locally operated. The regional economic conditions and information of the board served the model well.

Rather than focusing on variables, some other dynamic models paid attention to the change of concept drift, which is changes in the hidden context (Schlimmer and Granger, 1986). Sun and Li (2011, pp. 2567) defined the financial distress concept drift as 'the change in distribution of training data which dynamically increases with continuous emergence of new enterprises in financial distress'. They illustrated the financial distress of start-up and grown-up companies under different situations. The virtual concept drift of financial distress could be modelled by instance selection, a method of model rebuilding, and instance would be collected in batches at time intervals. Their window analysis indicated the concept change indeed existed and they concluded a fixed window (a fixed lag of time) was more suitable for dynamic prediction models.

Credit ratings for corporations given by credit rating agencies, such as the internationally renowned Standard and Poor's (S&P) and Moody's, are frequently used in dynamic models, since those ratings are recorded in a transition matrix for individual companies and inherently suitable for dynamic analysis. Among many studies on dynamics in ratings, the ordered probit model from Tsoukas and Mizon (2012) is a recent one which aims to capture momentum (previous upgrades and downgrades), drift (change of the proportions of upgrades and downgrades) and ageing (number of periods in previous state) effects. These effects are all related to time. They found the initial and previous states could help a model predict the credit rating. Other dynamic studies about credit ratings can be found in Bangia *et al* (2002) and Frydman and Schuermann (2008).

Discrete time survival analysis exists not only as parametric models but also as non-parametric ones, such as the survival trees and forests proposed by Bou-Hamad *et al* (2009). It was further extended to a survival tree method to incorporate TVCs in bankruptcy prediction (Bou-Hamad *et al*, 2011). Many trees could be assembled into a survival forest to give a better performance. They concluded the performance of their random survival forest model was stable in predictive accuracy across periods. However, typically, as a machine learning technique, it involved a complicated selection process on covariate transformation and interactions. So it brought difficulties in its application.

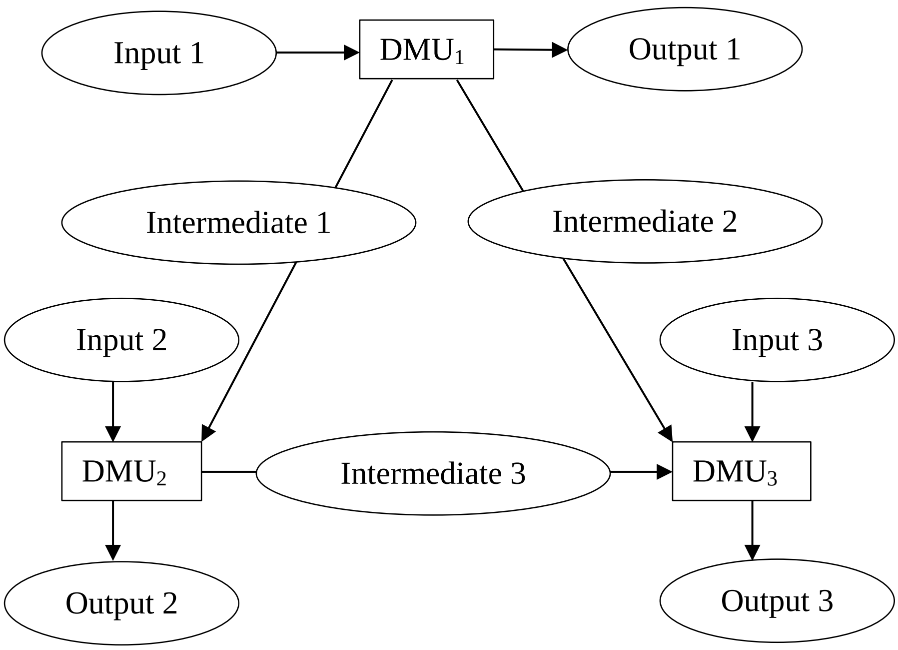
5.2.3 Dynamic models in DEA

In the domain of Data Envelopment Analysis, there are several variations of the basic DEA models CCR (Charnes *et al*, 1978), BBC (Banker *et al*, 1984), the additive model (Charnes *et al*, 1985) and SBM (Slacks-Based-Measures) models (Tone, 2001). Apart from some models which measure different distances to the frontier, control on inputs and outputs, apply cost/price on variables, and a series of multiplier models with various purposes, there are other several types of DEA models which investigate multilevel or multiperiod relative efficiency. This section will review such dynamic DEA models.

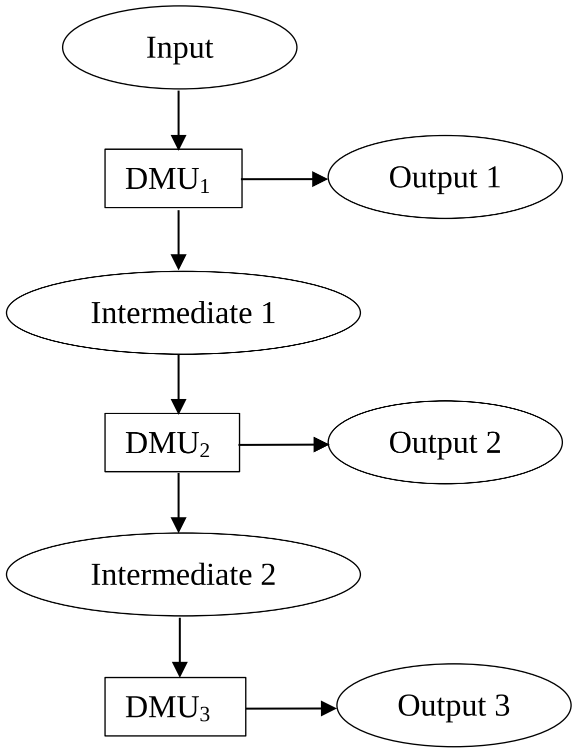
Network DEA deals with a system of many sub divisions which are linked together by intermediate inputs/outputs (Tone and Tsutsui, 2009). Each DMU may or may not have its own inputs and outputs which could be called direct inputs/outputs, but there must be intermediate inputs/outputs to link DMUs together. Network DEA provides a framework for systematically analysing a large organisation with a certain structure. Examples of Network DEA models are illustrated in Figure 5.2.1. Empirical analysis can be found in studies by Liu and Lu (2010) and Kao and Hwang (2010) which studied the performance of R&D and IT departments respectively.

Figure 5.2.1 Examples of Network DEA

Panel A



Panel B



The second example of multi levels in Figure 5.2.1 can actually be seen as a multi-period dynamic DEA model, where DMU_1, DMU_2, DMU_3 are the same DMU_i in period 1, 2, and 3. In the case of companies, the input could be the initial investment and the intermediates are retained earnings and net income in one year which could be left for expenditure in the next year and so on. An example by Lu *et al* (2014) measured the intellectual capital and performance in Chinese insurance companies.

Whilst conventional DEA models (referring to static DEA) are conducted in single periods, many researchers and practitioners are interested in the variation of data. Specifically, if a DMU can be observed at different points in time, its change in efficiency over the period is rather informative for analysis of both productivity and the purpose of this research - financial distress. One method could be that static DEA analysis is carried out in each period and in the second stage a standard regression used to estimate the change over time and extend it to further periods. Emel *et al* (2003) and Min and Lee (2008) used this two-stage method to forecast DEA scores and hence bankruptcy. However, Cook and Seiford (2009) commented that this approach was unsatisfactory because it failed to capture the interaction of one period with another. Window DEA was introduced by Charnes *et al* (1985) to deal with the efficiency change in the sense of time series. The idea of Window DEA, which is similar to other window analyses, is to set up a fixed observation period of k for each DMU and evaluate these $n \times k$ observations at the same time, so k different scores (time period 1 to k) for each DMU are obtained. The analysis then moves to period 2 to $k+1$ and so on. When $k=1$, we have a typical annual panel dataset. Pulina *et al* (2010) applied window DEA to investigate the relationship between size and efficiency in Italian hospitals, but Cooper *et al* (2006) argued that its shortcoming is in the beginning and last period when cases are less evaluated.

In dealing with panel data, the Malmquist DEA model may be the most capable one. Malmquist Index (MI) was initially suggested by the Swedish economist and statistician Professor Sten Malmquist in 1953. The idea of the MI is to compare the production technology of two economies so it is a bilateral index. If F_a is the production function of Economy A, conditional on x_a which could be labour and capital inputs, then $F_a = f_a(x_a)$. To calculate the MI of Economy A with respect to Economy B, we can substitute x_a in the production function $f_b(\cdot)$ and vice versa. So the MI is defined as

$$MI = \sqrt{\frac{f_b(x_a)}{f_b(x_b)} \bullet \frac{f_a(x_a)}{f_a(x_b)}} = \sqrt{[f_a(x_a) f_b(x_a)]/[f_a(x_b) f_b(x_b)]}$$

Inspired by Caves *et al* (1982), in two papers, Fare *et al* (1992) and Fare *et al* (1994) introduced MI into DEA and developed a DEA-based Malmquist productivity index which could make use of panel data from across 42 Swedish pharmacies over the period 1980-1989, and 17 OECD countries over the period 1979-1988. The Malmquist productivity index evaluates the total factor productivity change of a DMU between two periods. It is defined as the product of efficiency change (catch-up) and technological change (frontier-shift) where the catch-up effect described how much closer a DMU gets to the frontier and the frontier-shift effect describes the technology improvement in the sample. That is equivalent of saying that if a company's relative efficiency increases in period $t+1$ from period t, how much improvement is credited to its individual effort and how much attributed to innovation within the industry. The efficiency change reflects to what extent a DMU improves or worsens its efficiency, while technological change reflects the change of the efficiency frontiers between two periods. Since the introduction of MI by Fare *et al* (1992) and Fare *et al* (1994), there have been various applications and studies on the productivity change over time in various fields, for example: US hospitals (Burgess and Wilson, 1996), US large banks (Luo, 2003), Taiwanese hotels (Hwang and Chang, 2003), computer industry (Chen and Ali, 2004), Australian universities (Worthington and Lee, 2008), etc.. They looked into the efficiency changes over time for managerial implications and strategic recommendations.

Despite the wide applications of Malmquist DEA models in analysis of performance and change, and the fact that some scholars (*e.g.* Paradi *et al*, 2004; Cielen *et al,* 2004; Psillaki *et al*, 2010 etc.) have used DEA efficiency to detect business failure, it is surprising to see that none have tried to link them together and conduct panel analysis in predicting financial distress, because dynamic credit risk models are found to be superior to static models. It has to be stated that solving DEA problems period by period separately, and building a panel dataset when DMUs are observed at several points of time is not real panel analysis (*e.g.* Bryan *et al*, 2013) and methodologically the scores in different periods are not comparable because DEA scores are calculated based on the frontier formed by the peers in that period. That is, a relative efficiency of 0.5 in the second period may be no better than a relative efficiency of 0.3 in the first period, but it depends on the change within the industry. This research is the first to apply Malmquist DEA scores in dynamically predicting financial distress by taking time into account. The methodological calculation is introduced in detail in Section 5.3.

Other methodologies have been used to predict bankruptcy by using productive efficiency in multiple periods. Stochastic Frontier Analysis (SFA) introduced by Kumbhakar and Lovell (2000) is a regression approach to approximate efficiency scores by using inputs as given variables and one output, but essentially SFA is not a DEA model but an alternative parametric method to calculate ‘efficiency’ other than the relative efficiency. In addition, it can only include one output variable in the equation. Nevertheless, Becchetti and Sierra (2003) tried to employ SFA efficiency in predicting bankruptcy, but unfortunately, in their parametric equation of the production function, it is the other way round. The efficiency is the dependent variable and the 'active' or 'failed' dummy and the company size were two of their independent variables. They further used this 'efficiency' calculated by the dummy and the company size, in logit regression with the company size again and other variables to predict bankruptcy. There might be serious issues in their methodology. It is only acceptable if interpreting the inefficiency by the probability of default from one side as in Hwang *et al* (2011). The study of Hwang *et al* (2011) may still suffer criticism whether bankruptcy or not is a endogenous variable of inefficiency.

Another inappropriate empirical study into bankruptcy risk and productivity came from Bryan *et al* (2013). They claimed to follow the argument of Banker and Natarajan (2008) for the two-stage model (DEA and regression) to forecast DEA scores to yield consistent estimators of regression coefficients. However what they did was different because they used multi-period productivity scores to predict Altman's Z-score. It is still worth mentioning that their effort to include the firm's business strategy as an explanatory variable is a kind of innovation.

5.2.4 Industrial effect

As discussed in the last chapter, since homogeneity of DMUs to be evaluated is important in both stages of running DEA models and regression analysis, handling industry classification becomes an important issue in its success of modelling. This requirement, as Li *et al* (2014) commented, may increase the complexity of modelling, but in fact it coordinates with the findings from corporate credit risk modelling: the industrial effect.

The differences between industries in credit risk models have received academic attention for a long time. In the early days, this was addressed by matching failed and non-failed firms in the same industry and of similar size (*e.g.* Altman, 1968; Wilcox, 1973). Platt and Platt (1990) and Izan (1984) integrated the industrial effect into financial ratios by adjusting them by the average value within an industry because Lev (1969) found that the industry average value of a financial ratio is the optimal level for all companies in that industry. Later, by comparing Zmijewski (1984) and Ohlson (1980) models over two different periods: 1988-1991 and 1992-1999, Grice and Dungan (2001) suggested the predictive accuracy of a model would decline if one failed to apply it to the same industry for which the model is built. Bonfim (2009) used dummies as control for 11 industries as firm-specific characteristics. Alternatively, Glennon and Nigro (2005) integrated the industrial effect into macroeconomic conditions and calculated the deviations of income of the state and industry in the discrete hazard model. Chava and Jarrow (2004) included the industrial effect by the products of ratios and sector dummies as variables in regression.

Our models which treat industries separately align with these studies that have found that the industrial effect cannot be neglected.

5.3 Methodology

The preference of DEA model choices of input or output orientation, distance functions to the frontier and RTS, remains the same as in the cross-sectional models in the last chapter. The basic model used is input-oriented, slacks-based measures (SBM) with VRS assumed. The justification for them is discussed in Chapter Four, so it is not repeated here. Additionally for the indicator of level of RTS, since no significant relationship to financial distress was found in the cross-sectional analysis, is not investigated further. For other issues, such as dealing with negative values, selection of inputs and outputs, the arguments remain the same, hence the discussion about them in the last chapter still stands. The methodology of this part begins with an introduction to Malmquist DEA models.

5.3.1 Malmquist DEA

In order to build a panel dataset, the first step is to calculate the efficiency scores for each company in each year of observation. Malmquist DEA can actually handle multiple inputs and outputs when DMUs are repeatedly observed on a certain interval basis and can calculate period to period efficiency change.

Caves *et al* (1982) defined a distance function $D(\cdot)$ based on the Malmquist productivity index (Malmquist, 1953) to calculate the technical efficiency in the basic CCR model (Charnes *et al*, 1978). If company k is efficient, $D^k(x^k, y^k) = 1$. When x_{i0}^t is the i th input and y_{r0}^t is the r th output for DMU_0 both at period t, its relative efficiency ($D_0^t(x_0^t, y_0^t) = \theta_0^*$) is calculated by the amount of input that can be reduced while producing the given output level compared to the most efficient company on the frontier. Similarly, $D_0^{t+1}(x_0^{t+1}, y_0^{t+1})$ is its efficiency score at period $t+1$. So, in the situation of multiple periods, $D_0^t(x_0^{t+1}, y_0^{t+1})$ and $D_0^{t+1}(x_0^t, y_0^t)$ are actually efficiency scores using a set of inputs/outputs in one period compared with the frontier of the other period.

Then, following the ideas of Farrell (1957) to decompose the total factor productivity into efficiency change (EC) and technology change (TC), Fare *et al* (1992) defined the input-oriented Malmquist productivity index (MI) to measure the productivity change of DMU_0 in period t to $t+1$ as:

$$\begin{aligned} MI_0 &= \left[\frac{D_0^t(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)} \cdot \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^t, y_0^t)}\right]^{1/2} \\ &= \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)}\left[\frac{D_0^t(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})} \cdot \frac{D_0^t(x_0^t, y_0^t)}{D_0^{t+1}(x_0^t, y_0^t)}\right]^{1/2} \end{aligned} \quad (5.1)$$

The first part is the relative change of efficiency from period t to $t+1$. Hence they defined

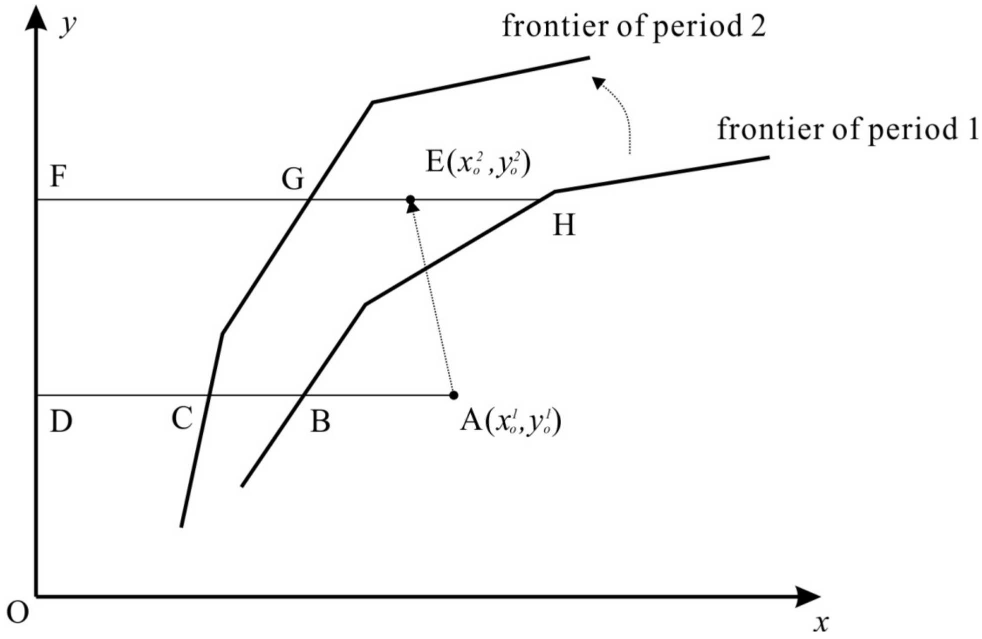
$$\mathrm{EC} = \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)} \quad (5.2)$$

and

$$\mathrm{TC} = \left[\frac{D_0^t(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})} \cdot \frac{D_0^t(x_0^t, y_0^t)}{D_0^{t+1}(x_0^t, y_0^t)}\right]^{1/2} \tag{5.3}$$

We can illustrate these concepts in a simple example with only one input and one output in Figure 5.3.1.

Figure 5.3.1 Malmquist Index in a simple example



Suppose the DMU to be evaluated is point A(x_0^1, y_0^1) at period 1 and it moves to point E(x_0^2, y_0^2) at period 2 and in the meanwhile the efficient frontier moves from 1 to 2. The efficiency change (or catch up) can be computed as

$$\text{catch-up} = \frac{FG}{FE} \Big/ \frac{DB}{DA}$$

If catch-up > 1, this indicates a progress in relative efficiency. Catch-up = 1 and catch-up < 1 indicate no change or regress in efficiency respectively.

In order to calculate the technology change (frontier-shift), the reference point for point A at period 1 moves from B to C and the frontier-shift effect for (x_0^1, y_0^1) is

$$\text{frontier-shift}_1 = \frac{DB}{DC} = \frac{DB / DA}{DC / DA}$$

$\frac{DB}{DA}$ is the relative efficiency of (x_0^1, y_0^1) to the frontier of period 1 and $\frac{DC}{DA}$ is the relative efficiency of (x_0^1, y_0^1) to the frontier of period 2.

Similarly, the frontier-shift effect for (x_0^2, y_0^2) is

$$\text{frontier-shift}_2 = \frac{FH}{FG} = \frac{FH / FE}{FG / FE}$$

Where $\frac{FH}{FE}$ is the relative efficiency of (x_0^2, y_0^2) to the frontier of period 1 and $\frac{FG}{FE}$ is the relative efficiency of (x_0^2, y_0^2) to the frontier of period 2.

Then the frontier shift is the geometric mean of the two:

$$\text{frontier-shift} = \sqrt{\text{frontier-shift}_1 \times \text{frontier-shift}_2}$$

If frontier-shift > 1, this indicates a progress in technology and frontier-shift = 1 and catch-up < 1 indicates no change or regress in technology. Fare *et al* (1992; 1994) commented that the frontier shift is measured locally but not overall. So sometimes recession in efficiency happens.

Other than using a distance function $D(\cdot)$ to calculate the efficiency, under the nonparametric framework, Fare *et al* (1994) calculated the MI by an oriented radial DEA model. Also, Cooper *et al* (2006) comment, other DEA models are also suitable to calculate MI.

Let $x_{ij}^t (i = 1, \ldots, m)$ and $y_{rj}^t (r = 1, \ldots, q)$ denote the inputs and outputs for DMU$_j$ ($j = 1, \ldots, n$) respectively at any given point of time t. The production possibility set is defined by

$$(X^t, Y^t) = \left\{ (\boldsymbol{x}, \boldsymbol{y}) \middle| \boldsymbol{x} \geq \sum_j^n \lambda_j \boldsymbol{x}_j^t, 0 \leq \boldsymbol{y} \leq \sum_j^n \lambda_j \boldsymbol{y}_j^t, L \leq \mathbf{e}\boldsymbol{\lambda} \leq U, \boldsymbol{\lambda} \geq 0 \right\}$$

where $\mathbf{e}$ is the row vector with all elements equal to one, $\boldsymbol{\lambda} \in R^m$ is the intensity vector and L and U are the lower and upper bounds for the sum of the intensity. For

BCC (VRS) model, $(L,U)=(1,1)$. Here we follow Tone (2001) and let $\theta_0^t(x_0^t, y_0^t)$ to be the optimal solution of equation (5.4)

$$
\begin{aligned}
\theta_0^t(x_0^t, y_0^t) = \min \quad & 1\text{-}\frac{1}{\mathrm{m}}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}^t} \\
s.t. \qquad & \mathbf{x}_0^t - X^t\boldsymbol{\lambda} - \mathbf{s}^- = \mathbf{0} \\
& \mathbf{y}_0^t \le Y^t\boldsymbol{\lambda} \\
& L \le \mathbf{e}\boldsymbol{\lambda} \le U \\
& \boldsymbol{\lambda} \ge \mathbf{0}, \mathbf{s}^- \ge \mathbf{0}
\end{aligned}
\tag{5.4}
$$

Where $\mathbf{s}^-$ is a vector of slacks and $\boldsymbol{\lambda}$ is a non-negative vector and $\sum_{j=1}^{n}\lambda_j = 1$.

And the reciprocal efficiency $\theta_0^t(x_0^{t+1}, y_0^{t+1})$ is the optimal solution of equation (5.5).

$$
\begin{aligned}
\theta_0^t(x_0^{t+1}, y_0^{t+1}) = \min \quad & 1\text{-}\frac{1}{\mathrm{m}}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}^t} \\
s.t. \qquad & \mathbf{x}_0^{t+1} - X^t\boldsymbol{\lambda} - \mathbf{s}^- = \mathbf{0} \\
& \mathbf{y}_0^{t+1} \le Y^t\boldsymbol{\lambda} \\
& L \le \mathbf{e}\boldsymbol{\lambda} \le U \\
& \boldsymbol{\lambda} \ge \mathbf{0}, \mathbf{s}^- \ge \mathbf{0}
\end{aligned}
\tag{5.5}
$$

By solving the linear program four times for $\theta_0^t(x_0^t, y_0^t)$, $\theta_0^{t+1}(x_0^{t+1}, y_0^{t+1})$, $\theta_0^t(x_0^{t+1}, y_0^{t+1})$, $\theta_0^{t+1}(x_0^t, y_0^t)$, we can calculate $M_0^{t \text{ to } t+1}$.

$$
M_0^{t \text{ to } t+1} = \sqrt{\frac{\theta_0^t(x_0^{t+1}, y_0^{t+1})}{\theta_0^t(x_0^t, y_0^t)} \bullet \frac{\theta_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{\theta_0^{t+1}(x_0^t, y_0^t)}} \tag{5.6}
$$

Actually, Cooper *et al* (2006) referred to the two intertemporal scores, $\theta_0^t(x_0^{t+1}, y_0^{t+1})$ and $\theta_0^{t+1}(x_0^t, y_0^t)$ as the exclusive schemes. In the exclusive scheme, (x_0^{t+1}, y_0^{t+1}) (point E in Figure 5.3.1) is removed from the evaluator group (X^t, Y^t) so its score may be greater than 1. It is understandable that for an efficiency unit at period t, if both of its efficiency and technology improve in the following periods, its relative efficiency should be larger than 1.

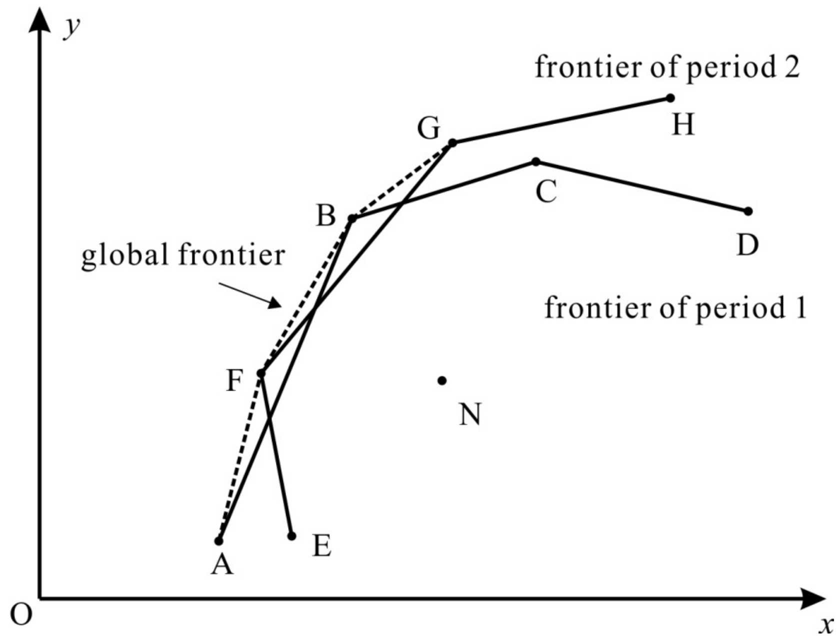
Unlike other studies (*e.g.* Burgess and Wilson, 1996; Luo, 2003) which employed Malmquist DEA models to study efficiency change, technology change or Malmquist change, we are only interested in the relative efficiency calculated for each period. By multiplying $\theta_0^t(x_0^t, y_0^t)$ by $M_0^{t \text{ to } t+1}$ we can get the relative efficiency at period $t+1$ compared to period t.

There is a concept of reference set in the definition above. More specifically, we define the model by comparing two continuing periods t and $t+1$, which can be called adjacent periods. This is the original design in Fare *et al* (1992). Suppose there are five periods $t = 1, \dots, 5$, by running Malmquist DEA with adjacent references, we can only get relative efficiency θ^1, θ^2 compared to period 1, θ^3 compared to period 2 and so on. It is not intuitive for θ^{3*} to be compared to period 1 or θ^{4*} compared to period 2. Then we are unable to interpret the relative efficiency directly with adjacent moving references. A solution is to use a fixed reference set as suggested by Berg *et al* (1992). Therefore, in this research, all relative efficiency is referred to the first period as the beginning of the observation. Thus it is not period $t+1$ compared to period t but period t ($t \geq 2$) compared to period 1. In this way, it is very likely that in later periods, efficiency scores are larger than 1 as economy and technology develops. We may note that apart from the scores at period 1, all other scores larger than 1 do not necessarily imply being efficient in that period. Conversely, we can also appoint the last period as the referent set and all others compared to it may get more ‘regular’ efficiency scores less than 1 (assuming technology improves). However in the sense of financial distress prediction, in the process of model training, predicting probability of default in the current period by using a relative efficiency score compared to a later period in the panel seems absurd, though it is an *ex post* test. Therefore the appointment of period 1 as the fixed reference set is appropriate.

5.3.2 Global reference

Furthermore, in the choice of reference set, another option could be found in Pastor and Lovell (2005) who introduced the global reference. In some cases where efficient frontiers of different periods cross each other, a global reference set can be chosen by the best practices in all periods. For example, in Figure 5.3.2, there are four DMUs lying on two frontiers ABCD and EFGH. The DMU to be evaluated, point N, could be referred to frontier ABCD, frontier EFGH or the most efficient units ever existing in history: AFBGH. It is acceptable that when the observation window is long enough, all DMUs at the current period are under the cover of the best historical DMUs, possibly including themselves. Thus the relative efficiency in this circumstance could be treated as absolute efficiency. Apparently the scores to the global reference would be less than or equal to 1. In practice, when we build the model, it is the historic data prior to the current moment used in modelling and the historic global reference of the past is available. Therefore the efficiency calculated by the global reference as an option is embedded into the comparative models.

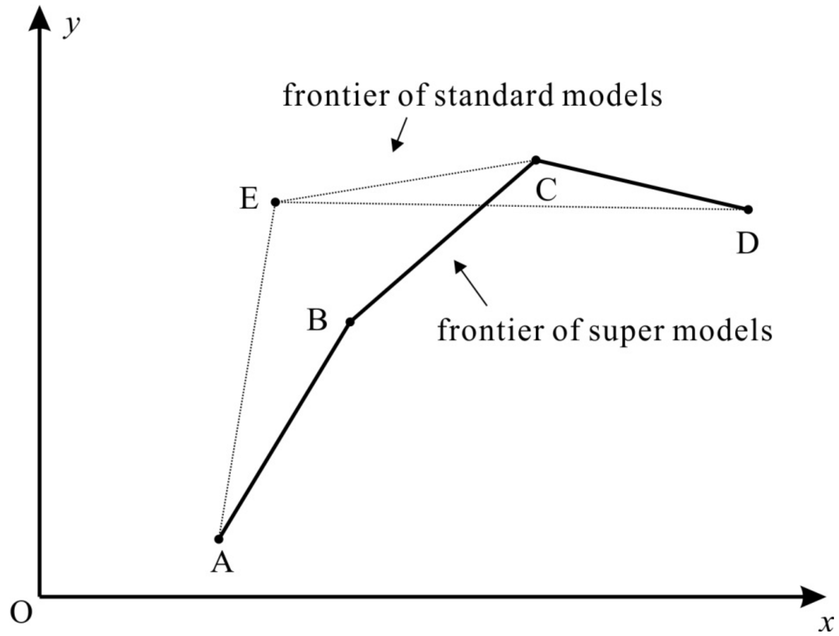
Figure 5.3.2 An example of Global reference



5.3.3 Super efficiency

As Cooper *et al* (2006) explained, the exclusive scheme in solving intertemporal programming treats the DMU to be evaluated to be removed from the evaluator group of the other period. This is mathematically equivalent to what is known as “super efficiency” in DEA. Super efficiency is used as a solution to the fact that common DEA models do not provide a ranking or difference for efficient units as their scores are equal to 1 (Andersen and Petersen, 1993). The difference between a super efficiency model and standard models is that in super models, the DMU to be evaluated is eliminated from the reference set, so its score can be greater than 1. We can illustrate it in Figure 5.3.3. Units A, B, C, D and E consist of the productivity possibility set. If unit E is to be evaluated, its efficiency score is 1 as it is on the frontier AECD of standard DEA models; but in super models, the new frontier ABCD is employed. For another unit C, its new reference frontier is AED. In this way, though unit E and C are both efficient (score = 1) in standard models, we can notice a difference between them by obtaining a new unbound score greater than 1.

Figure 5.3.3 An example of Super efficiency



DEA as a frontier technique is arguably an outlier analysis. But extreme outliers would change the local frontier dramatically enough so other units referring to them may not be correctly measured. In this circumstance, super efficiency can be used to identify outliers (Banker and Chang, 2006). Obviously, super efficiency scores offer more discriminant power in units which is particularly useful in classifying good and bad companies in credit risk models. This can be found that in the model of

Premachandra *et al* (2011) who employed super efficiency scores in predicting corporate failure. The research will follow them and calculate super efficiency in a model for comparison with the main model.

The Malmquist SBM DEA model with super efficiency consideration is described by Tone (2002) where $\xi_i = \frac{s_i^-}{x_{i0}^t}$:

$$
\begin{aligned}
\theta_0^t(x_0^t, y_0^t) = \min_{\xi,\ \lambda} \quad & 1 + \frac{1}{\mathrm{m}} \sum_{i=1}^{m} \xi_i \\
s.t. \qquad & (1+\xi_i) x_{i0}^t = \sum_{i=1}^{n} \lambda_j x_{ij} \quad (i = 1, \ldots, m) \\
& \mathbf{y}_0^t \le Y^t \boldsymbol{\lambda} \\
& L \le \mathbf{e}\boldsymbol{\lambda} \le U \\
& \boldsymbol{\lambda} \ge \mathbf{0}, \boldsymbol{\xi} \ge \mathbf{0}
\end{aligned} \tag{5.7}
$$

5.3.4 Discrete hazard model

Same as in the cross-sectional analysis in Chapter Four, this research uses a two-stage analysis. In the first stage, DEA efficiency scores for each company at each period are calculated by DEA models defined in the previous section. In the second stage, we follow the discrete hazard model introduced by Shumway (2001) and incorporate efficiency scores as covariates in a panel dataset.

In the hazard model (or survival model or duration model) where time is continuous, let T be a non-negative random variable as the time to a failure. Its cumulative distribution function is

$$F(t) = \Pr(T \le t)$$

and the survival function to report the probability of survival beyond time t is defined as

$$S(t) = 1 - F(t) = \Pr(T > t)$$

The survival function is a monotone, non-increasing function of time with a starting value of 1 ($t = 0$) and decreases to 0 when t goes to infinity.

The density function, the rate of failure per unit time, $f(t)$ can be obtained by

$$f(t)=\frac{dF(t)}{dt}=\frac{d}{dt}[1-S(t)]=-S'(t)$$

The hazard function, denoted by $h(t)$ is the event rate at time t conditional on survival until time t or later.

$$h(t)=\lim_{\Delta t\to 0}\frac{\Pr(t\le T<t+\Delta t \mid T\ge t)}{\Delta t}=\frac{f(t)}{S(t)}=-\frac{S'(t)}{S(t)}$$

The hazard rate can range from 0 to ∞ and the cumulative hazard function to measure the total risk that has been accumulated up to time t is

$$H(t)=\int_0^t h(u)du=-\int_0^t \frac{S'(u)}{S(u)}du=-\ln[S(t)]$$

Conveniently, we have

$$\begin{aligned} S(t)&=\exp[-H(t)]\\ F(t)&=1-\exp[-H(t)]\\ f(t)&=h(t)\exp[-H(t)] \end{aligned}$$

For a continuous hazard function, $h(t)$ can follow a popular distribution such as exponential, Weibull or lognormal distribution. And also we can use Cox and Oakes (1984) semi-parametric proportional regression to estimate the parameters $\boldsymbol{\beta}$ by assuming the proportional hazard remains constant.

$$h(t,\boldsymbol{x}(t),\boldsymbol{\beta})=h_0(t)\exp(\boldsymbol{\beta}^T\boldsymbol{x})$$

where $x(t)$ could be both time-variant and time-invariant covariates and $h_0(t)$ is the baseline hazard.

For a discrete time hazard function, we assume failure can only occur in a period of time t. The survival function and hazard function would be a little different (Cox and Oakes, 1984):

$$S(t,x;\beta)=\prod_{j<t_i}[1-h(j,x;\beta)]$$

The likelihood function for the panel of Shumway (2001) is the product of the probability of survival until each period and the hazard in that period.

$$l=\prod_{i=1}^{n}(h(t_i,x_i;\beta)\prod_{j<t_i}[1-h(j,x_i;\beta)])$$

Then the log-likelihood function of it (Allison, 1982) is

$$\log l = \sum_{i=1}^{n} y_{i,t_i} \log\left[\frac{h(t_i, x_{i,t_i};\beta)}{1-h(t_i, x_{i,t_i};\beta)}\right] + \sum_{i=1}^{n}\sum_{j=1}^{t_i}\log[1-h(j, x_{i,j};\beta)]$$

Where $y_{i,t_i} = 1$ if company i suffer financial distress in period t_i, 0 otherwise.

Assuming the hazard function is a logistic function to be consistent with Shumway (2001), we have

$$\Pr(y_{i,t} = 1 | x_{i,t}) = h(t, x_{i,t};\beta) = \frac{1}{1+\exp[-(\alpha+\theta h_0(t)+\beta^T x_{i,t})]} \tag{5.8}$$

where $h_0(t)$ is the function of the duration time, x_{it} is covariates and α is a constant. Then

$$\log l = \sum_{i=1}^{n} y_{i,t_i}[\alpha+\theta h_0(t)+\beta^T x_{i,t_i}] - \sum_{i=1}^{n}\sum_{j=1}^{t_i}\log\{1+\exp[\alpha+\theta h_0(t)+\beta^T x_{i,j}]\}$$

By the maximum likelihood method, parameters $\hat{\alpha},\hat{\theta},\hat{\beta}$ could be estimated. Cox and Oakes (1984) showed that $\hat{\alpha},\hat{\theta},\hat{\beta}$ are consistent for α,θ,β. Shumway (2001) proved a multi-period logit model is equivalent to a discrete time hazard model because the likelihood functions of the two are identical.

Alternatively, equation (5.8) can be written as

$$\text{logit}(h_{ST=1}(t)) = \alpha + \beta_0 h_0(t) + \beta_1 x^e_{i,t-2} + \beta_2 x^r_{i,t-2} \tag{5.9}$$

where the default indicator is ST, when a company suffers financial distress, $ST = 1$; $x^e_{i,t-2}$ and $x^r_{i,t-2}$ are covariates of company i at time $t-2$ when a fixed lag of 2 years is applied; β_0 is the coefficient of the baseline hazard; β_1, β_2 are vectors of coefficients.

If we take industrial classification into account and follow the specification in equation (4.20), we have

$$\text{logit}(h_{ST=1}(t)) = \alpha + \beta_0 h_0(t) + \sum_{s=1}^{S} D_s \beta_{1,s} \mathbf{x}^e_{i,s,t-2}{}^T + \beta_2 \mathbf{x}^r_{i,t-2}{}^T \tag{5.10}$$

Where $\beta_{1,s}$ denotes a parameter for efficiency score for sector s to be estimated;

$D_s = 1$ if company i is a member of sector s, 0 otherwise;

$\mathbf{x}^e_{i,s,t-2}$ denotes efficiency score for sector s company i;

$\mathbf{x}^r_{i,t-2}$ is a selection of financial ratios that may vary between periods.

In general, there is an issue of censoring in hazard models. Censoring occurs when cases are lost or not observed. When a failure happens before the observation time window, the value of the dependent variable is left censored. It is right censored when a case remains active till the end of observation and failure is not observed. The dependent variable ST is a binary indictor that equals 1 if financial distress is observed. For all companies they may meet several situations as new ones are listed and failed ones exit, described in Table 5.3.1.

Table 5.3.1 Examples of censoring data

Period / No.	1	2	3	4	5	6
1	0	0	0	0	0	0
2	0	0	1			
3			0	0	0	0
4		0	0	0	1	

There are four types of censoring in the sample of panel data. Company 1 is healthy throughout the observation (right censored). Company 2 was listed before period 1 but suffered distress at period 3 (left censored). Company 3 was listed at period 3 and survived until period 6 (right censored). Company 4 was listed at period 2 but was distressed at period 5 (not censored). For a hazard model, censoring is not a problem. Originally, Malmquist DEA models do not require the panel dataset to be completely balanced, i.e. a full set of observations across all periods for all DMUs, but most DEA solving packages[8] require a balanced dataset to be input into the program, which leads to a problem for prediction purposes if the panel is not balanced. This is because when a case is censored, there is no sense in which it remains in the

[8] For example, DEAP 2.1 and DEA Solver Pro.

productivity possibility set and participates in comparison. This is not realistic. Fortunately, the latest version of MaxDEA Pro 6.1 can handle unbalanced panel dataset. Therefore MaxDEA Pro 6.1 is the package to solve our Malmquist DEA models.

5.3.5 Model specification

In this section, we specify the models we use to predict financial distress.

As identified in the preceding chapter, there are generally two methods of using efficiency to predict financial distress. Firstly, efficiency score is used as a single classifier (Paradi *et al*, 2004; Cielen *et al*, 2004; Emel *et al*, 2003) and secondly, as a variable into the second stage analysis where other methods are used to classify (for example logistic regression in Chapter Four). As no one has tried panel DEA score in predicting financial distress before, it is rather interesting to see how it performs in a simpler and more direct way – to make predictions directly. Then efficiency scores calculated from a Malmquist DEA model with reference to the first period (equation (5.6)) is used directly as scores from standard credit scoring techniques. Model 1 is the pure Malmquist DEA model. However, industries are still specified, i.e. classification of Goods and Bads is only made according to the proportion of Goods and Bads within the company's industry.

Model 2, as introduced in Section 5.3.1, uses Malmquist DEA scores calculated by equation (5.6) as covariates in the DHM (equation (5.10)). The efficiency score is TE or CRS efficiency which has been found to be efficient in the cross-sectional analysis. Model 2 is actually the main model and basic model of this research.

In Model 3, TE is decomposed into PTE and SE by assuming VRS. As stated in Chapter Four, decomposition of the overall technical efficiency may provide more information and the cross-sectional analysis has found SE is more stable and significant in predicting financial distress. In this model, the term $\sum_{s=1}^{S} D_s \beta_{1,s} x_{i,s,t-2}^{e}$ in equation (5.10) is replaced by its components $\sum_{s=1}^{S} D_s^{PTE} \beta_{1,s}^{PTE} x_{i,s,t-2}^{PTE} + \sum_{s=1}^{S} D_s^{SE} \beta_{1,s}^{SE} x_{i,s,t-2}^{SE}$ that only take into effect the specific industry of the company.

Model 4 applies the global reference as introduced in Section 5.3.2. In this model, the relative efficiency score of company i in sector s at period t is calculated with reference to the most productive companies in all possible periods in the same sector.

Model 5 follows what has been described as the super efficiency model in Section 5.3.3. Super efficiency scores provide more discrimination for efficient companies. So it is expected to see its discriminative power increased in prediction.

Model 6 actually is the simplest method (in terms of DEA calculation and regression) but heterogeneous technologies are applied. In the first stage when calculating the efficiency scores, all industries are pooled together. So the efficient frontier may be pushed outward as more samples are considered. At the second stage, the term $\sum_{s=1}^{S} D_s \beta_{1,s} x_{i,s,t-2}^{e}$ in equation (5.10) is replaced by a simpler form $\beta_1 x_{i,t-2}^{e}$. This just provides a reference to our models as most previous literature considers heterogeneous samples in bankruptcy prediction.

Table 5.3.2 Model comparison 2

Model	Modelling process	Covariates in regression
Model 1	DEA	None
Model 2	DEA + DHM	Overall technical efficiency + financial ratios
Model 3	DEA + DHM	Pure Technical Efficiency + Scale Efficiency+ financial ratios
Model 4	DEA + DHM	Global reference efficiency + financial ratios
Model 5	DEA + DHM	Super efficiency + financial ratios
Model 6	DEA + DHM	Mixed industry efficiency+ financial ratios

Finally a summary of model specification can be found in Table 5.3.2. Their predictive accuracy is compared by measures AUR, Gini, KS and H introduced in Section 3.5.

5.4 Sample

5.4.1 Sample description

Following what has been stated in Section 4.4.1, because the number of employees is only available in annual reports after year 2000, the observation period begins in 2001 through to 2010, ten years in total. After the initial filtering, 2,027 individual listed companies over the period 2001 to 2010, a total of 12,431 firm years were left in the sample for analysis. Among them, there are 12,058 healthy firm years and 373 distressed firm years, which gives a bad rate of approximately 3%.

As industry classification is essential to this research, it is necessary to view the distribution of companies across all industries. Table 5.4.1 displays the distribution of the 12,431 firm years according to the second level industry classification in the Wind database. Banking and insurance companies are excluded from this sample as their accounting standards are different from that in other sectors. We notice that the industries Raw Materials (code 1510), Industrial Equipment (code 2010) and Real Estate (4040) account for nearly half of all distressed cases (49.87%). We select companies from these industries as the sample for analysis for the following reasons: firstly, as the panel analysis is ten years, the valid number of firm years falling in each period cannot be too small. Secondly, DEA models require that in each period the number of units is more than double as the number of inputs and outputs (8 in our case) for a good estimate (Dyson *et al*, 2001). Thirdly, because the cross-sectional analysis used these three sectors, it is better to keep the same for convenience of comparison. Finally, 5,490 firm years in these three industries were left in the sample.

Table 5.4.1 Sample by industry over 2001-2010

Industry	Sector code	ST			Total valid
		censored	0	1	
Energy	1010	205	375	10	385
Raw materials	1510	1465	2479	**66**	2545
Industrial equipment	2010	1758	2100	**62**	2162
Business services	2020	105	64	1	65
Transportation	2030	209	574	7	581
Vehicles and parts	2510	249	466	15	481
Consumer goods and apparels	2520	609	767	24	791
Consumer services	2530	98	186	6	192
Media	2540	77	111	2	113
Retail	2550	148	589	13	602
Food	3010	67	200	3	203
Beverage and tobacco	3020	447	699	24	723
Family and personal goods	3030	23	46	1	47
Medical equipment	3510	74	34	2	36
Pharmacy and biology technology	3520	458	747	25	772
Financial services	4020	4	5	1	6
Real estate	4040	380	952	**58**	1010
Software	4510	412	230	8	238
Hardware and equipment	4520	756	758	26	784
Semiconductor	4530	127	111	2	113
Telecommunication	5010	23	27	0	27
Public services	5510	145	538	17	555
Total		7839	12058	373	12431

Table 5.4.2 Distributions of samples in three industries over 2001-2010

Sector	1510			2010			4040			Total		
N	328			277			137			742		
year	ST		Total	ST		Total	ST		Total	ST		Total
	0	1		0	1		0	1		0	1	
2001	208	1	209	167	5	172	121	5	126	496	11	507
2002	217	8	225	176	6	182	115	9	124	508	23	531
2003	224	9	233	181	8	189	104	11	115	509	28	537
2004	234	6	240	193	7	200	101	5	106	528	18	546
2005	231	5	236	189	6	195	98	3	101	518	14	532
2006	237	7	244	189	13	202	86	14	100	512	34	546
2007	251	9	260	214	4	218	82	6	88	547	19	566
2008	273	5	278	221	5	226	82	2	84	576	12	588
2009	265	6	271	219	2	221	80	2	82	564	10	574
2010	254	10	264	214	5	219	79	1	80	547	16	563
Total	2394	66	2460	1963	61	2024	948	58	1006	5305	185	5490

Figure 5.4.1 Bad rates of three sectors over 2001-2010

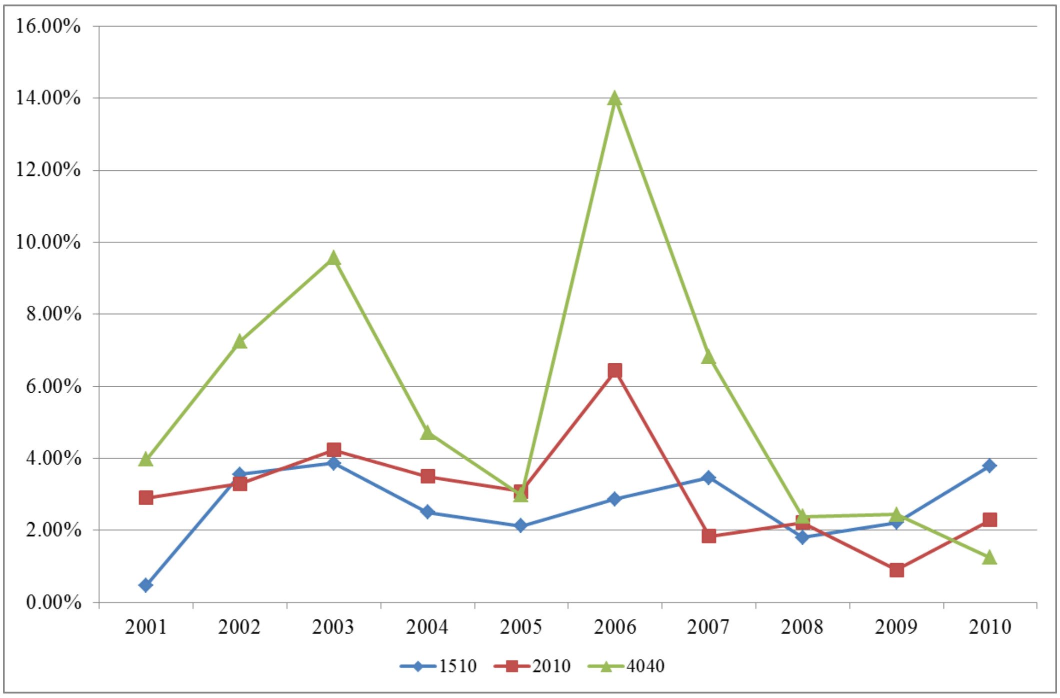


Table 5.4.2 indicates that the average distress rate is 3.37% ($185/5490 = 3.37\%$). The average number of observations for each company in ten years is 7.4 ($5490/742 = 7.40$). In the years 2002, 2003 and 2006 there are significantly more companies suffering financial distress than in other years. Figure 5.4.1 shows the ST rate of three industries at each period of observation. Generally, there are more distressed Real Estate companies than in the other two sectors. In later years (2008 to 2010) the distress rate is considerably lower than that during 2002-2003 and during 2006-2007.

In order to split the bad rate and industries as even as possible, the stratified sampling is applied within each industry (referring to Section 3.3) and finally the training sample (Panel A) contains 3648 firm years and the test sample (Panel B) contains 1842 firm years. Details can be found in Table 5.4.3.

Table 5.4.3 Sample 2

	Sector	1510	2010	4040	Total
Panel A	Non-ST (0)	1643	1215	666	3524
	ST (1)	44	38	42	124
	Total	1687	1253	708	3648
	Bad rate	2.61%	3.03%	5.93%	3.40%
Panel B	Non-ST (0)	751	748	282	1781
	ST (1)	22	23	16	61
	Total	773	771	298	1842
	Bad rate	2.85%	2.98%	5.37%	3.31%

The test sample with Panel B is actually out-of-sample validation and a hazard model is also capable of out-of-time prediction (Shumway, 2011). Therefore two extra datasets Panel C and Panel D are used to make out-of-time validation. Because there is a two-year lag in prediction, actually the observed data in 2009 and 2010 needs information of independent variable ST in 2011 and 2012 to be validated. There are 7 and 11 new ST companies in these three industries in 2011 and 2012 respectively[9]. So practically, Panel C (2009 and 2010) consists of the untouched data in the last two years of Panel A (2001 to 2010) and predicts financial distress in 2011 and 2012 (out-of-time validation). Panel D, similarly, consists of the untouched data in the last two years of Panel B (2001 to 2010) to predict financial distress in 2011 and 2012 (out-of-time and out-of-sample validation).

5.4.2 DEA inputs and outputs

We apply the same selection of DEA variables as in the cross-sectional analysis, all of which are expressed in physical or monetary items in standard annual reports. There are five inputs: number of employees, total liabilities, total costs, total assets, share capital and three outputs: total profits, total cash flow and total sales. For censored dependent firm years, $ST_{i,t}$ is recorded as missing. Although these firms are only distressed but not bankrupt and they still have in listing, their DEA inputs and outputs and other covariate values are all set to be missing because we assume they exit the sample and do not take part in the DEA comparison anymore.

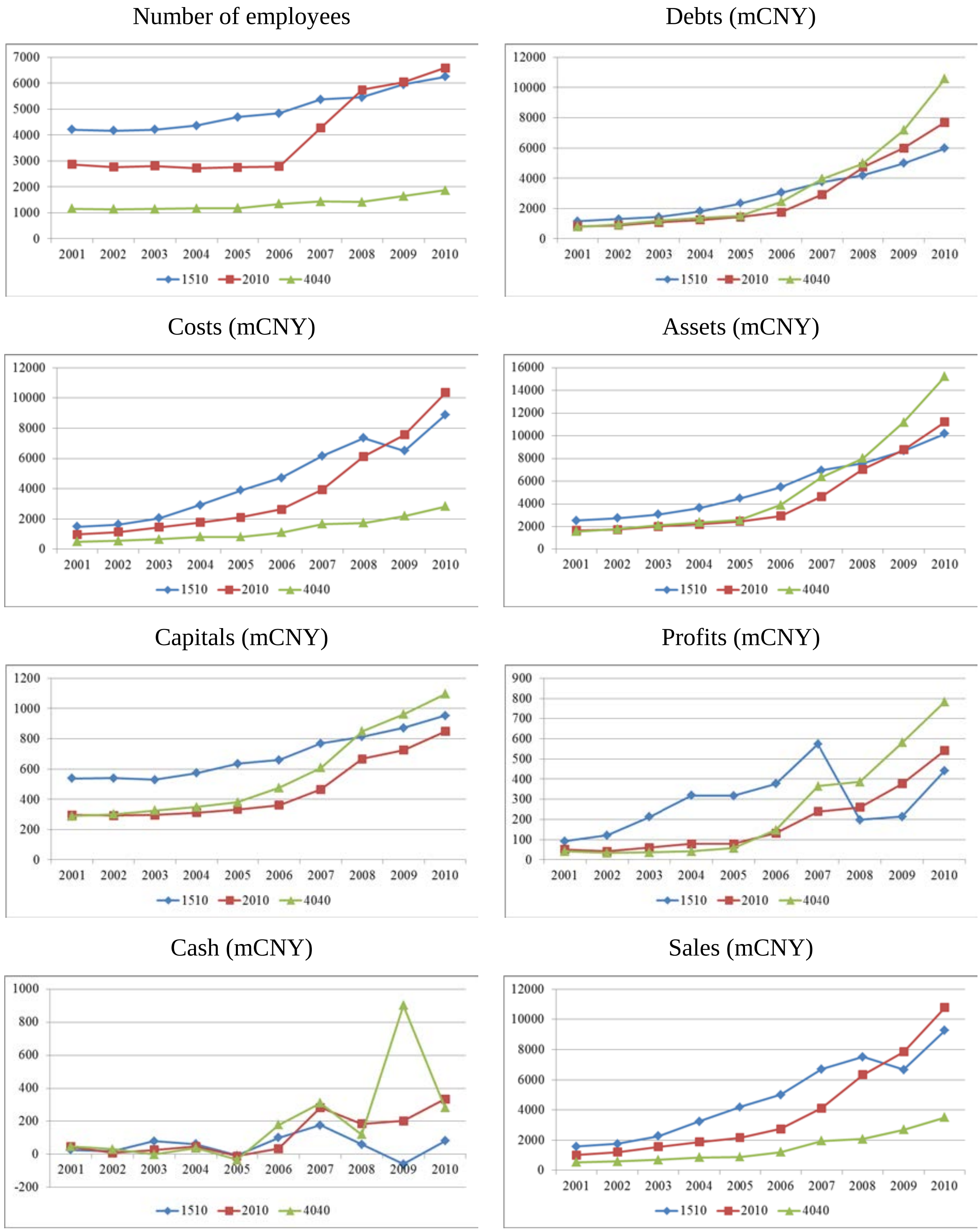
The descriptive statistics of the covariates are reported in aggregate because DEA models are conducted on the whole dataset (both training and test samples). For convenience of presentation, the descriptive tables are attached in Appendix B and only graphs of means over time are presented here (Figure 5.4.2).

Generally, the size of those listed companies (in terms of total assets) increased in those ten years. Along with it, their total debts, total costs and share capitals took similar pace of growth accordingly. It is the same in total sales for output. However, we can notice some changes in some periods that did not follow the trend. For example, the number of employees in sector 2010 nearly doubled in the three years 2006-2008. There was a large drop in profit for sector 1510 in year 2008 and in 2009, which might be the influence of the global financial crisis. Additionally, there was a

[9] The original observation window is till year 2010. However Panel C and Panel D do not require the restart of data collection but we only need to identify the new ST companies in 2011 (16) and 2012 (25).

sharp net cash inflow in sector 4040 in 2009. These large changes call for the importance of running DEA peer comparison analysis separately for each industry so that the relative efficiency scores are not biased.

Figure 5.4.2 Descriptions of DEA variables over 2001-2010



5.5 Results

5.5.1 Dynamic DEA score

Table 5.5.1 shows that generally the ST group has a lower efficiency than the non-ST group across all of the different measures. Values of TE range from 0.004 to 8.638 whilst its component PTE ranges from 0.135 to 15.738 and SE ranges from 0.008 to 8.638. Global efficiency scores are in a conventional sense, ranging from 0.002 to 1 because they refer to the best performance in history. As expected, Super Efficiency has a larger standard deviation than overall Technical Efficiency, which indicates a better discrimination for those efficient companies, especially in the non-ST group.

Table 5.5.1 Description of efficiency scores

Sector	ST	Stats	TE	PTE	SE	GE	SPE	ME
1510	0	N	2394	2394	2394	2394	2394	2394
		Mean	1.225	1.253	1.064	0.653	1.234	0.918
		SD	0.772	0.971	0.582	0.167	0.788	0.315
		Min	0.029	0.161	0.059	0.021	0.029	0.028
		Max	8.638	14.369	8.638	1.000	8.638	5.000
	1	N	66	66	66	66	66	66
		Mean	0.756	0.896	0.868	0.464	0.756	0.670
		SD	0.487	0.650	0.222	0.207	0.487	0.313
		Min	0.040	0.255	0.048	0.026	0.040	0.035
		Max	3.458	4.799	1.000	0.929	3.458	2.234
	All	N	2460	2460	2460	2460	2460	2460
		Mean	1.212	1.243	1.058	0.648	1.221	0.912
		SD	0.770	0.965	0.576	0.171	0.785	0.317
		Min	0.029	0.161	0.048	0.021	0.029	0.028
		Max	8.638	14.369	8.638	1.000	8.638	5.000
2010	0	N	1963	1963	1963	1963	1963	1963
		Mean	1.033	1.049	1.014	0.457	1.059	0.936
		SD	0.530	0.550	0.407	0.180	0.603	0.405
		Min	0.070	0.274	0.153	0.032	0.070	0.062
		Max	7.378	9.093	7.378	1.000	7.378	6.178
	1	N	61	61	61	61	61	61
		Mean	0.702	0.872	0.825	0.307	0.702	0.664
		SD	0.329	0.404	0.273	0.193	0.329	0.293
		Min	0.004	0.135	0.008	0.002	0.004	0.003
		Max	1.930	2.106	0.999	1.000	1.930	1.821
	All	N	2024	2024	2024	2024	2024	2024
		Mean	1.023	1.044	1.008	0.452	1.048	0.927
		SD	0.528	0.547	0.405	0.182	0.600	0.404
		Min	0.004	0.135	0.008	0.002	0.004	0.003
		Max	7.378	9.093	7.378	1.000	7.378	6.178

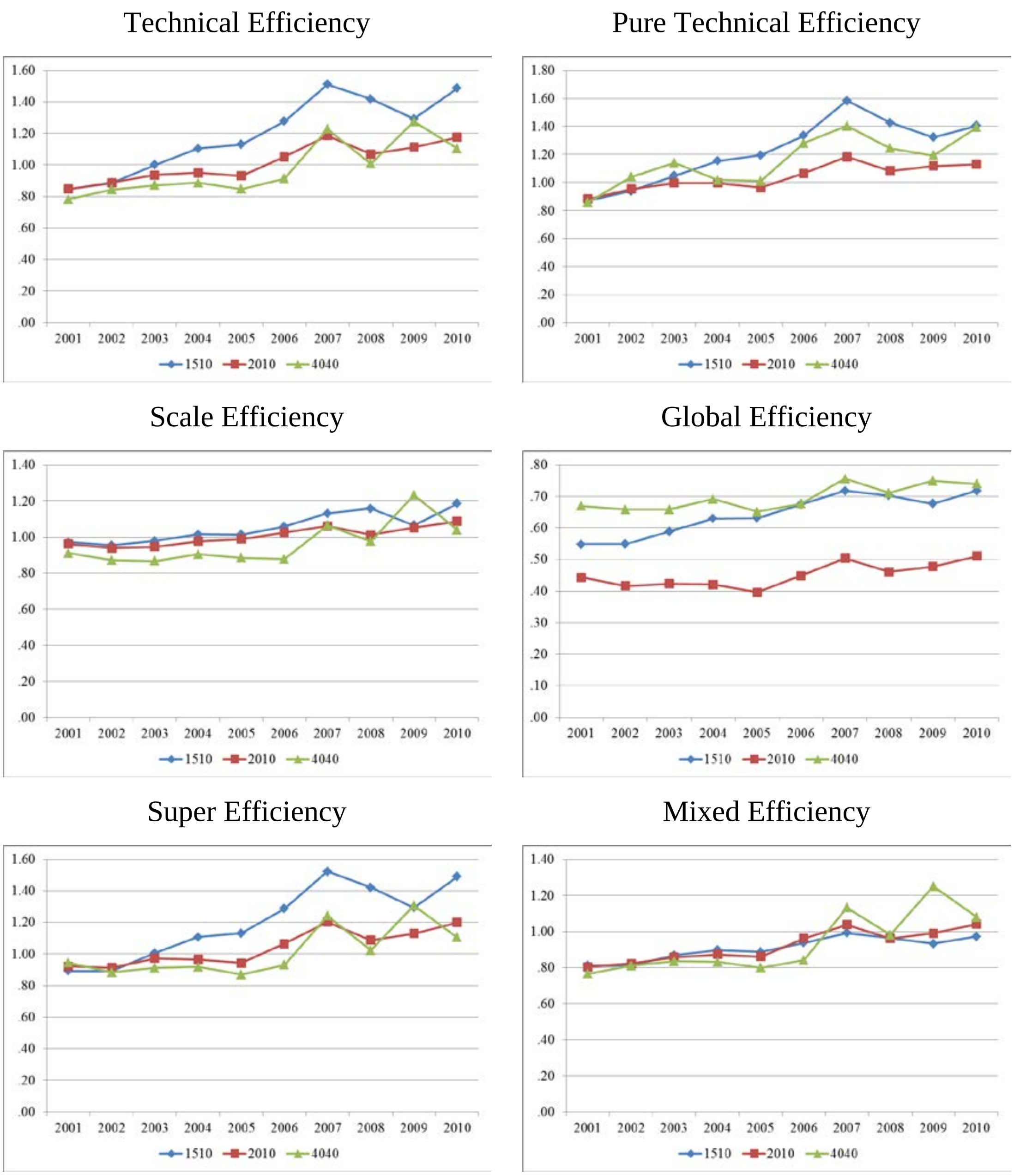
Table continued

4040	0	N	948	948	948	948	948	948
		Mean	0.972	1.142	0.964	0.702	1.017	0.929
		SD	0.569	1.084	0.448	0.196	0.666	0.503
		Min	0.059	0.276	0.065	0.049	0.059	0.059
		Max	6.277	15.738	5.931	1.000	8.204	5.931
	1	N	58	58	58	58	58	58
		Mean	0.660	1.042	0.714	0.518	0.667	0.628
		SD	0.381	0.641	0.321	0.260	0.389	0.350
		Min	0.024	0.202	0.022	0.021	0.024	0.023
		Max	1.805	3.750	1.570	1.000	1.805	1.603
	All	N	1006	1006	1006	1006	1006	1006
		Mean	0.954	1.137	0.950	0.691	0.996	0.911
		SD	0.565	1.064	0.445	0.204	0.658	0.500
		Min	0.024	0.202	0.022	0.021	0.024	0.023
		Max	6.277	15.738	5.931	1.000	8.204	5.931
Total	0	N	5305	5305	5305	5305	5305	5305
		Mean	1.109	1.158	1.027	0.589	1.131	0.926
		SD	0.665	0.869	0.501	0.205	0.709	0.388
		Min	0.029	0.161	0.059	0.021	0.029	0.028
		Max	8.638	15.738	8.638	1.000	8.638	6.178
	1	N	185	185	185	185	185	185
		Mean	0.708	0.934	0.806	0.429	0.710	0.655
		SD	0.407	0.579	0.279	0.237	0.409	0.318
		Min	0.004	0.135	0.008	0.002	0.004	0.003
		Max	3.458	4.799	1.570	1.000	3.458	2.234
	All	N	5490	5490	5490	5490	5490	5490
		Mean	1.095	1.150	1.020	0.584	1.116	0.917
		SD	0.662	0.862	0.497	0.208	0.705	0.389
		Min	0.004	0.135	0.008	0.002	0.004	0.003
		Max	8.638	15.738	8.638	1.000	8.638	6.178

TE, PTE, SE, GE, SPE and ME are referred to overall Technical Efficiency, Pure Technical Efficiency (component of TE), Scale Efficiency (component of TE), Global Efficiency, Super Efficiency and Mixed Efficiency respectively.

Alternatively, if we want to see if efficiency and technology change over time, we draw graphs of their mean scores across all periods (Figure 5.5.1). For convenience, graphs of three sectors are drawn on one chart. Generally the efficiency and technology levels increased while in the later years, there were some declines, which is presumably the influence of the recent financial crisis that has happened since 2008.

Figure 5.5.1 Distributions of efficiency scores over 2010-2010



5.5.2 Model 1

Model 1 uses DEA scores directly as a nonparametric method to predict financial distress, so there is no parameter to estimate. Therefore, it is not necessary to split the whole sample into training and test samples but that prediction is applied to the whole sample (2001-2010). The efficiency scores with reference to the first period, 2001 are directly applied on the dependent variable with a lag of two fixed years, i.e.

use efficiency scores at period $t-2$ to predict $ST_{i,t}$ (scores over 2001-2010 to predict ST over 2003-2012). A cut-off point on the score is applied according the observed proportion of healthy and distressed companies. The analysis must be carried out for each industrial sector separately because cross industries comparisons using DEA scores is invalid.

Table 5.5.2 Classification of Model 1

Sector	N	Non-ST	ST	Type I error	Type II error	Overall accuracy
1510	2328	2258	70	74.29%	2.30%	95.53%
2010	1911	1858	53	62.26%	1.78%	96.54%
4040	897	851	46	78.26%	4.23%	91.97%

In Table 5.5.2, the Type I errors are relatively high compared to that in Table 4.5.8, the Type II errors are reasonably good. The overall classification accuracy is lower in sector 4040 than others but basically they outperformed the out-of-sample prediction in Table 4.5.8.

Rather than using a single cut-off and confusion matrix, predictive power of these panel efficiency scores are given by H, AUC, Gini and KS measures. The average performance is weighted by the number of firm years in the specific sector to give an indicator of the predictive accuracy of Model 1. Table 5.5.3 shows a poorer predictive power than we found in Models 1-6 when only efficiency scores are used in prediction (Table 4.5.9).

Table 5.5.3 Predictive accuracy of Model 1

Sector	H	AUC	Gini	KS
1510	0.071	0.825	0.651	0.549
2010	0.128	0.888	0.776	0.678
4040	0.069	0.821	0.642	0.521
Weighted average	0.092	0.848	0.696	0.592

5.5.3 Selection of the duration time and financial ratios

There are several possible ways to calculate the survival (duration) time: the time since the foundation, the time since the IPO, the time since official listing at the stock exchange, and the time since the first year of the period of observation. All are available to be used as the duration time. Theoretically, for survival analysis, the survival time should be calculated from the birth of an object which remains observed until death or the end of the observation period. Therefore, the survival time would be ideally calculated from the foundation year of incorporation. However, the regulation of Special Treatment has been implemented only since 1998 as the policy makers then started to pay attention to financial risks in the security markets. Data shows the average real age of companies is about 10 years. Considering the observation window is much later than the time of incorporation, many periods are lost due to censoring.

Shumway (2001) used the trading age which was the time since listing as the duration time because companies were homogeneous to meet the requirements of listing at an exchange. Our samples are also listed companies so it is decided the trading age to be the duration time in the hazard model. In the sample, the average trading age is 7.79 years. Shumway (2001) also commented that any function of the duration time could be included in the model and t, t^2, $\ln(t)$ and $\ln(t^2)$ have all been tried in the preliminary analysis but only $\ln(t)$ fits well (significant) with the model. $\ln(t)$ was also the choice of Shumway (2001).

Note that the indicator of financial distress, ST, is a status indicator where a company can go to ST and recover from ST. Here, only the first occurrence of ST is regarded as the event of distress and the information after the year of ST is marked as missing. All companies entering the observation window in 2001 are ensured to be healthy companies in the beginning (not in the status of ST). So the model is actually predicting the probability of going into financial distress (ST) by lagged values of covariates given the duration time since its listing at the stock exchange.

In Table 3.4.1, there is a list of eligible financial ratios to be included in the regression models and in the previous chapter, stepwise selection process in the cross-sectional analysis was conducted. However, stepwise selection, no matter whether it is forward selection or backward elimination as appeared in most analytical packages, is problematic in multi period data. Greenland (1989) commented, stepwise selection leads to invalid estimates and tests of effect in survival analysis. We cannot use stepwise selection on those financial ratios and it is impossible to include them all either.

In the cross sectional analysis we found that each of the predefined groups of financial ratios can contribute to the probability of financial distress. We choose only one ratio from each group in Table 3.4.1 and they are decided by their significance in the model and by reference to previous literature.

Finally, six ratios from six groups have been chosen and the results presented in Table 5.5.4.

Table 5.5.4 Result of the model to select financial ratios

ST	Coef.	Std. Err.	z	P>z
ln(duration)	0.112	0.308	0.36	0.717
ROE	-12.837**	2.033	-6.31	0.000
Current Liabilities / Total Liabilities	8.681**	1.281	6.78	0.000
Tangible Assets / Total Assets	-1.975**	0.645	-3.06	0.002
Cash Flow from Operation per Share	-1.235**	0.275	-4.49	0.000
Total Assets Turnover	-3.570**	0.592	-6.03	0.000
Total Assets Growth	-2.794**	0.624	-4.48	0.000
Constant	-7.711**	1.320	-5.84	0.000
Log likelihood	-296.37			
Number of observations	2665			
LR chi2(8)	279.38			
Prob > chi2	0			
Pseudo R2	0.3203			

5.5.4 Model 2-6

These six ratios, Return on Equity, Current Liabilities / Total Liabilities, Tangible Assets / Total Assets, Cash Flow from Operation per Share, Total Assets Turnover and Total Assets Growth, together with efficiency scores, are integrated in Model 2-6 as specified in Table 5.3.2. Results are presented in Table 5.5.5.

Generally the five regression models are well fitted according to the χ^2 test. The coefficient for each type of efficiency has the expected sign, which indicates that the more efficient a company is, the less likely it goes into financial distress. The values of their coefficients are different between models because their mean values and distributions are different. For Models 2 to 5, when three industries were treated separately, their differences between each other are shown in the coefficients. Most parameters are significant at the 95% level of confidence. The only exception is that when TE is decomposed into PTE and SE, SE remains significant but PTE in some sectors does not.

There are four ratios in Table 5.5.5 which have been found significant in the cross sectional analysis, with the same signs. The other two ratios, Current Liabilities / Total Liabilities and Total Assets Turnover, are positively and negatively associated with the probability of financial distress.

Table 5.5.5 Results of Model 2-6

ST	Model 2	Model 3	Model 4	Model 5	Model 6
ln(duration)	0.262	0.394	0.192	0.219	0.194
Model 2					
TE1510	-1.451**				
TE2010	-1.964**				
TE4040	-2.132**				
Model 3					
PTE1510		-2.099*			
PTE2010		-1.803			
PTE4040		-1.266			
SE1510		-1.441**			
SE2010		-2.137**			
SE4040		-2.705**			
Model 4					
GE1510			-3.511**		
GE2010			-6.021**		
GE4040			-3.271**		
Model 5					
SPE1510				-1.436**	
SPE2010				-1.943**	
SPE4040				-2.063**	
Model 6					
ME					-3.805**
Return on Equity	-13.05**	-12.70**	-13.04**	-13.04**	-12.43**
Current Liabilities / Total Liabilities	8.994**	9.423**	8.766**	9.037**	8.533**
Tangible Assets / Total Assets	-1.401**	-1.890**	-1.400**	-1.453**	-1.586**
Cash Flow from Operation per Share	-1.076**	-1.156**	-0.960**	-1.067**	-0.983**
Total Assets Turnover	-3.193**	-3.194**	-2.656**	-3.171**	-2.160**
Total Assets Growth	-2.177**	-2.285**	-1.974**	-2.238**	-1.745**
Constant	-7.235**	-5.517**	-6.643**	-7.185**	-5.660**
Log likelihood	-285.59	-280.48	-282.93	-284.15	-280.01
Number of observations	2665	2665	2665	2665	2665
LR chi2	300.95	311.18	306.27	303.84	312.10
Prob > chi2	0	0	0	0	0
Pseudo R2	0.3451	0.3568	0.3512	0.3484	0.3579

TE, PTE, SE, GE, SPE and ME are referred to overall Technical Efficiency, Pure Technical Efficiency (component of TE), Scale Efficiency (component of TE), Global Efficiency, Super Efficiency and Mixed Efficiency respectively. Some of them are attached with the sector code.

5.5.5 Predictive accuracy

Table 5.5.6 Predictive accuracy of Model 2-6

	Panel A (training)				Panel B (within time out-of-sample)			
	H	AUC	Gini	KS	H	AUC	Gini	KS
Model 2	0.269	0.888	0.777	0.636	0.095	0.832	0.665	0.522
Model 3	**0.304**	**0.891**	**0.782**	0.638	**0.11**	0.841	0.682	**0.542**
Model 4	0.279	0.891	0.782	0.635	0.094	**0.842**	**0.684**	0.538
Model 5	0.275	0.89	0.781	**0.64**	0.097	0.834	0.668	0.52
Model 6	0.265	**0.901**	**0.801**	**0.651**	0.106	**0.855**	**0.709**	**0.566**
	Panel C (within sample out-of-time)				Panel D (out-of-time out-of-sample)			
	H	AUC	Gini	KS	H	AUC	Gini	KS
Model 2	0.018	0.862	0.724	0.601	0.086	0.824	0.647	0.586
Model 3	0.018	0.862	0.725	0.601	0.070	0.831	0.662	**0.594**
Model 4	0.018	**0.868**	**0.737**	**0.679**	**0.109**	**0.841**	**0.682**	0.570
Model 5	0.018	0.863	0.725	0.602	0.086	0.824	0.647	0.586
Model 6	**0.021**	**0.872**	**0.744**	**0.687**	**0.109**	**0.855**	**0.710**	0.575

The highest value for each statistic is in bold. If Model 6 performed the best, the next largest value is also highlighted.

If we look at the predictive accuracy based on the H, AUC, Gini and KS statistics (Table 5.5.6), we have different results from different preferences. We have to bear in mind that Model 1 is using the efficiency score directly to classify the distressed and non-distressed companies and the whole sample was used for validation. Model 6 is the model with heterogeneous samples (pooled industries) is only a reference to this study.

The predictive accuracy of Model 1 (H=0.092, AUC=0.848, Gini=0.696, KS=0.592) is generally better than the out-of-sample predictions (Panel B and Panel D) but poorer than the within sample out-of-time prediction (Panel C). This means if we build Malmquist DEA and DHMs on the same sample, Malmquist DEA is less capable in making dynamic predictions of financial distress than hazard models. Obviously, a DHM which takes additional ratios can be more informative in prediction. Nevertheless, Malmquist DEA as a direct classifier, is simple and does not require model training.

Model 6, regardless of industrial classification, seems to be consistently better than other models through four panels. This indicates that if we do not consider the assumption of homogeneity of DEA, pooling all industries together, calculating DEA scores and predicting using statistical regression may be a more effective and accurate way in detecting corporate distress. This is a practical method, though methodologically incorrect. This result may be caused by the limitation of sample size. When industries are pooled together, relative efficiency can be more objective by taking more peers into comparison than industry segmentation where certain group leaders have to be identified in each industry.

Apart from Model 6, Model 4 is the next best according to what most indictors indicate in Table 5.5.6. Particularly, Model 4 with global reference has larger AUC (Panel B=0.842, Panel C=0.868, Panel D=0.841) and Gini (Panel B=0.684, Panel C=0.737, Panel D=0.682) than that in Model 2, 3 and 5 in both out-of-sample and out-of-time predictions.

The decomposition of TE (Model 2) into PTE and SE (Model 3) provides more discriminant power in all H, AUC, Gini and KS measures. This is consistent with what has been found in the last chapter.

5.6 Conclusion

Dynamic models have inherent advantages over static models in the context of prediction because there may be changes over time in the values of covariates. By taking the effect of time into account, dynamic models are able to adjust predictions based on the influence of changes or predict the credit risk in a given period of time. More accurate predictions can be made by using more data in multiple periods. Hazard models considering the natural risk associated with the age of the company are particularly preferred because they can also incorporate time varying covariates and deal with censoring when information is lost. Shumway's (2001) discrete hazard model is even more convenient in corporate credit predictions because most corporate information and other TVCs are disclosed periodically. In the previous chapter, we successfully conducted a cross sectional analysis on decomposed DEA efficiency based on a sample of mixed industries. This chapter has extended it to a panel analysis when these three industries have been observed over ten years.

Hazard models need a panel dataset of covariates and the first task is to find a dynamic DEA model which is suitable to calculate the efficiency of a company relative to others over a period. Network DEA and Window DEA have been considered but Malmquist DEA is found to be the best because its efficiency is comparable in both cross sectional and time serial formats. A Malmquist productivity index is defined as the product of efficiency change (catch-up) and technological change (frontier-shift) and mathematically it is calculated by the standard DEA scores at two periods and two intertemporal scores with reference to the efficiency frontier of the other period.

The reference set in Malmquist DEA models may change the relative values in efficiency scores and both the fixed reference to the first period and the global reference which comes from the historically most efficient units were used in our models. In addition, super efficiency which removes the unit to be evaluated from the frontier was also used as an option. Efficiency with mixed industries was also included because most previous literature did not consider the differences between industries. The main model of this research uses the overall Technical Efficiency in the discrete hazard models with financial ratios to predict the probability of financial distress. Other efficiency including decomposed efficiency (Pure Technical Efficiency and Scale Efficiency), global efficiency, super efficiency and mixed efficiency has also been used on the Chinese data of 5,490 company years.

In the descriptive analysis, efficiency calculated from different methods of DEA has demonstrated different characteristics between industries. Global efficiency has the smallest mean and standard deviation whist Pure Technical Efficiency shows the largest dispersion in the values of scores. Generally all types of efficiency show a trend of improvement over the period of 2001 to 2010 though some rises and falls can also be observed.

DEA efficiency can be used to predict financial distress directly. Model 1 displays an overall accuracy of classification over 90%. When adding financial ratios in hazard models, it has found that various efficiency scores perform similarly as they are all negatively associated with the probability of financial distress. It confirms that the more efficient a company is, the less likely it incurs financial difficulties.

In all types of efficiency, if not considering the one calculated by mixed industries, the model with global efficiency is the best in both out-of-sample and out-of-time predictions. Global efficiency takes all historic records into account and chooses the most efficient company years as the reference units. When the sample is sufficiently large, the global efficiency could be seen as absolute efficiency which is generalised in all units and periods. In this way, efficiency will be precisely measured and used to predict credit risk accurately.

The simplest way of using DEA efficiency (Model 1) produces considerably good discriminant power. It outperforms the out-of-sample predictions. Using Malmquist DEA scores to directly predict financial distress in future time is not ideal as we find DHMs with financial ratios can do better. It is still an effective and efficient way to apply DEA to corporate credit risk as it only requires one step calculation (DEA programming) compared to a two stage analysis (DEA and regression).

Pooling all industries together to calculate DEA scores may be practically effective but it ignores the assumption of homogenous industries. However it is not sure yet whether its outperformance over other models comes from its inherent advantages or from combining more comparative samples. It requires further analysis by taking various sectors into modelling to conclude on this but our sample has a limit which prevents this.

Super efficiency models show no special features among other models. More discrimination in efficient companies seems unnecessary.

As no literature has attempted a panel analysis of DEA efficiency in predicting the probability of financial distress, this chapter has bridged this gap by calculating dynamic relative efficiency using Malmquist DEA and using it in two ways. The first simple way is using the efficiency scores directly to classify good and bad companies and secondly, it can be incorporated as variables in the hazard models. Both methods produce relatively good predictions and future work can be extended within the scope of Malmquist DEA and hazard models.

Chapter Six

Corporate Governance Measures and Financial Distress

6.1 Introduction

One of the classical theories in corporate governance, agency theory explains the bankruptcy risk internally. Agency theory describes the agency problem that cooperative parties have different goals and interests in their agency relationship where the principal delegates the work to the agent who perform the work (Eisenhardt, 1989). As Eisenhardt (1989) stated the future of organisations (bankruptcy, prosperity or intermediaries) is in the hands of organisational members. They have to think about the uncertainty of the future and rewards they may get. The agency problem between the principal and the agent may influence the willingness to take risks and the subsequent outcomes. Keasey and Watson (1991) also mentioned that it is necessary not only to understand the economic process behind a business becoming insolvent but also how the agents determine the fate of a company in terms of its financial condition and financial support.

Previous research provides evidence to show that corporate governance has indeed influenced the probability of financial distress. Chaganti *et al* (1985) was the first investigate the association between board size, outsiders on a board, the number of offices and the chances of failure. This work was followed by Daily and Dalton (1994a; 1994b), Simpson and Gleason (1999), Fich and Slezak (2008) and Platt and Platt (2012). This chapter will follow their work and extend it to panel analysis with a comprehensive selection of corporate governance measures.

In China, due to its unique social background and history, State-Owned Enterprises (SOEs) have played a significant role in its great economic achievement in the last thirty years. Corporate governance in SOEs is very different from private companies. However, this aspect of corporate governance has not been fully investigated in relation to predicting financial distress. In this chapter we will try to incorporate

corporate governance measures into prediction models and see how they increase predictive accuracy of financial distress models for Chinese listed companies.

This research is the first comprehensive and thorough study to date using more variables in a panel data structure covering the recent financial crisis. There will be a focus on SOEs and SOE ownership to explain the time to distress. SOEs exist in nearly all countries. China's planned economy provides a sufficient number of cases to study the effect of state ownership. This chapter will also model time to default using a DHM proposed by Shumway (2011) rather than cross sectional logistic regression as in other research. The hazard probability produced by the dynamic model ensures the robustness of prediction under different macroeconomic conditions.

This research has found that some aspects of board composition, ownership structure, management compensation and director characteristics can impact on the probability of financial distress. However, using corporate governance measures alone, does not make sufficiently accurate predictions. If they are assisted by financial ratios, models can then be applicable in detecting early financial distress, and the best model comes from this combined with macroeconomic variables. Furthermore, it also finds that the predictive accuracy is heavily reduced when the prediction window is more than three years.

The structure of this chapter is organised as follows. Firstly, the main findings from previous research on some aspects of corporate governance in the application of bankruptcy or financial distress are reviewed. Various corporate governance measures are generally classified into four groups: (1) board composition, (2) ownership structure, (3) management compensation and (4) director characteristics and these are discussed separately. Secondly, the background to corporate governance in China is introduced to help with the selection of variables and understanding of the results. Thirdly, the methodology including the model specification, corporate governance measures and other variables are presented. The chapter then proceeds with the results including data description, variable selection process, and discussion of model output.

6.2 Literature review

6.2.1 Corporate governance and its importance

It is difficult to trace back to who first proposed the concept of corporate governance but its simplest definition comes from the Cadbury Committee at the London Stock Exchange: “corporate governance is the system by which companies are directed and controlled” (Financial Reporting Council, 1992, Section 2.5). It aims to fulfil the long-term strategic goals of owners, take care of the interests of employees, show consideration for the environment and local community, maintain relationships with customers and suppliers and follow applicable legal and regulatory requirements. A more concrete definition comes from Blair (1995) that it is “the whole set of legal, cultural, and institutional arrangements that determine what publicly traded corporations can do, who controls them, how that control is exercised and how the risks and returns from the activities they undertake are allocated.” Although his definition was focused on publicly traded corporations, it still needs pointing out that all other types of corporations should also have a proper governance structure to make their management more efficient and benefit their business in the long term. Because maximising the value of shareholders’ benefits is the ultimate goal for common corporations, appropriate corporate governance can ensure investors get back the return on their investment (Shleifer and Vishny, 1997).

Effective corporate governance can improve corporate performance by optimising the total cost of managers’ and shareholders’ incentives and avoid self-interested managerial behaviour (Jensen and Meckling, 1976). Good corporate governance should provide proper incentives for the Board and management to pursue objectives that are in the interests of shareholders, and should facilitate effective monitoring to encourage managers to use their resources more efficiently. In contrast, poor corporate governance can damage the interests of shareholders, and may lead to poor performance and even the collapse of the corporation (Chen, 2005).

According to the framework proposed by the World Bank (OECD, 2004), corporate governance involves a set of relationships between a company’s management, its board, its shareholders and its stakeholders. Like previous research defining corporate governance measures from those aspects, this research will discuss literature in credit assessment from the perspectives of board composition, ownership structure, management compensation and director characteristics. However, many corporate governance theories are built on private companies. In SOEs, the situation is likely to be different. Therefore, the issues of SOEs are discussed first.

6.2.2 State Owned Enterprises

Under the central planning system, SOEs in China have contributed to and dominated the Chinese economy in all important industries such as banking, transport and energy. SOEs have inherent advantages in many aspects: they do not have to fully cover expenses from sales and income; unprofitable SOEs and losses are subsidised; they receive funds from state-owned banks regardless of risks (Kornai, 1986). On the one hand, they take the benefits of being part of a planned economy and so rarely go bankrupt while on the other hand, they are criticised by corporate governance theory - the agency theory that many levels of agents and their conflicts exist (Han, 2012). Wang and Deng (2006) found that large shareholder ownership and state ownership reduced on the probability of distress. Similarly, Li *et al* (2008) found that ownership concentration and state ownership are negatively associated with the likelihood of bankruptcy. Zeitun and Tian (2007) agreed with this negative association and suggested government ownership could be used as a predictor to detect default. However, at the same time, they commented that although reducing government ownership can increase a firm's performance it could also cause some firms to go bankrupt in the short term.

Clarke (2006) referred to two explanations of why state control causes poor performance: firstly, the government is not as effective a monitor as outside investors and secondly, the government does not pursue maximisation of profit or value of shares as the ultimate goal which is normally the aim of common private companies. Shleifer and Vishny (1997) also noticed that the agency problems in large companies in many countries are not between investors and managers but between outside investors and concentrated shareholders who have dominant full control over the managers. In state companies where the government has large concentrated shares, it leads to problems of harm to social interests and low efficiency.

If the state is the controlling owner, it makes the situation very complicated. As Claessens and Fan (2002) summarised, firstly, the state is not the real owner but the agent of the ultimate owner - all citizens and tax payers, and usually it is the governance agencies, such as SASAC (State-owned Assets Supervision and Administration Commission) in China that control the equity of an SOE. Below them, there are representative directors and managers. There are too many levels of agencies but a lack of incentive to maximise the value. Secondly, there are conflicts of interests because the state is both the regulator and manager of the banking system at the same time.

Faccio (2006) found that SOEs have higher leverage, lower taxation and take larger market shares by achieving dominant positions, but in the meanwhile, in most cases they have a high level of corruption, barriers to foreign investment and less transparent systems. Therefore, state ownership is more like a double-edged sword. Both advantages and disadvantages interact to influence the firm's performance. It still needs empirical evidence to find out the relationship between state ownership and financial distress.

6.2.3 Board composition

Many countries have regulations on the composition of the board. For example, in the UK, the Companies Act 2006 (2006) dictates that a private company must have at least one director and a public company must have at least two. The directors are responsible for the day-to-day management of the company. In some companies the

CEO and the Chair of the Board may be the same people (duality), even though their roles are very different.

Hambrick and D'Aveni (1992) found a significant relationship between dominant CEOs and the likelihood of bankruptcy in a sample of 165 American companies. Moreover, Daily and Dalton (1994) studied 57 firms that filed for bankruptcy between 1972 and 1982 and their empirical results confirmed that CEO duality is positively related to bankruptcy. In a survey of the role of the board of directors, Abdullah (2006) provided Malaysian evidence that board independence and CEO duality (the same person taking two roles) are not associated with financial distress status while surprisingly management and non-executive directors' interests (for those who own shares) are associated negatively with financial distress.

Generally, a board could consist of inside directors (executive directors), grey directors (non-independent non-executive directors) and outside directors (independent directors) (Hsu and Wu, 2009). Much literature (Hsu and Wu, 2009; Chaganti *et al*, 1985; Fich and Slezak, 2008; Santen and Soppe, 2009; Salloum *et al*, 2013) has discussed the influence of directors on the performance of companies. However, they have not reached agreement. For example Hermalin and Weisbach (2003) found insider-outsider ratio was not significantly related to firms' performance but Mangena and Chamisa (2007) found that a small proportion of non-executive directors and a lack of an audit committee were all positively related to the likelihood of delisting.

In addition, in recent years, the role of independent or outside directors within the board structure has received much attention, since this is believed to strengthen the monitoring of firm's performance and diverse backgrounds. In the research of Li *et al* (2008), independent directors turned out to be negatively associated with the probability of financial distress. Daily (1996, p.372) explains the relationship between outside directors and bankruptcy. The actual possibility of bankruptcy can be reduced because an independent outside director in the negotiation process may assist the firm in "convincing creditor groups to agree to a proposed reorganisation plan prior to the formal bankruptcy filing". However, Chaganti *et al* (1985) used a retail example to argue that the influence of outside directors is not significant in corporate failure. Also Hsu and Wu (2009) agreed that more outside directors on the board and an audit committee could not effectively contribute to the decrease in the likelihood of corporate failure. They argued that a high percentage of outside directors on an audit committee is even unfavourable to firm survival. The Netherlands case study from Santen and Soppe (2009) even showed that distressed firms have a higher percentage of independent non-executive directors. Whether independent directors have any positive or negative effect on financial distress remains an open question.

Board size effect has been mentioned in many studies. Daily and Dalton (1994a), Lipton and Lorsch (1992) and Jensen (1993) suggested that small boards are more efficient and have lower productivity costs during any coordination process. This argument was later confirmed by Yermack (1995) and Simpson and Gleason (1999). Recently, Hermalin and Weisbach (2003) and Hsu and Wu (2009) also believed that more executive directors on a board given a fixed board size would increase the likelihood of corporate failure. This is the same in Santen and Soppe's research (2009). However, in retailing firms, non-failed ones tend to have bigger boards within the size range suggested by regulators (Chaganti *et al*, 1985). Darrat *et al*, (2010) even found a mixed effect of board size that having a larger board reduces the risk of bankruptcy for complex firms with diverse business segments, but not for simpler (less diversified, single market oriented) firms. The effect of board size was not very clear. There appeared to be an interacted effect.

6.2.4 Ownership structure

Ownership structure is a crucial aspect when judging the governance of a corporation because it states the relationship of inside and outside investors (Lemmon and Lins, 2003). A great deal of research has addressed issues in ownership structure, for example, the type of controller, the proportion of shares owned by institutional holders, the proportion held by all inside holders, the proportion held by block holders and so on.

Lee and Yen (2004) used a Taiwanese case to comment that in a concentrated ownership environment such as ownership by a family, weak corporate governance will lead to a greater chance of going to distress, but they did not explain what exactly ‘weak corporate governance’ is. In Taiwan, family control is very common and this is also true in many East Asian countries especially in emerging markets such as Thailand and Singapore. Polsiri and Sookhanaphibarn (2009) and Claessens *et al* (1999) have also addressed this issue. Focusing on the UK data, Wilson *et al* (2013) documented that family business is more likely to survive than nonfamily companies. In China, family controlled companies do exist, but there is not enough information to determine whether a company is a family business. What really matters is state ownership, which has been discussed in Section 6.2.2.

In addition to the type of ownership, the role of institutional shareholders also receives attention. Lee and Yen (2004) found that institutional shareholding is smaller in distressed companies than in healthy ones. This was confirmed by Campbell *et al* (2008) and the distress risk was also linked to analyst coverage. Fich and Slezak (2008), Daily (1996) and Donker *et al* (2009) found institutional ownership has no relationship with bankruptcy. Wang and Deng (2006) found block ownership and institutional holdings offered mixed results. In Mangena and Chamisa’s case (2008) using listing suspension as the indicator, institutional shareholding also had mixed effects. It remains open for discussion.

Furthermore, Simpson and Gleason (1999), Abdullah (2006) and Salloum *et al* (2013) agreed that the nature of share ownership had no definite link to financial distress.

6.2.5 Management compensation

Salary, bonus and options are three common forms of compensation for managers. Mann (2005) investigated the relationship between CEO compensation and credit risk. He found that large, unexplained bonuses and option awards increased credit risk while a salary did not seem to have the same effect. High levels of unexplained compensation may indicate that board oversight is loose and, as a result, management has insufficient pressure to deliver good financial performance. He argued that directors tend to pursue short term profits instead of longer term financial benefits. They have an incentive to adopt high risk business strategies which may result in strong positive but also adverse potential payoffs.

Gilson and Vetsuypens (1993) carried out a survey about CEO compensation in financial distressed firms. One-third of the CEOs in their sample were replaced in a given year around default, and those who remained often took substantial cuts in salary and bonus. They suggested management compensation is a potentially significant variable to predict financial distress. Li *et al* (2008) also found that administrative expense ratio is positively related to the likelihood of financial distress. Furthermore, Chan *et al* (2010) tested the association between bankruptcy and both executive compensation and the size of the remuneration committee and found that compensation was positively related to the likelihood of bankruptcy whereas the size of the committee was negatively related.

6.2.6 Director and manager characteristics

Santen and Soppe (2009) incorporated non-executive directors' (NEDs) personal characteristics in prediction models. They set up six variables to describe directors: workload, nationality, dependency, interlocking directorships, age and education. It was found that a foreign NED or a 'very busy' NED on the board are positively related to financial distress. However, there was no relevant relationship between experience, education or network and financial distress.

Other literature has focused on the characteristics of general directors rather than non-executive directors only. Wilson and Altanlar (2011) built a survival model on a large dataset of 6 million observations and found strong links between director characteristics (networks, proximity and involvement) and survival. They found that having female directors on a board reduces the likelihood of insolvency and that companies with female directors appear to take on less debt and have better cash flow. They suggested there is gender difference in risk preference and behaviour. Males are more likely to take excessive risks while females are more conservative. A ‘balanced’ board of directors has a better performance due to the balance of skills. Darrat *et al* (2010) referred to the female as ‘diversified’ on the board and that is helpful. The finding from Wilson *et al* (2013) on this is similar with them.

Ruigrok *et al* (2007) concluded that a foreigner on the board brings different perspectives, skills and knowledge on the one hand, but different values, norms and understanding on the other. The accumulated effect of these two aspects of foreign nationality is unclear.

Educational background is likely to affect managerial performance. Higher education at least indicates a person’s previous learning abilities and skills in solving problems. Holding an MBA degree is evidence of both theoretical and practical experience in business management and therefore is preferred by the board. D'Aveni (1990), Daily and Dalton (1994a) and Ruigrok *et al* (2007) used education to partly represent the quality of a board. Basically they agreed business education may affect the prestige of a company but no one has yet linked education to the probability of financial distress directly.

Experience is hard to measure in a simple way since it is personal and unique. But even so some common results can be seen. Wilson and Altanlar (2011) concluded that directors with previous insolvency experiences or recent resignations have a higher insolvency hazard risk. Previous failure experience of a director may lead to a high risk of bankruptcy in the future (Wilson *et al*, 2013) but Salloum *et al* (2013) did not find enough evidence to conclude that the shorter time a director has served on a board (experience), the greater the probability its company goes to distress.

Age is often used as a proxy for experience and basically older people have more living and working experience than the young. Zahra and Pearce (1989) mentioned age as one of the relevant characteristics in their study and it is probably linked to financial performance. Ruigrok *et al* (2007) applied age as a control variable. Platt and Platt (2012) found the increase in both the CEO's age and the average age of the board decreased the chance of bankruptcy, but Fich and Slezak (2008) only found the CEO's age as significant in one of their four models of bankruptcy prediction.

6.2.7 International studies

The effect of corporate governance could vary from country to country. Most studies that have investigated corporate governance and financial distress were conducted in the US, for example, Daily and Dalton (1994b), Simpson and Gleason (1999), Parker *et al* (2002). Elloumi and Gueyle (2001) introduced corporate governance variables into their financial distress prediction model within Canada, and identified the reasons why some firms find themselves in financial distress. Hsu and Wu (2009) investigated similar issues in the UK and find that grey directors, defined as non-independent non-executive directors, are more informative and knowledgeable than independent directors in management oversight. Lee and Yeh (2004) examined Taiwanese firms by using the number of director seats held by the controlling shareholders. Their results indicated there exists significant relationships between corporate governance variables and financial distress in the following year. Studies using samples from South African (Mangena and Chamisa, 2008), the Netherlands (Donker *et al*, 2009) and Taiwan (Chen, 2008) found some associations between corporate governance variables and the likelihood of financial distress using cross-sectional models.

There are also studies using Chinese samples, but they have weaknesses. Wang and Deng (2006) explained the relationship between corporate governance and financial distress in Chinese companies. Their sample size is rather limited, consisting only of 96 healthy and 96 distressed cases. Li *et al* (2008) have a slightly larger sample but they used a cross sectional logistic model. Li and Liu (2009) extended the sample to panel data, however, their model is a multi-period logistic regression without time. In addition, their indicators of financial distress are 'Special Treatment' and 'Particular

Transfer' which involved consequences other than financial distress only. Han (2012) built her own indicator of distress in a hazard model but she only included a dummy to distinguish SOEs and private companies, no other governance variables were included. Our research clears up all of the limitations of those Chinese studies by constructing a dynamic survival model with a group of corporate governance measures over a long period of time.

Finally, it is worth mentioning that among international studies of corporate governance, a popular quantitative method is to build a corporate governance index (GCI) to measure the overall standard and make it comparable across nations. Examples are G-Index from Gompers *et al* (2003), and an entrenchment index from Bebchuk *et al* (2009). Besides, there are the Credit Lyonnaise Securities Asia's (CLSA) governance index and the S&P disclosure score. In China, there is a China Corporate Governance Index Nankai (CCGINK) which was developed by Naikai University and the National Audit Office, but their methodology and data are not disclosed to the public. In academia, Cheung *et al* (2008) built their own CGI to measure the quality of corporate governance practice. However, in the light of the purpose of this study, employing an external index may look convenient but essentially introduce extra model risk and errors to our model. Neither can we know which aspect of governance is important to financial distress.

Although previous research successfully incorporated corporate governance measures into financial distress prediction, they did not reach a comprehensive consensus as to whether, how and to what extent corporate governance variables determined financial distress. Different countries have different regulatory systems of company structure. This complexity might lead to controversy in this field. Compared to other corporate credit modelling, the work on the effects of corporate governance on credit risk is far from extensive although they generally agree that corporate governance measures will improve the accuracy of the financial distress prediction model. This chapter will investigate the relationship between corporate governance measures and the probability of financial distress again, with a large sample size of more than 1600 companies over 8 years covering the recent financial crisis which ensures the robustness of the modelling results. A wide coverage of corporate governance measures from board composition, ownership structure, management compensation and director characteristics is built into a collection of 35 potential predictive variables. The case of China is a supplement to the study in this field where SOEs are critical in affecting the ability to finance and create credibility.

6.3 Corporate governance in China

As this research mainly uses corporate governance measures as predictive variables and applies them to Chinese data, it is necessary to introduce the background of corporate governance in Chinese listed companies. One cannot simply apply knowledge in the West to China. It has unique features and without understanding Chinese corporate governance, it would be hard to interpret the results. According to Clarke's (2006, p.145) definition, Chinese corporate governance is "the set of rules and practices regulating relationships among participants in a post-traditional Chinese business enterprise and governing decision-making within that enterprise." It includes all stakeholders from governors, regulators, shareholders, directors, managers and other employees. Particularly, it is the laws, rules and regulations that define Chinese corporate governance today. In this part, a brief history of the securities market in China will be introduced and relevant topics in corporate governance regarding board composition, ownership structure and management compensation will be raised.

6.3.1 Chinese securities market: a short history

The Chinese economy has started to fast track since the Economic Reform in late the 1970s. Since then, the Chinese economy has grown at an average speed of over 10% annually for more than thirty years. But its securities markets were opened very late. The Shanghai Stock Exchange was established in 1990 and the Shenzhen Stock Exchange was established in 1991 and now they are still the only two exchanges in Mainland China. Both exchanges were initially aimed to finance SOEs by providing private funds (Liebman and Milhaupt, 2008). Data shows by 2000, over 80% of listed companies in the two exchanges were SOEs (Tam, 2002) and by 2001, over 84% of them were ultimately controlled by the state (Liu *et al*, 2003) and even as recently as 2006, 60% of listed companies were state controlled (Liebman and Milhaupt, 2008). In this circumstance where SOEs totally controlled and overwhelmed the securities market, corporate governance did not seem necessary. After the gradual progress of the Chinese economy and the securities market, the Chinese government finally realised the importance of corporate governance in 1999 and wanted to build a modern enterprise system (Tam, 2000). Since 2005, a reform of non-tradable shares has begun as the latest effort to reform the SOEs. As a result, though it may take long, eventually investors will be able to trade state shares and other restricted shares in a traditional SOE (Jingu, 2007).

The *Company Law*[10] is the fundamental basis for corporations, corporate governance and the securities market. It has evolved several times by means of amendments in 1999, 2004 and 2006 because its first draft in 1994 mainly was focused on SOEs. Other regulations and rules mostly affecting corporate governance are the *Securities Law*[11] (2006) , the *Code of Corporate Governance for Listed Companies*[12], the *Guidelines of Election and Behaviour of Directors in listed companies*[13] and the Guidelines on the *Establishment of the Independent Director System in Listed Companies*[14]. The frequency of the introduction and revision of regulation over a short timeframe in two decades indicates a speedy improvement. By applying the widely recognised LLSV indicator for shareholder rights protection (LLSV, 1998), Liu (2006) concluded that law enforcement in China is relatively weak.

[10] The Company Law of the People's Republic of China, 2006, http://www.gov.cn/flfg/2005-10/28/content_85478.htm
[11] The Securities Law of the People's Republic of China, 2006, http://www.gov.cn/flfg/2005-10/28/content_85556.htm
[12] The Code of Corporate Governance for Listed Companies, China Securities Regulatory Commission, 2002, http://www.sse.com.cn/lawandrules/regulations/listed/c/c_20120917_49179.shtml
[13] The Guidelines of Election and Behaviour of Directors in listed companies, Shanghai Stock Exchange, 2013, http://www.sse.com.cn/lawandrules/sserules/listing/stock/c/c_20130613_3720551.shtml
[14] The Guidelines on the Establishment of the Independent Director System in Listed Companies, China Securities Regulatory Commission, 2001, http://www.sse.com.cn/lawandrules/regulations/listed/c/c_20120917_49182.shtml

However, as Roe (2002) commented, proper corporate governance depends not only on the laws but also the participation of other institutions. The regulatory authority is one of the most important ones. Shi (2007) summarised that there are three models of securities regulation: the American model, the English model and the hybrid model. The American model employs a series of laws and regulations and the US Securities and Exchanges Commission (SEC) implements them to protect investors. The English model paid much attention to self-regulation by market players and did not rely on a lot of regulations. However, the UK government has strengthened the regulations and their enforcement by using the Financial Services Authority (FSA) which leads to the combination of both, the hybrid model. Shi (2007) commented that many emerging economies such as China try to apply the hybrid model with both law regulation and self-regulation in the securities market. The CSRC is the major administrative agency of the central government to regulate the activities in the securities market. The other important institutions are the stock exchanges organised by membership. Under the securities law, they require self-regulatory autonomy and in theory, the CSRC is supposed to delegate some power to the two stock exchanges. In fact, the government maintains its high centralisation of authority and it is the CSRC not the exchange that has the power to approve new listings and delist companies (Shi, 2007). Besides, the CSRC also appoints and has the power to dismiss the general managers of the two stock exchanges (Liebman and Milhaupt, 2008). The lack of self-regulation causes problems of fraud, poor disclosure and inefficient pricing (Liebman and Milhaupt, 2008). Nonetheless, the two stock exchanges in China continue to expand. While the Shanghai Stock Exchange mainly takes listings of large corporations and traditional SOEs, the Shenzhen Stock Exchange opened the SME board in 2004 and the Growth Enterprises Market (GEM) board in 2009. At the end of 2012, there were a total of 2,494 listed companies valued at 3.7 trillion USD, the second largest in the world only after the US.

Table 6.3.1 below records some important events in Chinese securities market history.

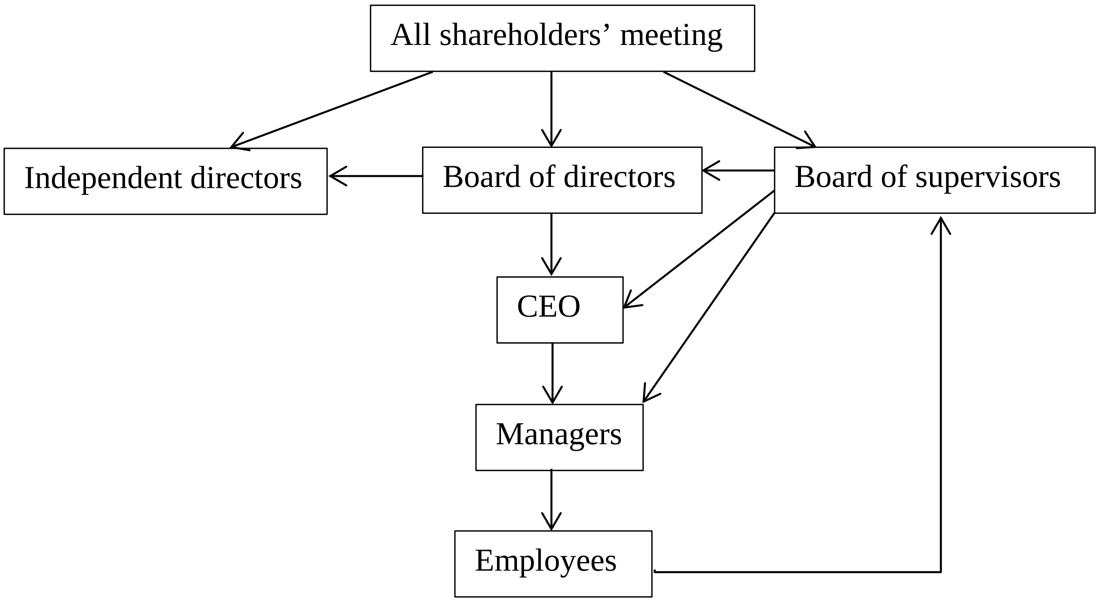
Table 6.3.1 Important events in Chinese securities market history

Year	Event
1978	The Economic Reform began.
1979	The Reform of SOEs began.
1990	Shanghai Stock Exchange was established.
1991	Shenzhen Stock Exchange was established.
1992	The Chinese Securities Regulatory Commission (CSRC) was set up.
1993	The first Company Law was promulgated.
1998	The first Securities Law was promulgated.
2005	The Reform of Non-Tradable Shares began.
2006	The latest Company Law and the latest Securities Law were promulgated.
2007	Stock Indices in Shanghai and Shenzhen reached historic peak.

6.3.2 Board composition

Berle and Means (1932) were amongst the first to empirically examine the separation of ownership from control. There are different types of models of corporate governance. Firstly there is an outsider-based model or one tier model represented by the Anglo-American model (Tan and Wang, 2004) where the governance structure is vertical: the shareholders' meeting, the Board of directors and management. The shareholder's meeting elects the Chair and other directors of the board and the board monitors the management for shareholders. Secondly, there is an insider-based model, represented by the German and Japanese models where a board of supervisors is set up alongside the board of directors (Tan and Wang, 2004). The supervisory board consists of representatives from employees, shareholders and work unions who can be regarded as insiders. They supervise the management, examine accounts and influence the decision making. The Chinese corporate governance model stems from the Anglo-American model and also incorporates the German model by setting up a board of supervisors (Tam, 1999). Therefore it is a two tier model as described in Figure 6.3.1.

Figure 6.3.1 Corporate governance structure in Chinese listed companies



According to the *Company Law* (2006), for common limited liability corporations, there should be 5 to 19 members on the board of directors and at least 3 supervisors. At least one third of directors are independent directors who are appointed by the shareholders' meeting. The *Guidelines on the Establishment of the Independent Director System in Listed Companies* (CSRC, 2001) emphasises that independent directors should be independent from major shareholders, the controller and other listed companies but, interestingly, it also says a person can be an independent director in up to 5 listed companies. This means there are 'professional' independent directors who serve in and are independent from several listed companies at the same time.

Internal governance was criticised by Tan and Wang (2004) in that the Chair of the Board and the CEO are often the same person, and independent directors are not independent enough to protect shareholder's interests. Clark (2006) also has negative comments that the supervisory board is completely useless except in meeting the minimum requirement of regulations. It is understandable that in circumstances where large shareholders exist, usually in SOEs, they can appoint anyone who can protect the interests of large shareholders rather than those of small shareholders.

6.3.3 Ownership structure

One feature of a Chinese listed company is that it can issue several types of shares to investors in terms of their location listing: A shares, B shares and H shares and Overseas shares. A shares are issued in Shanghai and Shenzhen and traded in Chinese currency (CNY). B shares are issued in Shanghai and Shenzhen and traded in foreign currency. H shares are issued in Hong Kong and traded in Hong Kong dollars. Overseas listing may be in NYSE (New York), NASDAQ (New York) and LSE (London). In the early days of the Chinese securities market, most listed companies were SOEs but later the government realised the security market was not efficient as a financing method. In 2005, the CSRC (2005) issued the *Measures for the Administration of the Share trading Reform of Listed Companies*. Since then many shares in SOE have been released to the public but shares of a company's equity can still be divided into tradable shares and restricted shares (non-tradable). Thus the total share capital of a Chinese listed company can be described in Table 6.3.2 and the descriptive data is from the sample of this research.

Table 6.3.2 Share types in Chinese listed companies

All types of shares in total of 2472 listed companies	restricted shares (1808 or 73.1% of listed companies)	state owned shares	481 (19.5%)
		sponsor legal person shares	929 (37.6%)
		private placement of legal person shares	9 (0.4%)
		senior management shares	1232 (49.8%)
		others	654 (26.5%)
	tradable shares (all companies)	A shares	2472 (100%)
		B shares	86 (3.5%)
		H shares	81 (3.3%)
		Overseas shares	2 (0.1%)

The term ‘legal person’ is a well-established concept which can be found in Germany, Italy and the US. By their Civil Laws, it is described as the organisation that has the capacity for civil rights, civil conduct and civil obligations in accordance with the law (Martin, 2003). In many cases, legal persons are state-controlled so Clarke (2006) argued that to some extent many legal person shares could be regarded as state shares. SOEs typically have more responsibilities than maximisation of profits only (Clarke, 2003). Examples of extra responsibilities are maintaining employment levels, absolute control over critical industries such as national security, transportation and energy, and some diplomatic trading agreements.

Xu and Wang (1999) studied the relationship between the performance and corporate governance in Chinese listed companies with specific attention to ownership structure. They found profitability was positively correlated with ownership concentration and legal person shares and they suggested the importance of institutional shareholders and the inefficiency of state ownership.

6.3.4 Management compensation

Shleifer and Vishny (1997) explained that the agency problem in large companies also exists in how to restrict expropriation of minority shareholders by controlling shareholders. In Chinese SOEs, both the Chair and chief manager are appointed by the government and those enterprises are actually places where the government trains their senior governors and promotes government officials (Jingu, 2007). For example, the current vice-premier of China used to be the CEO of the China Construction Bank in the 1990s. Thus, apart from common incentives, people in the top management of SOEs have extra expectations of political rewards. Their jobs are not to maximise profits but correctly implement the intentions of the government. These government representatives are paid according to their ranks (Li *et al*, 2008), but generally they are underpaid. So in Chinese SOEs, it is common for directors and executives to misuse their powers to seek personal gains or even to seize corporate properties (Chen, 2005). For instance, some SOE directors and managers control the power to appoint and dismiss treasurers, and therefore have the means to force treasurers to keep several different accounting books for fraudulent purposes. The irresponsibility of directors and executives has resulted in the insolvency or bankruptcy of many SOEs. A survey (cited in Chen 2005) in 1997 revealed that directors and executives were responsible for more than half of the insolvency or bankruptcy cases in 110 SOEs. Another example is, the former Chair and CEO of Hongta Tobacco Corporation who embezzled millions of US dollar in corporate funds. His lawful yearly salary was only 3,000 USD, just like an ordinary worker, while the corporation's annual income was 2.3 billion USD in 1996 (New York Times, 1998). In other words, his lawful income accounted for only 0.00014% of the corporation's total income. In contrast, in western countries the CEO averagely receives 0.014% of corporate revenue (Core *et al*, 1999) which is one hundred times as that in China. It is essential to improve the compensation mechanism for directors and executives in SOEs. To help attain this objective, innovative compensation mechanisms, such as stock option programs, should be made available to directors and executives in most SOEs (Chen, 2005).

In other companies, it is often found that the bonus system is not clearly defined or not disclosed so the performance bonus may not applicable in practice. The CSRC launched the *Measures for the Administration of Equity Incentive Plans of Listed Companies* in 2006 but it is more like a recommendation for guidance but not a compulsory scheme. Our data shows that only about a quarter of companies have stock option incentive plans and their rules so various that they cannot be used as a measure of compensation. Furthermore, Firth *et al* (2006) find that the sensitivities of pay to performance for CEOs in China are low so the effectiveness of incentive systems could be in question.

Several researchers (Hovey *et al*, 2003; Clarke, 2006; Tam, 2002; Allen *et al*, 2005) have found the problems of corporate governance in China including high concentration ratios, insider trading, collusion, dysfunction of independent directors and supervisors, inadequate legal systems. We still need to bear in mind that China is in the process of transition and its great success in economic development has indicated that those problems are not serious. We have carefully taken them into consideration in selecting corporate governance measures. All governance data collected is valid across the years and changes in regulations such as reform of non-tradable shares are reflected in the values of state shareholding. This study has limited interest in exploring those problems further but prefers to investigate the relationships between corporate governance measures and the probability of financial distress. Understanding certain facts could assist us in interpreting the results.

6.4 Methodology

Studies that have considered corporate governance variables have used different classification algorithms. Platt and Platt (2012) compared means of governance attributes between bankrupt and non-bankrupt companies. Lizal (2002) used a probit model and Polsiri and Sookhanaphibarn (2009) used Neural Networks. The majority (e.g. Lee and Yeh, 2004), not surprisingly, have applied logistic regression models and they worked well in prediction. However, Lee and Yeh (2004) applied a fixed cut-off point of 0.5 to predicted probabilities based on a 2:1 sample, which made their classification problematic.

The DHM introduced by Shumway (2001) has been discussed in Section 5.2.1 and defined in Section 5.3.4. In the studies of corporate governance measures, some researchers have followed this lead, for example Fich and Slezak (2008) and Darrat *et al* (2010). Furthermore, Han (2012) and Parker (2002) have tried the Cox Proportional Hazards Regression. Chan *et al* (2010) compared logit, probit and a survival model and found predictions using Corporate Governance Variables, Executive Compensation Variables and Shumway (2001) Control Variables were the best.

From the literature review, we can see many tests of hypotheses based on corporate governance theories have been inconsistent or even controversial, regarding the issues of whether it is positive or negative and to what degree those corporate governance measures are associated with the probability of financial distress. But overall, some papers (Lee and Yeh, 2004; Fich and Slezak, 2007; Polsiri and

Sookhanaphibarn, 2009; Chan *et al*, 2010) have found predictive accuracy is improved by the incorporation of corporate governance measures. In this research, we mainly focus on predicting the probability of financial distress using new variables. Including as many variables as possible may increase the predictive accuracy because more information is added. It is, however, not practical to do so and we may suffer the problem of overfitting. We want our model to be simple and dedicated by including only the most significant and informative ones. Therefore, although we have a large collection of corporate governance measures, it is impossible that all of them are useful and it is unwise to keep those insignificant ones. We thus select them based on their significance.

6.4.1 Model specification

During the sample period, few listed companies experienced a change from SOE to private or from private to SOE. The dummy of the actual controller of each company remains constant in all periods. All other variables are time varying. Therefore we follow the DHM of Shumway (2001) to incorporate TVCs. The form is as follows:

$$\text{logit}(h_{\text{ST}=1}(t)) = \alpha + \beta_0 h_0(t) + \beta_1 {\mathbf{x}^g_{i,t-2}}^T + \beta_2 {\mathbf{x}^r_{i,t-2}}^T + \beta_3 {\mathbf{x}^m_{i,t-2}}^T \qquad (6.1)$$

Where t is the survival time;

$h_{\text{ST}=1}(t)$ is the probability of being ST in duration time t;

$h_0(t)$ is the hazard in duration time t;

$\mathbf{x}^g_{i,t-2}$ is column vectors of corporate governance variables for company i in duration time t-2;

$\mathbf{x}^r_{i,t-2}$ is a selection of financial ratios of predictive power;

$\mathbf{x}^m_{i,t-2}$ is a selection of macroeconomic factors;

β_0 is the coefficient of the baseline hazard;

$\beta_1, \beta_2, \beta_3$ are vectors of coefficients to be estimated;

α is the constant.

First of all, we include four groups of corporate governance measures (board composition, ownership structure, management compensation and director and manager characteristics) into equation (6.1) but without any other covariates. In this way, significant corporate governance measures are identified and they enter the first model to make predictions (Model 1). The second model uses the financial ratios only (Model 2) and the third model combines both significant corporate governance measures and financial ratios (Model 3). Model 4 then incorporates macroeconomic factors. The predictive accuracy is measured by the H measure, AUR, Gini and KS (Hand, 2009) (defined in Section 3.5). Four groups of results of both in-sample and out-sample predictions are given for comparison (Table 6.4.1).

Table 6.4.1 Model comparison 3

Model	Specification
Model 1	DHM with corporate governance measures only
Model 2	DHM with financial ratios only
Model 3	DHM with governance measures and financial ratios
Model 4	DHM with governance measures, financial ratios and macroeconomic variables.

6.4.2 Sample

Much information about corporate governance was only disclosed after 2001 or 2002. This significantly reduced the sample size of companies and the observation period. Finally, the sample data consists of 2014 companies over an eight year period between 2003 to 2010.

Table 6.4.2 Number of ST in 2003 - 2010

year	ST 0	ST 1	Total	Bad rate
2003	1123	39	1162	3.36%
2004	1189	35	1224	2.86%
2005	1177	26	1203	2.16%
2006	1177	58	1235	4.70%
2007	1234	55	1289	4.27%
2008	1291	22	1313	1.68%
2009	1359	27	1386	1.95%
2010	1370	39	1409	2.77%
Total	9920	301	10221	2.94%

Table 6.4.2 shows the whole sample used in the analysis. There are a total of 301 distressed cases which lie in 10,221 company-years across eight years. It can be noticed that in some years such as 2006 and 2007, more distressed companies are observed (4.7% and 4.27%) but in some years such as 2008 and 2009, a smaller proportion of distressed companies are observed (1.68% and 1.95%). In order to make out-of-time predictions, another two years of ST information has been collected to make use of the data in year 2009 and 2010 because of the two year lag. There were 11 and 22 new ST companies in 2011 and 2012 respectively.

The whole sample of 1,688 companies is divided into two samples in a 2:1 ratio. According to the sampling strategy proposed in Section 3.3, similarly to the last chapter, the whole sample is broken down into the four panel datasets shown in Table 6.4.3. We applied a two-year lag when making predictions in the main models, i.e. it uses covariates from year $t - 2$ to predict whether a company is distressed in year t.

Table 6.4.3 Sample 3

Sample One						Sample Two					
	Year	ST 0	ST 1	Total	Bad rate		Year	ST 0	ST 1	Total	Bad rate
	2003	744	28	772	3.63%		2003	379	11	390	2.82%
	2004	793	21	814	2.58%		2004	396	14	410	3.41%
Panel A	2005	785	18	803	2.24%	Panel B	2005	392	8	400	2.00%
	2006	787	44	831	5.29%		2006	390	14	404	3.47%
	2007	827	33	860	3.84%		2007	407	22	429	5.13%
	2008	866	14	880	1.59%		2008	425	8	433	1.85%
	2009	907	17	924	1.84%		2009	452	10	462	2.16%
	2010	911	26	937	2.77%		2010	459	13	472	2.75%
Panel C	2011	904	7	911	0.77%	Panel D	2011	455	4	459	0.87%
	2012	889	15	904	1.66%		2012	448	7	455	1.54%
	Total	8413	223	8636	2.58%		Total	4203	111	4314	2.57%

The average proportion of bad cases across all years is 2.58% in Sample One and 2.57% in Sample Two (Table 6.4.3), which are very similar. Some variation could be noticed, for example, in 2006 and 2007, just before the financial crisis, there are more ST companies (4.7% and 4.27% compared to a mean of 2.94%) than in other years (Table 6.4.2), while more recently the proportion of distressed companies has been lower than in the early 2000s.

6.4.3 Corporate governance measures

As discussed in the literature review and according to availability of date in the database, corporate governance variables are classified into four groups and explained in Table 6.4.4. Variable abbreviations indicated by ‘d’ are binary dummies.

Table 6.4.4 List of corporate governance measures

Category	Name	Abb.	Definition
Board composition (6)	Board size	Boardsize	number of total directors
	Independent director	IndependentDirector	proportion of independent director in board
	Number of supervisors	Supervisor	number of supervisors
	Number of senior managers	SeniorManager	number of senior managers
	Duality of Chair and CEO	Duality_d	1 if the Chair and CEO is the same person
	Independent director working location	WorkLocation_d	1 if independent directors working office is the same as registered office
Ownership structure (10)	State ownership	StateShares	proportion of state owned shares to total shares
	State control	SOE_d	1 if the ultimate controller is the government
	Board shares	BoardShares	shares held by the board to total shares
	Supervisor shares	SupervisorShares	shares held by the supervision board to total shares
	Top 10 shareholders	Top10Shares	Total shares of largest 10 shareholders to total shares
	Institutional share holding	InstitutionShares	Total shares of institutional shares to total shares
	Average share holding	AverageShares	Average shareholding to total shares
	Listing somewhere else	OtherListing_d	1 if it issues B, H or overseas shares
	Share capital change	CapitalChange_d	1 if it changes from previous year
	Connected top 10 shareholders	ConnectedShareholder_d	1 if any two top 10 shareholders are related
Management compensation (5)	Salary of senior management	ManagementSalary	salary of directors, supervisors and senior managers to total salary cost
	Salary of top 3 directors	DirectorSalary	salary of top 3 directors to total salary cost
	Salary of top 3 independent directors	IndependentDirectorSalary	salary of top 3 independent directors to total salary cost
	Salary of top 3 senior managers	SeniorSalary	salary of top 3 senior managers to total salary cost
	Number of non-paid senior staff	NonpaidSeniorStaff	number of non-paid directors, supervisors and senior managers

Table continued

Director and manager characteristics (14)	Chair age	ChairAge	age in the year
	Chair gender	ChairGender_d	1 if it is female
	Chair education	ChairCollege_d ChairUndergraduate_d ChairMasters_d ChairDoctorate_d	4 dummies (1 for college level or under, 0 otherwise; 1 for undergraduate, 0 otherwise; 1 for master, 0 otherwise; 1 for doctorate, 0 otherwise),
	Chair professional qualification	ChairQualification_d	1 if it has professional qualification
	Chair nationality	ChairNationality_d	1 if it is not Chinese
	Chair get paid	ChairPaid_d	1 if it is get paid
	Chair concurrent post	ChairConpost_d	1 if it has another position in other companies
	CEO age	CEOAge	age in the year
	CEO gender	CEOGender_d	1 if it is female
	CEO education	CEOCollege_d CEOUndergraduate_d CEOMasters_d CEODoctorate_d	4 dummies (1 for college level or under, 0 otherwise; 1 for undergraduate, 0 otherwise; 1 for master, 0 otherwise; 1 for doctorate, 0 otherwise)
	CEO professional qualification	CEOQualification_d	1 if it has professional qualification
	CEO nationality	CEONationality_d	1 if it is not Chinese
	CEO get paid	CEOPaid_d	1 if it is get paid
	CEO concurrent post	CEOConpost_d	1 if it has another position in other companies

Lee and Yen (2004) discussed the issue of ultimate control which is very common in the emerging markets where highly concentrated shares are held by family or the state. They defined the ultimate controller as the largest shareholder that controls at least 20% of voting rights. Claessens *et al* (1999) argued that the controlling shareholder needs to be considered in bankruptcy prediction models. In China, due to the strong background of SOEs, one may find that the government remains the controlling power of SOEs even though the share-holding by the government does not place it in a dominant position. This leads to the concept of the Ultimate Controller in Chinese listed companies. Its definition can be found in CSRC (2008). An individual or organisation shall be considered to have ultimate control of a listed company in any situation below:

- if the shareholder has over 50% shares of the listed company;
- if it has over 30% of voting rights of the listed company;

- if it is able to decide the election of more than half of the members of the board of directors by means of exercising its voting rights;
- if its voting rights can have influential impact on organisational decisions;
- in other circumstances determined by the CSRC.

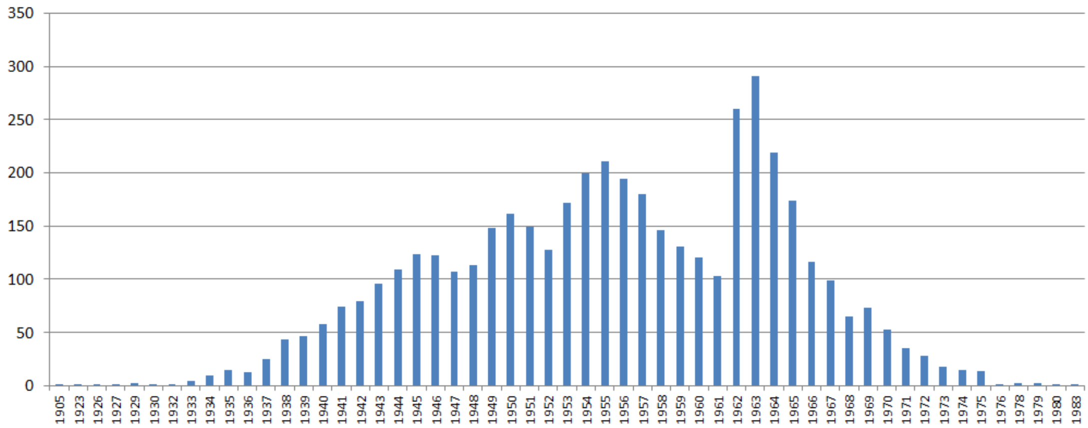
Therefore, the ultimate controller is an important variable to denote the nature of a company, and it is available in the database. It indicates whether a company is a SOE.

There is a variable in ownership structure to denote the connection between large shareholders. According to Platt and Platt (2012), interlinked directorship provides benefits for the company.

Whilst some papers (Fich and Slezak, 2008; Platt and Platt, 2012) are interested in the characteristics of the CEO who is the highest administrator in charge of the company, this research takes into account characteristics of both the Chair and the CEO. Generally the CEO's power is authorised by the board and he or she is responsible for the overall management, decision making, execution and the daily operation of the company. Therefore, the personality and characteristics of the CEO will be reflected in the development of the business. This is why the CEO is more important to the performance of a company than other directors. In the situation that the Chair of the board has control of the company and is more involved in the management and decision making, the Chair will have more influence on the performance. This is the case in many Chinese companies where the founders have made major contributions to the company's success during the development of the Chinese economy and they would like to have control of the companies created by themselves. In these cases, their influence and their characteristics should not be ignored.

Personal information concerning both the Chair and the CEO for each company is recorded in the database including four types of personal demographic information, age, gender, nationality, and education and another three types of information regarding their professions: whether they have professional qualifications, whether they get paid by the company and whether they possess another position in any other organisation.

Figure 6.4.1 Distribution of the year of birth



Preliminary analysis of over 4,500 individual chairs and CEOs indicated that 95.9% of the Chairs and the CEOs are males, and females only account for 4.1% of the total. To calculate their ages, their real year of birth is used. We remark on two points relating to age in the bar chart (Figure 6.4.1). The first is that the oldest Chairman was born in 1905. The second is that there is a big dip in relative frequency during years from 1958 to 1961. This was the result of the Three Years of Great Chinese Famine caused by political mistakes and natural disasters. Over 15 million deaths were recorded during this period according to government statistics (Grada, 2010), not to mention new births.

The distribution of director nationalities shows that there are 97.9% Chinese, 0.4% Taiwanese, 0.3% Hong Kong people, and the others are from countries such as US, UK, and Canada. Therefore, we included a dummy variable to indicate nationality as 1 if the person was not Chinese and 0 if they were not.

For education level, the original data is very detailed. The lowest to highest is represented by middle school, college, undergraduate degree, master degree and doctorate. College educated people (15%), undergraduates (36.2%) and masters (40.1%) are the largest three groups. Four dummies are used to denote whether the director has college or below, undergraduate level, master level and doctorate level education. The reference category is other types of education and unknown education.

6.4.4 Financial ratios and macroeconomic variables

The argument of the selection of financial ratios and the duration time remains the same as in Section 5.5.3. Six ratios selected from each group in Table 3.4.1 are Return on Assets, Current liabilities / Total Liabilities, Tangible Assets / Total Assets, Cash Flow from Operating / Total Liabilities, Receivables Turnover and Total Assets Growth. The duration is the time since listing at the exchange and its function is the natural logarithm of the duration.

There is a series of macroeconomic indicators available for analysis and they are typical time varying covariates. However unlike firm-specific covariates, macroeconomic factors are variant in period but not in case. So for all companies existing in a period, we assume macroeconomic conditions have the same impact on them. As previously discussed, some researchers (*e.g.* Nam *et al*, 2008) use macroeconomic changes as the baseline hazard and others (*e.g.* Carling *et al*, 2007) argue that macroeconomic conditions have a lagged impact on the real economy. With reference to literature and professional opinions, we include four macroeconomic variables in the model. They are GDP growth, unemployment, the inflation rate and interest rates.

Gross Domestic Product (GDP) is one of the most important indicators which reflect a country's economic status. It is defined as the market value of all officially recognised final goods and services produced within a country. It generally indicates how wealthy a country is. China has overtaken Japan to become the second largest economy in the world, only after the US, since the end of 2010 (BBC News, 2011). That is the achievement of China's economic reform which contributes to a continuous growth of over 9% per annum (See Table 6.4.5). GDP growth is simply measured by GDP change rate over time.

In calculating GDP growth, using real values of the current year may cause distortion because of the inflation on the price of goods and services. The inflation rate is then included in this research. Essentially, inflation is another important indictor to describe consumer prices, where a positive inflation rate indicates a reduction in the purchasing power per unit of money. Usually a fast growing economy has a problem of inflation while most economists prefer a low and steady rate of inflation.

The unemployment rate is a key indicator to influence domestic consumption of a country. A high unemployment rate indicates that it is difficult to find a job and people may have limited income to support consumption, which brings a negative impact on businesses.

Table 6.4.5 List of macroeconomic factors

	GDP growth (%)	Inflation, consumer prices (%)	Unemployment (% of total labour force)	Lending interest rate (%)
2003	10	1.16	4.3	5.31
2004	10.1	3.88	4.2	5.58
2005	11.3	1.82	4.2	5.58
2006	12.7	1.46	4.1	6.12
2007	14.2	4.75	4	7.47
2008	9.6	5.86	4.2*	5.31
2009	9.2	-0.70	4.3*	5.31
2010	10.4	3.31	4.1	5.81

The interest rates basically are the prices for borrowing money. As most companies have liabilities and loans, the interest rates will affect the financial costs of a company. In this research, the base lending interest rate (one year maturity) is used. Since the interest rate may change in a year, it is aggregated weighted interest rates that are employed in analysis.

All these four macroeconomic indicators are annualised in percentage terms. The data is extracted from the database of the World Bank, World Databank (Table 6.4.5[15]).

6.4.5 Data description

Table 6.4.6 Description of corporate governance measures 1

	Variable	N	Mean	Std. Dev.	Min	Max
Board composition	Boardsize	10221	9.46	2	3	19
	IndependentDirector	10221	0.35	0.05	0	0.8
	Supervisor	10221	4.08	1.37	0	13
	SeniorManager	10221	6.29	2.37	1	45
Ownership structure	StateShares	10221	0.25	0.25	0	0.86
	BoardShares	10221	0.13	0.11	0.03	0.75
	SupervisorShares	10221	0.0014	0.01	0	0.27
	Top10Shares	10221	0.58	0.15	0.07	0.99
	InstitutionShares	10221	0.14	0.18	0	0.93
	AverageShares	10221	0.0004	0.0004	0	0.005
Management compensation	ManagementSalary	10221	0.5	0.11	0.03	0.85
	DirectorSalary	10221	0.17	0.07	0	0.51
	IndependentDirectorSalary	10221	0.05	0.04	0	0.33
	SeniorSalary	10221	0.2	0.07	0	0.65
	NonpaidSeniorStaff	10221	4.29	3.17	0	19
Director and manager characteristic	ChairAge	10221	50.08	7.28	28	84
	CEOAge	10221	46.27	6.47	24	75

For descriptive statistics, variables are observed separately according to their levels of measurement. For ratio variables in corporate governance measures (Table 6.4.6), results show that there are on average 9.46 directors on the board, among which 3.31 (or 35%) are independent directors. And there are on average 4.08 supervisors and 6.29 senior managers in each listed company. The government holds about one quarter of the total shares which means the influence of government on Chinese listed companies could not be ignored. Supervisors own relatively small proportions

[15] The unemployment rates in 2008 and 2009 marked with * in the table are missing but replaced by the data from the National Bureau of Statistics of China.

of the shares (0.14%) because they consist of shareholder and employee representatives. On average, the top 10 shareholders own over half of total shares (58%) and so they are often the block holders who make important decisions. Institutional shareholders hold a considerably large part of all shares and in some cases they can own up to 93% of total shares.

Table 6.4.7 Description of corporate governance measures 2

		N	0	1	0 (% to total)	1 (% to total)
Board composition	Duality_d	10221	8835	1386	86.4	13.6
	WorkLocation_d	10221	6390	3831	62.5	37.5
Ownership structure	SOE_d	10221	3226	6995	31.6	68.4
	OtherListing_d	10221	9368	853	91.7	8.3
	CapitalChange_d	10221	3731	6490	36.5	63.5
	ConnectedShareholder_d	10221	6058	4163	59.3	40.7
Director and manager characteristic	ChairGender	10221	9833	388	96.2	3.8
	ChairCollege_d	10221	8937	1284	87.4	12.6
	ChairUndergraduate_d	10221	7470	2751	73.1	26.9
	ChairMasters_d	10221	6936	3285	67.9	32.1
	ChairDoctorate_d	10221	9673	548	94.6	5.4
	ChairQualification_d	10221	4374	5847	42.8	57.2
	ChairNationality_d	10221	10130	91	99.1	0.9
	ChairPaid_d	10221	3487	6734	34.1	65.9
	ChairConpost_d	10221	3951	6270	38.7	61.3
	CEOGender_d	10221	9757	464	95.5	4.5
	CEOCollege_d	10221	9036	1185	88.4	11.6
	CEOUndergraduate_d	10221	7367	2854	72.1	27.9
	CEOMasters_d	10221	6922	3299	67.7	32.3
	CEODoctorate_d	10221	9830	391	96.2	3.8
	CEOQualification_d	10221	4750	5471	46.5	53.5
	CEONationality_d	10221	10120	101	99	1
	CEOPaid_d	10221	321	9900	3.1	96.9
	CEOConpost_d	10221	6589	3632	64.5	35.5

For the categorical variables relating to corporate governance measures (Table 6.4.7), we present only their frequencies and percentages. It should be noted that that the incidence in Table 6.4.7 is recorded according to the company year but not the company case, but it is still surprising to find that in over two thirds of company years, companies are state controlled. In 40.7% of companies, some of their largest 10 shareholders are connected, which means they share similar benefits and goals in management.

Financial ratios and macroeconomic factors (Table 6.4.8) are transformed into percentages for ease of interpretation. Generally, if only looking at the means, Chinese listed companies have been getting positive returns and growing in the past few years. The Chinese economy has been growing comparatively quickly for decades while keeping inflation and unemployment rates at a relatively low level.

Table 6.4.8 Description of financial ratios and macroeconomic factors

	Variable	N	Mean	SD	Min	Max
Financial ratios	Return on Assets	10221	4.98	7.01	-18.94	28.64
	tangible Assets / Total Assets	10221	39.65	20.00	-35.64	96.53
	Current Liabilities / Total Liabilities	10221	79.81	13.52	28.29	100.00
	Net cash flow from operation / Total Liabilities	10221	9.64	24.18	-106.98	101.45
	Receivables Turnover	10221	57.14	52.18	-8.42	244.66
	Total Assets Growth	10221	15.45	31.00	-93.33	126.21
Macroeconomic factors	GDP	10221	10.92	1.61	9.20	14.20
	Inflation	10221	2.70	2.04	-0.70	5.86
	Unemployment	10221	4.17	0.10	4.00	4.30
	Interest	10221	5.81	0.68	5.31	7.47

Before moving to further analysis, the correlation coefficient matrix between all covariates has been calculated. High correlation or collinearity between explanatory variables could lead to serious problems in testing the significance of covariates. For example, it may cause the performance of variables to be unstable, reduce the significance of correlated variables, and sometimes reverse the sign of coefficients (Farrar and Glauber, 1967). By checking the correlation matrix, highly correlated variables can be deleted in a pre-analysis, but whether collinearity is a problem is subjective and whether one of the correlated variables should be omitted would really depend on the theoretical framework of specific research (Farrar and Glauber, 1967). In this study, we focus on corporate governance measures so they are carefully examined. The matrix of current variables shows that there is not any pair of variables with high correlation over 0.7, but between corporate governance measures, state ownership and dummy of state control is highly correlated (0.64), and professional qualifications and the concurrent position of the Chair and CEO are correlated, 0.53 and 0.69 respectively. This may be because in some cases, the Chair and the CEO is the same person. GDP growth, inflation and interest rates are often highly correlated in economic models. We would like to keep them all because there are no better indicators. Between corporate governance and financial ratios, all VIFs are smaller than 3 and the average VIF is 1.57. The only problem is with macroeconomic variables which have large VIF values and low tolerance, but as explained, they are still retained but will be carefully considered in analysis.

6.5 Results

6.5.1 Model 1

As there is no stepwise method for a panel regression, corporate governance measures are selected manually based on their significance. Firstly, measures of different aspects of corporate governance were entered into separate models. The tables show the results of DHMs.

Board composition

Table 6.5.1 Variable selection of board composition

ST	Coef.	Std. Err.	z	P>z
ln(duration)	1.296**	0.287	4.52	0.000
Boardsize	-0.092*	0.051	-1.78	0.075
IndependentDirector	-2.466	1.574	-1.57	0.117
Supervisor	-0.093*	0.072	-1.3	0.195
SeniorManager	-0.117**	0.044	-2.67	0.008
Duality_d	-0.090	0.258	-0.35	0.728
WorkLocation_d	-0.770**	0.199	-3.88	0.000
Constant	-3.685**	1.121	-3.29	0.001

Apart from the duration time and constant term, significant variables in board composition are board size, the number of senior managers and whether independent directors work at the registered office of the company. Generally, the larger the board and the more senior managers in a company, the lower the risk it will experience financial difficulty in the following years. If the independent directors work location is in the company, there is evidence that they will perform and reduce the risk of wrong managerial decisions. In other words, if independent directors work remotely, they do not really fulfil their duties. This finding is similar to that in Wilson *et al* (2013) who found that if directors live close to companies, they can better monitor their management.

The duality of the Chair and CEO and the proportion of independent directors on the board do not present any significance to the probability of financial distress.

Ownership structure

Table 6.5.2 Variable selection of ownership structure

ST	Coef.	Std. Err.	z	P>z
ln(duration)	1.409**	0.353	3.99	0.000
StateShares	-0.312	0.524	-0.59	0.552
SOE_d	-0.704**	0.234	-3	0.003
BoardShares	-1.993	2.252	-0.88	0.376
SupervisorShares	-1387.530	981.066	-1.41	0.157
Top10Shares	-0.076	0.730	-0.1	0.917
InstitutionShares	-8.139**	1.658	-4.91	0.000
AverageShares	75.538	269.263	0.28	0.779
OtherListing_d	-0.576*	0.340	-1.69	0.090
CapitalChange_d	-0.375**	0.178	-2.11	0.035
ConnectedShareholder_d	-0.222	0.189	-1.17	0.241
Constant	-5.554**	1.140	-4.87	0.000

For ownership structure variables, if the company is state controlled, it has a lower chance of becoming distressed. This may be taken as evidence that the government has provided abundant resource to support the company. The possible advantages have been discussed in previous sections. The results also suggest that when the institutional investor has a stake in a listed company, it has less chance of becoming distressed. The institutional investors have expertise and skills in detecting companies worthy of investment. If the share capital structure is different from a previous year, despite lack of clarity about the reasons for any change, the company has lower risk of financial distress. The variable of listing at any other exchange implies that when companies are regulated and invested by different backgrounds of people, they are less likely to be distressed.

Management compensation

Table 6.5.3 Variable selection of management compensation

ST	Coef.	Std. Err.	z	P>z
ln(duration)	1.316**	0.290	4.54	0.000
ManagementSalary	0.871	0.837	1.04	0.298
DirectorSalary	-0.565	1.247	-0.45	0.650
IndependentDirectorSalary	6.567**	1.910	3.44	0.001
SeniorSalary	1.150	1.267	0.91	0.364
NonpaidSeniorStaff	-0.074**	0.030	-2.44	0.015
Constant	-7.414**	0.848	-8.74	0.000

Among the variables of management compensation, if the salary cost of an independent director is large, the company has a high risk of financial distress. There may be two reasons for this. On one hand, the salary cost for an independent director places a burden on a company’s financial condition. On the other hand, more importantly, when an independent director is paid a lot of money, he or she tends not to speak negatively or disagree with the management. When there are more unpaid senior staff, it is a possible indicator that the company’s future is promising. Unpaid senior staff who may be the founders of the company can then be rewarded by the growth of the company or by share ownership.

Director characteristics

Table 6.5.4 Variable selection of director and manager characteristics

ST	Coef.	Std. Err.	z	P>z
ln(duration)	1.427**	0.294	4.86	0.000
ChairGender_d	-0.788	0.596	-1.32	0.186
ChairAge	-0.041**	0.012	-3.27	0.001
ChairCollege_d	0.143	0.454	0.32	0.753
ChairUndergraduate_d	0.451	0.346	1.3	0.192
ChairMasters_d	0.083	0.356	0.23	0.815
ChairDoctorate_d	0.277	0.511	0.54	0.588
ChairQualification_d	-0.434	0.278	-1.56	0.118
ChairNationality_d	-0.268	1.088	-0.25	0.806
ChairPaid_d	0.245	0.199	1.23	0.218
ChairConpost_d	-0.147	0.204	-0.72	0.469
CEOGender_d	-0.023	0.405	-0.06	0.955
CEOAge	-0.019	0.014	-1.34	0.181
CEOCollege_d	0.326	0.400	0.81	0.416
CEOUndergraduate_d	-0.071	0.341	-0.21	0.835
CEOMasters_d	-0.669*	0.372	-1.8	0.072
CEODoctorate_d	-0.097	0.583	-0.17	0.868
CEOQualification_d	0.110	0.273	0.4	0.687
CEONationality_d	1.262*	0.669	1.89	0.059
CEOPaid_d	-0.172	0.479	-0.36	0.720
CEOConpost_d	-0.685**	0.251	-2.73	0.006
Constant	-3.888**	1.152	-3.38	0.001

Among those seven characteristics for both the Chair and the CEO, only four of them are significant at 10% level of significance. They are: the Chair's age, the CEO's education if he or she has a master degree, the CEO's nationality and whether the CEO has another position in other organisations. As the Chair grows older, his or her experience increases and they become more cautious in doing business than young entrepreneurs. When the CEO has a Master's degree, our data shows one third of them hold an MBA degree (Master for Business Administration) which is helpful in chief executive jobs. Compared to the Chair, only a quarter of them possess MBA degrees out of all master degrees. When the CEO is not Chinese, they may have difficulties in adapting to the business culture in China. When the CEO has another position in other organisations, they possess more social relationships and resources. In a country like China where social relationships (*guanxi)* are important in doing business (Xin and Pearce, 1996), such concurrent posts provide extra benefits for the listed companies.

All significant variables above the 10% significance level enter the next step of regression and those remaining significant at 5% significance level compose Model 1. This procedure can keep the most explanatory variables in the model.

ST	Coef.	Std. Err.	z	P>z
ln(duration)	1.481**	0.312	4.75	0.000
Boardsize	-0.054	0.050	-1.08	0.282
Supervisor	-0.024	0.075	-0.32	0.749
SeniorManager	-0.072	0.046	-1.59	0.111
WorkLocation_d	-0.593**	0.203	-2.93	0.003
SOE_d	-0.451**	0.195	-2.31	0.021
InstitutionShares	-8.368**	1.751	-4.78	0.000
Otherlisting_d	-0.128	0.347	-0.37	0.712
CapitalChange_d	-0.556	0.368	-1.51	0.103
IndependentDirectorSalary	2.226**	0.648	3.43	0.001
NonpaidSeniorStaff	-0.031	0.031	-1.01	0.314
ChairAge	-0.034**	0.012	-2.86	0.004
CEOMasters_d	-0.597**	0.253	-2.35	0.019
CEONationality_d	0.942	0.643	1.47	0.143
CEOConpost_d	-0.818**	0.231	-3.54	0.000
Constant	-3.951**	1.081	-2.85	0.004

It can be noted that the board size, the number of senior managers, indicator if the share capital is changed, and the number of non-paid senior staff become insignificant when putting them together into one model. Finally, Model 1 consists of seven corporate governance measures, one from the board composition, two from the ownership structure, one from the management compensation, three from the director’s characteristics (Table 6.5.5). With the exception of the salary cost of the top 3 independent variables which increase the probability of financial distress when it goes up, all the rest will reduce the probability when they are of specific quality.

Table 6.5.5 Results of Model 1

ST	Coef.	Std. Err.	z	P>z
ln(duration)	1.670**	0.304	5.49	0.000
WorkLocation_d	-0.726**	0.219	-3.32	0.001
SOE_d	-0.969**	0.181	-5.35	0.002
InstitutionShares	-12.916**	2.152	-6.00	0.000
IndependentDirectorSalary	3.866**	0.601	6.42	0.000
ChairAge	-0.064**	0.012	-5.32	0.000
CEOMasters_d	-0.827**	0.274	-3.02	0.003
CEOConpost_d	-1.119 **	0.252	-4.45	0.000
Constant	-3.277**	0.757	-4.33	0.000

Logistic Regression Log likelihood = -542.607
Number of obs = 4635 LR chi2(8) = 245.89
Prob > chi2 = 0 Pseudo R2 = 0.185

6.5.2 Model 2

Table 6.5.6 Results of Model 2

ST	Coef.	Std. Err.	z	P>z
ln(duration)	0.0466*	0.285	1.62	0.87
Return on Assets	-0.069**	0.016	-4.28	0.000
tangible Assets / Total Assets	-0.028**	0.005	-5.85	0.000
Current Liabilities / Total Liabilities	0.078**	0.012	6.72	0.000
Net cash flow from operation / Total Liabilities	-0.025**	0.005	-5.22	0.000
Receivables Turnover	0.007**	0.001	4.67	0.000
Total Assets Growth	-0.026**	0.005	-4.68	0.000
Constant	-8.938**	1.170	-7.64	0.000

Logistic Regression Log likelihood = -505.959
Number of obs = 4635 LR chi2(7) = 319.19
Prob > chi2 = 0 Pseudo R2 = 0.240

In Model 2 (Table 6.5.6), all six financial ratios are forced into the model and they all appear to be significant in making a prediction about whether the company will have financial difficulty. Return on assets, tangible assets / total assets, net cash flow from operation / total liabilities and total assets growth, are negatively associated with the probability of financial distress. Current liabilities / total liabilities and receivables turnover, are positively associated with the probability of financial distress.

6.5.3 Model 3

In Model 3, all significant corporate governance measures and financial ratios are combined and all of them remain significant with the same signs as in Model 1 and Model 2. Details of results are presented in Table 6.5.7.

Table 6.5.7 Results of Model 3

ST	Coef.	Std. Err.	z	P>z
ln(duration)	1.048**	0.347	3.02	0.003
WorkLocation_d	-0.718**	0.233	-3.08	0.002
SOE_d	-0.877**	0.195	-4.50	0.000
InstitutionShares	-6.782**	2.010	-3.38	0.001
IndependentDirectorSalary	3.649**	0.660	5.53	0.000
ChairAge	-0.061**	0.013	-4.61	0.000
CEOMasters_d	-0.836**	0.295	-2.83	0.005
CEOConpost_d	-0.881**	0.270	-3.26	0.001
Return on Assets	-0.065**	0.017	-3.70	0.000
tangible Assets / Total Assets	-0.028**	0.005	-5.70	0.000
Current Liabilities / Total Liabilities	0.069**	0.011	5.96	0.000
Net cash flow from operation / Total Liabilities	-0.020**	0.005	-3.86	0.000
Receivables Turnover	0.006**	0.001	3.69	0.000
Total Assets Growth	-0.022**	0.005	-4.04	0.000
Constant	-7.510**	1.340	-5.61	0.000

Logistic Regression	Log likelihood = -438.580
Number of obs = 4635	LR chi2(14) = 453.95
Prob > chi2 = 0	Pseudo R2 = 0.341

6.5.4 Model 4

In Model 4, macroeconomic factors are added into Model 3. Finally it was found that the consumer price inflation rate is significant in the model. Accordingly coefficients of other covariates are slightly changed.

Table 6.5.8 Results of Model 4

ST	Coef.	Std. Err.	z	P>z
ln(duration)	0.482	0.340	1.20	0.228
WorkLocation_d	-0.649**	0.235	-2.76	0.006
SOE_d	-0.877**	0.196	-4.48	0.000
InstitutionShares	-7.861**	2.104	-3.74	0.000
IndependentDirectorSalary	3.915**	0.676	5.79	0.000
ChairAge	-0.061**	0.013	-4.58	0.000
CEOMasters_d	-0.863**	0.296	-2.91	0.004
CEOConpost_d	-0.802**	0.272	-2.95	0.003
Return on Assets	-0.066**	0.017	-3.76	0.000
tangible Assets / Total Assets	-0.029**	0.005	-5.79	0.000
Current Liabilities / Total Liabilities	0.069**	0.011	5.93	0.000
Net cash flow from operation / Total Liabilities	-0.019**	0.005	-3.81	0.000
Receivables Turnover	0.006**	0.001	3.73	0.000
Total Assets Growth	-0.022**	0.005	-4.09	0.000
Inflation	0.197**	0.070	2.81	0.005
Constant	-7.341**	1.345	-5.46	0.000

Logistic Regression   Log likelihood = -434.551
Number of obs = 4635   LR chi2(15) = 462.01
Prob > chi2 = 0   Pseudo R2 = 0.3471

6.6 Predictive accuracy

Table 6.6.1 presents the results of predictive accuracy which is measured by Hand’s H measure, AUR, Gini and KS. Four panels were built where Panel A is the estimation of parameters. Generally in-sample prediction produces the best results among out-of-sample or out-of-time predictions and the within time out-of-sample prediction comes the next. Understandably, results in Panel D is underperformed because neither the sample nor the time is attached to the model training.

Table 6.6.1 Predictive accuracy of Model 1-4

	Panel A (training)				Panel B (within time out-of-sample)			
	H	AUC	Gini	KS	H	AUC	Gini	KS
Model 1	0.064	0.829	0.658	0.523	0.024	0.811	0.622	0.498
Model 2	0.082	0.871	0.743	0.591	0.056	0.833	0.666	0.545
Model 3	0.158	0.915	0.831	**0.687**	0.094	0.902	0.803	**0.671**
Model 4	**0.170**	**0.916**	**0.833**	0.686	**0.110**	**0.903**	**0.805**	0.666
	Panel C (within sample out-of-time)				Panel D (out-of-time out-of-sample)			
	H	AUC	Gini	KS	H	AUC	Gini	KS
Model 1	0.137	0.694	0.389	0.301	0.034	0.768	0.536	0.512
Model 2	0.065	0.826	0.651	0.528	0.002	0.785	0.570	0.516
Model 3	0.105	0.868	0.736	0.568	0.019	0.852	0.704	0.628
Model 4	**0.169**	**0.876**	**0.752**	**0.586**	**0.111**	**0.860**	**0.721**	**0.688**

The highest value for each statistic is in bold.

The performance of Model 1 with only governance measures is acceptable in the in-time validation (Gini=0.622). However it declines dramatically when it is applied to the other period. Its Gini coefficients are only 0.389 and 0.536 in Panel C and Panel D respectively, which means using only corporate governance measures to predict financial distress is not practical. When combined with financial ratios in Model 3, the predictive accuracy is much improved. The larger KS values indicate the probabilities of the Good and Bad are enhanced as the absolute distance between them is wider.

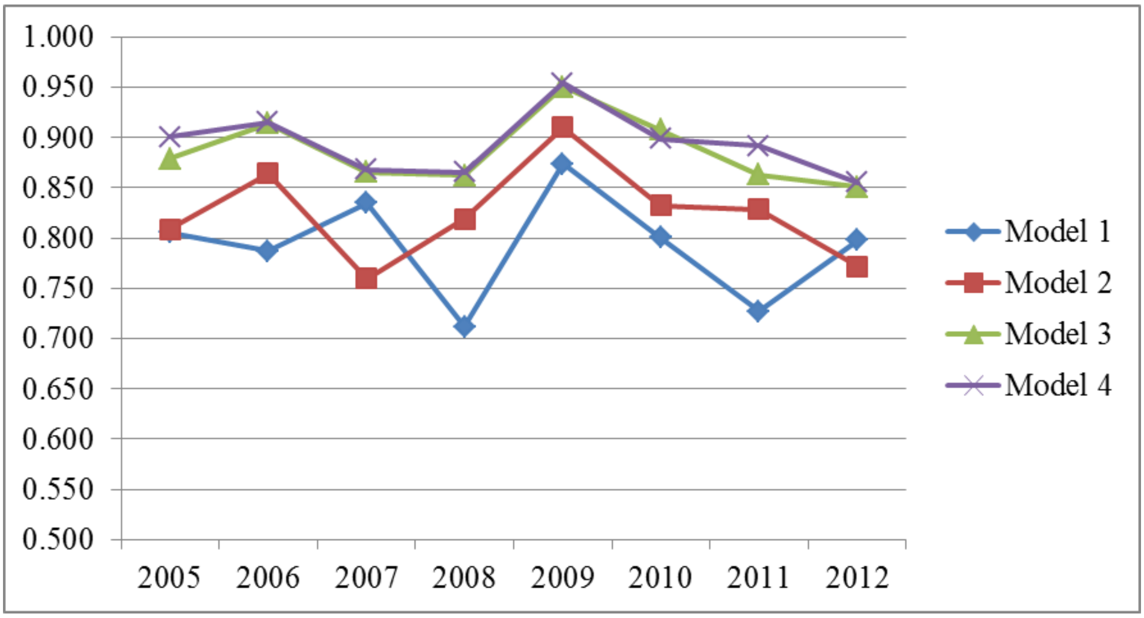
The best performance comes from Model 4 when corporate governance measures, financial ratios and macroeconomic factors are all used in the modelling. If the differences in the within-time predictions are not that clear (0.833 to 0.831 and 0.805 to 0.803), in the out-of-time predictions, macroeconomic factors make a significant contribution to the predictive accuracy (0.752 to 0.736 and 0.721 to 0.704). The economic condition does have great impact on corporate financial performance.

In the further analysis when looking at the predictive accuracy in separated years, we take AUC as an example (Table 6.6.2). Figure 6.6.1 may present the contrast clearly. The predictive accuracy of Model 1 is poorer than that of Model 2 except in 2007. The difference between Model 3 and Model 4 is very close because only one macroeconomic factor (inflation) is added to Model 4.

Table 6.6.2 Model performance (AUC) in separated years

Year	2005	2006	2007	2008	2009	2010	2011	2012
Model 1	0.806	0.787	0.835	0.712	0.874	0.800	0.727	0.798
Model 2	0.809	0.864	0.760	0.819	0.910	0.833	0.829	0.772
Model 3	0.879	0.914	0.865	0.862	0.950	0.908	0.863	0.851
Model 4	0.901	0.915	0.868	0.866	0.954	0.899	0.891	0.856

Figure 6.6.1 Model performance (AUC) in separated years



6.7 Conclusion

Corporate governance has attracted wide academic attention in many subjects in recent 20 years and some studies have found that certain aspects of the corporate governance of a company were linked to corporate performance or financial conditions. However, such studies cannot completely be regarded as applicable to corporate credit modelling because most of them looked into their relationships and testing hypotheses. A good credit scoring model should also apply them to making predictions in advance on the probability of becoming distressed.

This research is the first to apply a large selection of corporate governance measures in predicting corporate credit risk by using a large panel dataset of 8 years for 1688 companies. The data of Chinese listed companies has provided an opportunity to look in more detail at the ownership structure of SOEs which are common in China and the influence on other corporate governance practices. A discrete time hazard methodology is applied to investigate the question. The discrete time hazard model not only gives dynamic results which are more robust and reliable but also is able to take into account time-varying covariates such as macroeconomic factors. Four models of different groups of covariates are compared.

In total, thirty-five corporate governance measures were extracted from the database. They are grouped into four categories: board composition, ownership structure, management compensation and director and manager characteristics. For board composition, a large board, more supervisors and senior managers will lead to a low chance of having financial difficulty, but only the independent director’s working location is significant in prediction. This is because an independent director could be hired by many companies, and only when he does work within the company and carries out his duties can he provide suggestions and improve performance.

For ownership structure, the indicator of SOEs, the indicator of share capital change and institutional ownership are found to be strongly significant. Their signs are all negative which means SOEs are not easily distressed. When active investors such as institutional shareholders have the ability to detect potential risks so when to the companies in which they have large investment, there is lower risks of financial distress. For management compensation, when independent directors are paid more, the company can easily go into distress because the independent directors are reluctant to comment negatively on their employers. When there are more senior staff including directors, supervisors and managers who are not paid, the company has less probability of distress. As for director and manager characteristics: the Chair's age, the CEO's Masters education and positions in other organisations could help the company reduce the probability of distress. Six financial ratios are selected in prediction and model comparison. In macroeconomic factors, only the inflation rate has been found to be positively correlated with the distress risk.

In terms of predictive accuracy, corporate governance measures alone have limited capacity in detecting financial distress no matter whether by H, AUROC, Gini and KS. Financial ratios can do relatively well in predicting alone. However, when combining the two together, the predictive accuracy is significantly improved. The best prediction model comes from the combination of corporate governance measures, financial ratios and a macroeconomic factor (inflation). It outperforms the other three models in both out-of-sample and out-of-time predictions. In the performance separated by individual years, the ranking of models in most years remains the same.

There are some other points which could be further investigated in the scope of corporate governance in predicting corporate credit risk, such as shareholders' meetings, accountancy and audit opinions, and the director's previous experience. This is further research for the future.

Chapter Seven
Conclusions

7.1 Summary

While accounting and market related information has dominated corporate credit models for decades, researchers are still trying to find some other explanatory variables to predict bankruptcy or financial distress to improve the classification accuracy or act as the main variables when financial information is not available. This thesis mainly investigates the use of corporate efficiency and corporate governance measures in standard statistical credit models including cross-sectional and discrete hazard models.

In Chapter Two, various literature regarding the algorithms and variables in credit models was reviewed. The definition of ‘default’ in corporate credit models is rather a broad concept and in many papers, different definitions have been used. This research focuses on financial distress which is common in business. Generally the development of classification algorithms started from discriminant analysis, and then regression models dominated. In recent years, artificial intelligence models have become popular and other classification methods such as mathematical programming have also been used. Each has its own advantages and disadvantages and usually hybrid models, which can make use of their strengths and eliminate their weaknesses, are preferred. The models with DEA in this research are a kind of hybrid model because they combine both DEA and logistic regression in two stages. Accounting and market-related information is the most used predictive variables in previous models but at the same time, nonfinancial and management related information is generally useful. This thesis follows the studies of nonfinancial information by investigating the use of corporate efficiency and governance measures whist we do not disregard the importance of financial ratios.

In Chapter Three, the data used in modelling was introduced. Over 2,000 Chinese listed companies made up the sample for this research. A stratified sampling method is applied to ensure the distributions of good samples and bad samples are similar across industries. The indicator of financial distress, Special Treatment, is officially imposed by the government on all Chinese listed companies. The measurement of model performance is Type I and Type II errors, AUC, Gini, KS and the H measure which takes the cost of misclassification into account.

Chapter Four is the first main project of this thesis which is a cross sectional analysis using corporate efficiency measures. Unlike most previous literature that does not consider the VRS and homogeneity industry assumptions in DEA, our models carefully addressed these issues in both the calculation of DEA efficiency and regression parameters. Two periods of time were selected to be the training and test samples and three industries were used in modelling. DEA inputs and outputs were chosen to be physical and monetary items in annual reports. Results have revealed that efficiency measures can improve the predictive accuracy among which Scale Efficiency is more significant.

Chapter Five extended Chapter Four to a panel analysis based on three industries over the period of 2001-2010. It was found that the latest credit models in the literature have changed from static models to multi period dynamic models because the latter are more capable and suitable in the context of prediction. The different characteristics between industries were addressed by recognising the heterogeneity of them in both DEA and hazard models. Malmquist DEA can deal with panel data and all efficiency scores were calculated with reference to the first period. Global referenced efficiency and super efficiency scores were also calculated. Dynamic models were successfully built up in two ways: DEA scores to predict financial distress directly and to be used in the simple hazard models as a variable with some financial ratios.

Chapter Six turned to investigate the use of corporate governance measures. Corporate governance in China is a little different from that practised in Western countries because of its socialism background, short history of the securities market and heavy concentration on state ownership. Nevertheless, important features have been captured in four groups of corporate governance measures. There were 35 governance variables integrated in simple hazard models and used in predictions on 1688 companies over 8 years. Each of those four groups of corporate governance were found to contribute to the probability of financial distress and macroeconomic variables were also helpful to improve the predictive accuracy.

7.2 Conclusions

In the cross sectional analysis, the empirical results confirmed that companies of lower efficiency have higher risks of financial distress. We further decomposed the overall technical efficiency into Pure Technical Efficiency and Scale Efficiency and found that an inefficient company should improve the efficiency of its use of inputs or adjust its operating scale to the optimum level to achieve better performance. However the decomposition offers little help in improving predictive accuracy. In the out-of-time validation, a simple model using technical efficiency to assist financial ratios is more effective than in the others. The inclusion of a indicator has no influence on the predictive accuracy. DEA efficiency cannot predict financial distress well enough without the information of financial ratios because financial ratios are still powerful and dominant in their explanatory ability. The industry specific regression model made it possible to use DEA efficiency correctly and models considering homogeneity of sample are recommended for other similar research.

In the panel analysis, some results of the cross sectional analysis were further validated by multi period data and the discrete hazard models which take account of the effect of time. Malmquist DEA is found to be capable of calculating dynamic efficiency scores because its efficiency is comparable in both cross sectional and time serial formats. A Malmquist productivity index is defined as the product of efficiency change (catch-up) and technological change (frontier-shift) and mathematically it is calculated by the standard DEA scores at two periods and two intertemporal scores with reference to the efficiency frontier of the other period. The reference set in Malmquist DEA models may change the relative values in efficiency scores and both the fixed reference to the first period and the global reference which comes from the historically most efficient units were used in our models. Six types of efficiency scores were tried in hazard models and the model with Global Efficiency performed best in both out-of-time and out-of-sample. In practice, the global reference could be obtained by utilising a considerably long period of historic data on a large sample. This then gave a better prediction on the probability of financial distress when taking corporate efficiency into account. Using Malmquist DEA scores to directly predict financial distress in future time is still an effective and efficient way to apply DEA to corporate credit risk as it only requires a one-step calculation (DEA programming) compared to a two stage analysis (DEA and regression).

In the research of corporate governance measures, it was found that a large board, more supervisors and senior managers will lead to a low chance of having financial difficulty. SOEs are less likely to have financial difficulties. When independent directors are paid less or fewer senior staff are not paid, the company has a lower probability of distress. Additionally the Chair's age, the possession by the CEO of a Master's degree and positions in other organisations could help the company reduce the probability of distress. When activist investors such as institutional shareholders have the ability to detect potential risks in the companies in which they have large investment, there will be have lower risks of financial distress. In terms of the predictive accuracy, the best model comes from the combination of corporate governance measures, financial ratios and the inflation rate. The discriminant power of governance measures is heavily reduced in out-of-time predictions.

7.3 Contributions

Distinctive contributions have been made by this thesis to the literature. They are generally divided into three parts consequential to each research project.

First, it is concerned with the assumptions of DEA to calculate the relative efficiency scores. In DEA models, the efficiency of a company is relative to the most efficient one in its peer group. Homogeneity of comparable samples is required to be consistent across similar activities, similar resources and a similar environment according to Dyson *et al* (2001). Almost all studies such as Cielen *et al,* (2004); Premachandra *et al,* (2009); Premachandra *et al,* (2011) did not pay attention to this so their relative efficiency may not be valid. This thesis has corrected this by treating each industry separately and built industry specific regression models. Our cross sectional models have also applied VRS and further decomposed the overall Technical Efficiency into Pure Technical Efficiency and Scale Efficiency to add extra information in predictive models. This has not been done before.

Second, no study has ever carried out a panel analysis of DEA scores in predicting credit risk. Chapter Five has successfully extended the cross sectional analysis into a multi period analysis, more specifically a survival analysis. Hazard models are not unfamiliar in this field after Shumway (2001) commented that the likelihood function of discrete hazard models are the same as those for multi period logistic regression. Many examples of discrete hazard models in corporate risk can be found in Carling *et al* (2007), Nam *et al* (2008), De Leonardis and Rocci (2013), Wilson and Altanlar (2014) etc. and some DEA models of multi period capacity can be found in Tone and Tsutsui (2009), Charnes *et al* (1985) and Fare *et al* (1994) but our model is the first to join together Malmquist DEA in the first stage and a discrete hazard model in the second stage. In this way, it is possible to combine the benefits from the previous paragraph with the advantages of hazard models into prediction of credit risk. More robust and informative results can be provided for academics and businessmen. Various reference sets in Malmquist DEA models have some differences in the results and modellers can choose the best for their preferences.

Third, this research is the first to integrate four aspects of corporate governance measures: board composition, ownership structure, management compensation and director and manager characteristics in a panel analysis to predict the probability of financial distress. Though some attributes of these four aspects have been tested individually in past literature (Dalton, 1994; Simpson and Gleason, 1999; Fich and Slezak, 2008; Platt and Platt, 2012; etc.), this research is the most comprehensive, including 35 variables in predictive models. In each of the four aspects of corporate governance, we conclude that SOE status, institutional shareholding, the salary of independent directors, their working location, the Chair's age, the CEO's Masters degree all can contribute significantly to a prediction of the probability of financial distress.

Fourth, this research uses Chinese data, which is different from most studies that instead have concentrated on the US, the UK or other EU countries. It is one of the very few studies in the literature of credit models focusing on China (Wang and Deng, 2006; Sun and Li, 2008). Credit scoring and corporate credit models originated in Western countries and we can also see the importance of applying them to emerging markets represented by China. Financial risks have to be addressed despite its great economic development. As the volume of foreign investment increases every year, the corresponding increased use of credit scoring should be followed as an efficient way of evaluating loan requests.

Fifty, the empirical data used in this research covers the recent global financial crisis. Though the default rate in China over the crisis period was unlike that found in other parts of the world (in China the peak was prior to the crisis as in Figure 3.4.1), it is certainly because of China's unique economic trend and default also follows the pattern of its economy. The model with macroeconomic variables has given evidence that inflation rate is a significant predictor of the probability of financial distress. The panel models that included the effect of changes over the crisis period make predictions robust over time.

7.4 Policy implications

Apart from the academic contributions, this thesis can also give policy makers insightful thoughts which can be implemented in practice.

It is found that Scale Efficiency is more significant than Pure Technical Efficiency in predicting financial distress which means that practically a firm which wants to perform better should pay more attention to optimising its scale of business rather than optimising resources or applying new technology. This can benefit managers and owners of companies and tell them how to improve the efficiency of their management to generate more output and profits for shareholders.

In this thesis we find that measures of corporate governance have been found significantly linked to financial distress. It is not only the responsibility of shareholders, owners and managers of companies to carefully address the appropriate corporate governance structure but also regulators who supervise listed companies and other forms of companies have to realise the importance of corporate governance, specifically for aspects of state ownership and independent directors. Policy makers set standards for companies to follow.

Unlike China's economic success, the financial regulations and corresponding risk management system in China have not been well established. Although BIS has implemented the Basel Accords for decades, in China, the China Banking Regulatory Commission (CBRC, 2007) finally, in 2007, put the *Guidance on the Implementation of New Capital Accord Chinese Banking* into effect. The Chinese version of the Capital Accord has followed a progressive plan that it is compulsory for large international Chinese banks which are required to implement it by the end of 2013 but it has been voluntary for other small commercial banks since 2011. The banking policy makers in China need to pay attention to credit risk and its control and management to prevent any possible crisis. It is obvious that most banks in China have not established their own internal risk management tools because the *Guidelines on Advanced Capital Measurement Method and Validation* just came out in 2009 and it takes slow steps in its implementation. Because credit risk control is one of the focuses, Chinese banks may be interested in the calibration of the credit risk of their portfolios and this thesis can provide them with some options. Other investors who want to invest in Chinese stocks can clearly import the models in this thesis and build their ratings and scores to predict how Chinese listed companies are going to perform in the future.

In addition, policy makers should also pay attention to the influence of the economy in order to foresee the possibility of any form of financial crisis.

7.5 Limitations and future research

Although this thesis has made several contributions, at the same time it has some limitations as is reasonable for all kinds of research. The availability of data is one of the biggest concerns in this research. Due to the consideration of the credibility and reliability of data, because we wished to focus on Chinese data, listed companies was the only option we could choose. Despite the short history of the Chinese securities markets, the slow development of regulations restricts the availability of data even further as regulations adhered to the market cannot be sound in the beginning. It is only since 1998 or even 2000 that the important information about financial distress, accounting and corporate governance started to become usable. This has significantly reduced the available data to be more or less ten years. For a panel analysis, it is acceptable.

Apart from this, the sample size in the cross sectional analysis is relatively small. In 2000, there were only 1,000 listed companies and by the end of 2012, there were nearly 2,500 (Figure 3.2.1). Though the growth of the size of the market (both the value and the number) was fast, over 900 companies were newly listed after 2008. These are relatively young and can hardly be used by the model. For the sample of distressed companies, as we used the indicator imposed by the government, there were only about 450 such companies from 2000 to 2010, including those with multiple ST experiences. As the first two projects have to consider industrial classification, a smaller sample and less bad cases can only be employed in analysis. In the process of modelling, because of censoring and the time lag, only 2,665 observations were actually useful in training the model, which is not comparable with some studies with millions of samples. For statistical analysis, the larger the sample size the better to make the results statistically robust. Future research can be easily extend the work here by including data of recent years or applying the methods to other countries.

The models with DEA efficiency only applied them in three industries. These were Raw Materials, Industrial Equipment and Real Estate as we wanted to fit the models with the most bad cases. At the same time, we should bear in mind that the risks of financial distress between industries are naturally different, which can be reflected in the baseline hazard. As our industry specific models can deal with DEA efficiency in different industries, more sectors can be added in both DEA and regression but we still need to pay attention to the requirements of DEA and require that the samples from each industry be large enough. When the target is not restricted in large or listed companies, there may be no problem in model training. The only argument may lie in the debate between complexity of models and accuracy of predictions, and it largely depends on the preference of practitioners and modellers. There were studies such as Bonfim (2009) who used 11 dummies to control for 11 sectors. Furthermore, if one wants to keep the homogeneity of DMUs even more rigid, a further detailed level of industry classification can be applied. According to the Standard Industry Classification (SIC), dozens of subsectors can be defined so the predictive models can be correspondingly segmented.

Another limitation may be concerned with the indicator of financial distress – Special Treatment. In the survival analysis, some cases of ST were censored before and after the observation period. The former cases were left out of the sample and the latter cases were treated as healthy. ST is a financial condition state which means a company may remain in ST for years and move into this state several times. It would be interesting to model the severity (length in distress) or behaviour (the number of occasions) when a company moves in to ST. Besides, the Chinese government imposes a marker of '*' (star) on those distressed companies which have three consecutive losses in profits to give a warning of delisting for investors. Therefore Chinese listed companies actually have four states of financial conditions: normal, ST, ST* and delisted where stochastic models may be suitable. Further work could be done by the combination of DEA and the stochastic process, which may be inspired by the stochastic DEA from Bruni *et al* (2014).

The evolution of corporate governance in China also brings limitations to Chapter Six. The transition in regulations and enforcement of laws can be viewed as positive changes in terms of corporate governance but it is harmful for modelling. The study of corporate governance measures may come from countries such as the UK and the US where sound systems have already been established. In the case of China, we still would like to see the compensation schemes being clearer, including bonus and option incentives for senior managers and directors being disclosed, as one of the important variables in this research. The database also provides information about auditing, shareholder meetings, dividends distribution and the resumes of directors and managers, which could all be used in modelling as they have been tried in past literature. Particularly, the resumes can be coded into qualitative data such as previous experience and employment and this saves much time in collecting data by qualitative methods for so many people.

Finally, although this research focuses on large corporations, the methodology can also be applied to SMEs whose efficiency and governance are especially important to their survival.

References

Abdullah, S.N. (2006). Board structure and ownership in Malaysia: the case of distressed listed companies. *Corporate Governance*, 6(5), 582-594

Abidali, A. F., and Harris, F. (1995). A methodology for predicting company failure in the construction industry. *Construction Management and Economics*, *13*(3), 189-196.

Agarwal, V., and Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance*, 32(8), 1541-1551.

Aharony, J., Jones, C. P., and Swary, I. (1980). An analysis of risk and return characteristics of corporate bankruptcy using capital market data. *Journal of Finance*, 35(4), 1001-1016.

Ahn, B. S., Cho, S. S., and Kim, C. Y. (2000). The integrated methodology of rough set theory and artificial neural network for business failure prediction. *Expert Systems with Applications*, 18(2), 65-74.

Allen, F., Qian, J., and Qian, M. (2005). Law, finance, and economic growth in China. *Journal of Financial Economics*, 77(1), 57-116.

Allison, P. D. (1982). Discrete-time methods for the analysis of event histories. *Sociological Methodology*, 13(1), 61-98.

Altman EI (1983). *Corporate Financial Distress: A Complete Guide to Predicting, Avoiding and Dealing with bankruptcy*. Wiley: New York; Chichester.

Altman EI (1993). *Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting from Bankruptcy*. Wiley: New York.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589-609.

Altman, E. I., and Eisenbeis, R. A. (1978). Financial applications of discriminant analysis: a clarification. *Journal of Financial and Quantitative Analysis*, 13(01), 185-195.

Altman, E. I., and Loris, B. (1976). A financial early warning system for over-the-counter broker-dealers. *Journal of Finance*, *31*(4), 1201-1217.

Altman, E. I., and Sabato, G. (2007). Modelling credit risk for SMEs: Evidence from the US market. *Abacus*, 43(3), 332-357.

Altman, E. I., Haldeman, R. G., and Narayanan, P. (1977). ZETA analysis A new model to identify bankruptcy risk of corporations. J*ournal of Banking and Finance*, *1*(1), 29-54.

Altman, E. I., Marco, G., and Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of Banking and Finance*, 18(3), 505-529.

Altman, E. I., Sabato, G., and Wilson, N. (2010). The value of non-financial information in small and medium-sized enterprise risk management. *Journal of Credit Risk*, 2(6), 95-127.

Altman, E., Sabato, G., and Wilson, N. (2008). The value of qualitative information in SME risk management. *Journal of Financial Services Research*, 40(2), 15-55.

Altman, E.I., Zhang, L. and Yen, J., (2007), Corporate financial distress diagnosis in China, NY University Salomon Center Working Paper

Andersen, P., and Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science*, 39(10), 1261-1264.

Argenti, J., (1976). *Corporate Collapse: The Causes and Symptoms*. London: McGraw-Hill.

Atiya, A. F. (2001). Bankruptcy prediction for credit risk using neural networks: A survey and new results. *Neural Networks,* IEEE Transactions on, 12(4), 929-935.

Aziz, A., Emanuel, D.C., and Lawson, G.H., (1988). Bankruptcy prediction—An investigation of cash flow based models. *Journal of Management Studies,* 25 (5), 419–437.

Aziz, M. A., and Dar, H. A. (2004). *Predicting Corporate Financial Distress: Whither do We Stand*?. Department of Economics, Loughborough University.

Aziz, M. A., and Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand?. *Corporate Governance*, 6(1), 18-33.

Back, B., Laitinen, T., and Sere, K. (1996). Neural networks and genetic algorithms for bankruptcy predictions. *Expert Systems with Applications*, 11(4), 407-413.

Bahrammirzaee A. (2010). A comparative survey of artificial intelligence applications in finance: Artificial neural networks, expert systems and hybrid intelligent systems. *Neural Computing and Applications*. 19(8), 1165–1195.

Bajgier, S. M., and Hill, A. V. (1982). An experimental comparison of statistical and linear programming approaches to the discriminant problem. *Decision Sciences*, 13(4), 604-618.

Balcaen, S. and Ooghe H. (2006). 35 years of studies on business failure: An overview of the classical statistical methodologies and their related problems. *The British Accounting Review*. 38(1), 63–93.

Bangia, A., Diebold, F., and Schuermann, T. (2002). Ratings migration and the business cycle, with applications to credit portfolio stress testing. *Journal of Banking and Finance*, 26(2), 445–474.

Banker, R. D., and Chang, H. (2006). The super-efficiency procedure for outlier identification, not for ranking efficient units. *European Journal of Operational Research*, 175(2), 1311-1320.

Banker, R.D., and Natarajan, R. (2008). Evaluating contextual variables affecting productivity using data envelopment analysis. *Operations Research*, 56(1), 48-58.

Banker, R.D., and Thrall, R.M., (1992). Estimation of Returns to Scale using Data Envelopment Analysis. *European Journal of Operational Research*. 62(1), 74–84.

Banker, R.D., Charnes A and Cooper WW (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*. 30(9), 1078–1092.

Barnes, P. (1987). The analysis and use of financial ratios: a review article. *Journal of Business Finance and Accounting*, 14(4), 449-461.

BarNiv, R., and Hershbarger, R. A. (1990). Classifying financial distress in the life insurance industry. *Journal of Risk and Insurance*, 110-136.

Barr, R.S., Seiford LM and Siems TF (1993). An envelopment analysis approach to measuring the managerial efficiency of banks. *Annals of Operations Research*, 45(1), 1–19.

Barr, R.S., Durchholz ML and Seiford LM (2000). *Peeling the DEA onion: Layering and rank-ordering DMUs using tiered DEA*. Southern Methodist University technical report.

Basel Committee on Banking Supervision (BCBS), (2000), *Principles for the Management of Credit Risk*, Basel

BBC News, (2011), China overtakes Japan as world's second-biggest economy, http://www.bbc.co.uk/news/business-12427321

Beaver, W. H., McNichols, M. F., and Rhie, J. W. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies*, 10(1), 93-122.

Beaver, W.H. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research*. 4, 71-111

Bebchuk, L., Cohen, A., and Ferrell, A. (2009). What matters in corporate governance?. *Review of Financial Studies*, 22(2), 783-827.

Becchetti, L., and Sierra, J. (2003). Bankruptcy risk and productive efficiency in manufacturing firms. *Journal of Banking and Finance*, 27(11), 2099-2120.

Beck, N., Katz, J. N., and Tucker, R. (1998). Taking time seriously: Time-series-cross-section analysis with a binary dependent variable. *American Journal of Political Science*, 42(4), 1260-1288.

Bellotti, T., and Crook, J. (2008). Credit scoring with macroeconomic variables using survival analysis. *Journal of the Operational Research Society*, 60(12), 1699-1707.

Bellotti, T., and Crook, J. (2009). Support vector machines for credit scoring and discovery of significant features. *Expert Systems with Applications*, 36(2), 3302-3308.

Bennett, D. Scott. (1997). Testing Alternative Models of Alliance Duration, 1816-1984. *American Journal of Political Science*, 41, 846-78

Berg, S. A., Førsund, F. R., and Jansen, E. S. (1992). Malmquist indices of productivity growth during the deregulation of Norwegian banking, 1980-89. *The Scandinavian Journal of Economics*, S211-S228.

Berger, A. N., and Frame, W. S. (2007). Small business credit scoring and credit availability. *Journal of Small Business Management*, 45(1), 5-22.

Berger, A. N., Cowan, A. M., and Frame, W. S. (2011). The surprising use of credit scoring in small business lending by community banks and the attendant effects on credit availability, risk, and profitability. *Journal of Financial Services Research*, 39(1-2), 1-17.

Berle, A. A., and Means, G. G. C. (1932). *The Modern Corporation and Private Property*. Transaction Books.

Betts J. and Belhoul D., (1987), The Effectiveness of Incorporating Stability Measures In Company Failure Models, *Journal of Business Finance and Accounting*, 14(3), 323-334

Bharath, S. T., and Shumway, T. (2008). Forecasting default with the Merton distance to default model. *Review of Financial Studies*, 21(3), 1339-1369.

Bhattacharjee, A., and Han, J. (2010). Financial distress in Chinese industry: Microeconomic, macroeconomic and institutional influences. (CRIEFF Discussion Papers). St. Andrews.

Black, F., and Scholes, M. (1973). The pricing of options and corporate liabilities. The *Journal of Political Economy*, 637-654.

Blair, M. M. (1995*). Ownership and Control: Rethinking Corporate Governance for the Twenty-First Century*. Brookings Institution Press.

Bonfim, D. (2009). Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics. *Journal of Banking and Finance*, 33(2), 281-299.
Bou-Hamad, I., Larocque, D., and Ben-Ameur, H. (2011). Discrete-time survival trees and forests with time-varying covariates application to bankruptcy data. *Statistical Modelling*, 11(5), 429-446.
Bou-hamad, I., Larocque, D., Ben-Ameur, H., Mâsse, L. C., Vitaro, F., and Tremblay, R. E. (2009). Discrete-time survival trees. *Canadian Journal of Statistics*, 37(1), 17-32.
Breiman, L. (Ed.). (1993). *Classification and Regression Trees*. CRC press.
Bruni, M. E., Beraldi, P., and Iazzolino, G. (2014). Lending decisions under uncertainty: a DEA approach. *International Journal of Production Research*, 52(3), 766-775.
Bryan, D., Fernando, G. D., and Tripathy, A. (2013). Bankruptcy risk, productivity and firm strategy. *Review of Accounting and Finance*, 12(4), 309-326.
Bryant, S. M. (1997). A case-based reasoning approach to bankruptcy prediction modeling. *Intelligent Systems in Accounting, Finance and Management*, 6(3), 195-214.
Burgess, J. F., and Wilson, P. W. (1996). Hospital ownership and technical inefficiency. *Management Science*, 42(1), 110-123.
Campbell, J.Y., Hilscher, J. and Szilagyi J, (2008), In Search of Distress Risk, *Journal of Finance*, 63(6), 2899-2939
Cao, Y. (2012). Aggregating multiple classification results using Choquet integral for financial distress early warning. *Expert Systems with Applications*, 39(2), 1830-1836.
Carling, K., Jacobson, T., Lindé, J., and Roszbach, K. (2007). Corporate credit risk modeling and the macroeconomy. *Journal of Banking and Finance*, 31(3), 845-868.
Caves, D. W., Christensen, L. R., and Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica: Journal of the Econometric Society*, 1393-1414.
Chaganti, R., Mahajan, V., and Sharma, S.(1985). Corporate board size, composition and corporate failures in retailing industry. *Journal of Management Studies*, 22(4), 400-417.
Chan, C.Y., Chou D.W. and Lin J.R., (2010) An empirical study on corporate governance and the financial failure prediction model, *Asian Finance Association 2010 International Conference*
Charitou, A., Neophytou, E., and Charalambous, C. (2004). Predicting corporate failure: empirical evidence for the UK. *European Accounting Review*, 13(3), 465-497.
Charnes, A, Cooper, W.W. and Rhodes, E.L. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444.
Charnes, A., Clarke, C., Cooper, W.W., Golany, B., (1985). A development study of DEA in measuring the effect of maintenance units in the U.S. Air Force. *Annals of Operations Research*, 2, 95–112.
Chava, S., and Jarrow, R. A. (2004). Bankruptcy prediction with industry effects. *Review of Finance*, 8(4), 537-569.

Chen, HH., (2008), The Timescale Effects of Corporate Governance Measure on Predicting Financial Distress, *Review of Pacific Basin Financial Markets and Policies*, 11(1),35-46

Chen, J, (2005), *Corporate Governance in China*, New York: RoutledgeCurzon

Chen, X., Wang, X., and Wu, D. D. (2010). Credit risk measurement and early warning of SMEs: An empirical study of listed SMEs in China. *Decision Support Systems*, 49(3), 301-310.

Chen, Y., and Iqbal Ali, A. (2004). DEA Malmquist productivity measure: New insights with an application to computer industry. *European Journal of Operational Research*, 159(1), 239-249.

Cheng G, Zervopoulos P and Qian Z (2013). A variant of radial measure capable of dealing with negative inputs and outputs in data envelopment analysis. *European Journal of Operational Research*, 225(1), 100–105.

Cheung, Y. L., Jiang, P., Limpaphayom, P., and Lu, T. (2008). Does corporate governance matter in China?. *China Economic Review*, *19*(3), 460-479.

China Banking Regulatory Commission (CBRC), (2007), *Guidance on the Implementation of New Capital Accord Chinese Banking*, http://www.cbrc.gov.cn/govView_C0015CF9E28A41198373752F0C8631BA.html

China Securities Regulatory Commission (CSRC), (2005), *Measures for the Administration of the Sharetrading Reform of Listed Companies*

China Securities Regulatory Commission (CSRC), (2007), Administrative Measures for the Disclosure of Information of Listed Companies, *Order of China Securities Regulatory Commission,* No.40

China Securities Regulatory Commission (CSRC), (2008), *Administration of the Takeover of Listed Companies Procedures*

China Securities Regulatory Commission (CSRC), (2001), *The Guidelines on the Establishment of the Independent Director System in Listed Companies*

Cho, S., Kim, J., and Bae, J. K. (2009). An integrative model with subject weight based on neural network learning for bankruptcy prediction. *Expert Systems with Applications*, 36(1), 403-410.

Cielen A, Peeters L and Vanhoof K (2004). Bankruptcy prediction using a data envelopment analysis. *European Journal of Operational Research*, 154(2), 526–532.

Claessens, S., and Fan, J. P. (2002). Corporate governance in Asia: A survey. *International Review of Finance*, 3(2), 71-103.

Claessens, S., Fan, P. H. J., Djankov, S., and Lang, H. P. L. (1999). On expropriation of minority shareholders: evidence from East Asia. Available at SSRN 202390.

Clarke, D. (2006). The independent director in Chinese corporate governance. *Delaware Journal of Corporate Law*, 31(1), 125-228.

Clarke, D. C. (2003). Corporate governance in China: An overview. *China Economic Review*, 14, 494

Cleves, M. A., Gould, W. W., and Gutierrez, R. G. (2008). *An Introduction to Survival Analysis Using Stata*. Stata Press.

Companies Act 2006, (2006), Chapter 46, http://www.legislation.gov.uk/ukpga/2006/46/pdfs/ukpga_20060046_en.pdf

Cook, W. D., and Seiford, L. M. (2009). Data envelopment analysis (DEA)–Thirty years on. *European Journal of Operational Research*, 192(1), 1-17.

Cooper, W.W., Seiford, L.M. and Tone, K., (2000). *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-solver Software*. Kluwer Academic Publishers: Boston.

Cooper, W. W., Seiford, L. M., and Tone, K. (2006). *Introduction to data envelopment analysis and its uses* (p. 14). New York: Springer.

Core, J. E., Holthausen, R. W., and Larcker, D. F. (1999). Corporate governance, chief executive officer compensation, and firm performance. *Journal of financial economics*, 51(3), 371-406.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society*. Series B (Methodological), 187-220.

Cox, D. R., and Oakes, D. (1984). Analysis of survival data (Vol. 21). CRC Press.

Cram, D. P., Karan, V., and Stuart, I. (2009). Three Threats to Validity of Choice-based and Matched-Sample Studies in Accounting Research. *Contemporary Accounting Research*, 26(2), 477-516.

Crook, J. N., Edelman, D. B., and Thomas, L. C. (2007). Recent developments in consumer credit risk assessment. *European Journal of Operational Research*,183(3), 1447-1465.

Crook, J., and Bellotti, T. (2010). Time varying and dynamic models for default risk in consumer loans. *Journal of the Royal Statistical Society: Series A* (Statistics in Society), 173(2), 283-305.

Daily, C.M., (1996), Governance patterns in bankruptcy reorganizations, Strategic Management Journal, 17(5), 355-375

Daily, C.M., Dalton, D.R., (1994a), Bankruptcy and Corporate Governance: The Impact of Board Composition and Structure, *Academy of Management Journal*, 37(6), 1603-1617

Daily, C.M., Dalton, D.R., (1994b), Corporate Governance and the Bankrupt Firm: An Empirical Assessment, *Strategic Management Journal*, 15(8), 643-654

Dambolena, I. G., and Khoury, S. J. (1980). Ratio stability and corporate failure. *Journal of Finance*, 35(4), 1017-1026.

Darrat A.F., Gray S. and Wu Y., 2010, Does Board Composition Affect the Risk of Bankruptcy, Corporate Finance: Governance, Corporate Control and Organization eJournal, working paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1710412

D'Aveni, R.A. (1990). Top managerial prestige and organizational bankruptcy. *Organization Science*, 1, 121-142.

De Andrés, J., Landajo, M., and Lorca, P. (2012). Bankruptcy prediction models based on multinorm analysis: An alternative to accounting ratios. *Knowledge-Based Systems*, 30, 67-77.

De Andrés, J., Lorca, P., de Cos Juez, F. J., and Sánchez-Lasheras, F. (2011). Bankruptcy forecasting: A hybrid approach using Fuzzy c-means clustering and Multivariate Adaptive Regression Splines (MARS). *Expert Systems with Applications*, 38(3), 1866-1875.

De Leonardis, D., and Rocci, R. (2013). Default risk analysis via a discrete-time cure rate model. *Applied Stochastic Models in Business and Industry*.

Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research*, 167-179.

Dimitras, A. I., Slowinski, R., Susmaga, R., and Zopounidis, C. (1999). Business failure prediction using rough sets. *European Journal of Operational Research*,114(2), 263-280.

Dimitras, A. I., Zanakis, S. H., and Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. *European Journal of Operational Research*, 90(3), 487-513.

Ding, Y, Song X and Zen Y (2008). Forecasting financial condition of Chinese listed companies based on support vector machine. *Expert Systems with Applications*, 34(4), 3081–3089.

Distinguin, I., Rous, P., and Tarazi, A. (2006). Market discipline and the use of stock market data to predict bank financial distress. *Journal of Financial Services Research*, 30(2), 151-176.

Donker, H., Santen, B., and Zahir, S., (2009), Ownership structure and the likelihood of financial distress in the Netherlands, *Applied Financial Economics*, 19, 1687-1696

Donoher, W. J. (2004). To file or not to file? systemic incentives, corporate control, and the bankruptcy decision. *Journal of Management*, *30*(2), 239-262.

Duffie, D., Saita, L., and Wang, K. (2007). Multi-period corporate default prediction with stochastic covariates. *Journal of Financial Economics*, 83(3), 635-665.

Dyson, R.G., Allen, R., Camanho, A.S., Podinovski VV, Sarrico CS and Shale EA (2001). Pitfalls and protocols in DEA. *European Journal of Operational Research*, 132(2), 245–259.

Edmister, R. O. (1971). Financial ratios and credit scoring for small business loans. *Journal of Commercial Bank Lending*, 53, 10-23.

Edmister, R. O. (1972). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial and Quantitative Analysis*, 1477-1493.

Eisenbeis, R. A. (1977). Pitfalls in the application of discriminant analysis in business, finance, and economics. *Journal of Finance*, 32(3), 875-900.

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of Management Review*, 14(1), 57-74.

Elloumi, F. and Gueyle J.P. (2001). Financial distress and corporate governance: An empirical analysis. *Corporate Governance*, 1, 15-23.

Emel, A.B., Oral M, Reisman A and Yolalan R (2003). A credit scoring approach for the commercial banking sector. *Socio-Economic Planning Sciences*, 37(2), 103–123.

Emrouznejad, A., Anouze, A.L. and Thanassoulis, E. (2010). A semi-oriented radial measure for measuring the efficiency of decision making units with negative data, using DEA. *European Journal of Operational Research*, 200(1), 297–304.

Faccio, M. (2006). Politically connected firms. *The American economic review*, 96(1), 369-386.

Färe, R., Grosskopf, S., Lindgren, B., and Roos, P. (1992). Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis*, 3(1-2), 85-101.

Färe, R., Grosskopf, S., Norris, M., and Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review*, 66-83.

Farrar, D. E., and Glauber, R. R. (1967). Multicollinearity in regression analysis: The problem revisited. *The Review of Economics and Statistics*, 49(1), 92-107.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*. Series A (General), 120(3), 253-290.

Fich, E.M. and Slezak S.L., (2008), Can corporate governance save distressed firms from bankruptcy? An empirical analysis, *Review of Quantitative Finance and Accounting*, 30(2), 225-251

Fidrmuc, J., and Hainz, C. (2010). Default rates in the loan market for SMEs: Evidence from Slovakia. *Economic Systems*, 34(2), 133-147.

Financial Reporting Council, London Stock Exchange, 1992, *Report on the Committee on The Financial Aspects of Corporate Governance*.

Finlay, S. (2011). Multiple classifier architectures and their application to credit risk assessment. *European Journal of Operational Research*, 210(2), 368-378.

Firth, M., Fung, P. M., and Rui, O. M. (2006). Corporate performance and CEO compensation in China. *Journal of Corporate Finance*, 12(4), 693-714.

Freed N and Glover F (1981b). A linear programming approach to the discriminant problem. *Decision Sciences*, 12(1), 68–73.

Freed, N., and Glover, F. (1981a). Simple but powerful goal programming models for discriminant problems. *European Journal of Operational Research*, 7(1), 44-60.

Friedman, J. H. (1991). Multivariate adaptive regression splines. *The Annals Of Statistics*, 1-67.

Frydman, H., Altman, E. I., and KAO, D. L. (1985). Introducing recursive partitioning for financial classification: the case of financial distress. *Journal of Finance*, 40(1), 269-291.

Frydman, H., and Schuermann, T. (2008). Credit rating dynamics and Markov mixture models. *Journal of Banking and Finance*, 32, 1062–1075.

Gentry, J. A., Newbold, P., and Whitford, D. T. (1985). Predicting bankruptcy: if cash flow's not the bottom line, what is?. *Financial Analysts Journal*, 47-56.

Gepp, A., Kumar, K., and Bhattacharya, S. (2010). Business failure prediction using decision trees. *Journal of Forecasting*, 29(6), 536-555.

Gestel, T.V., Baesens B, Suykens J, Poel DV, Baestaens DE and Willekens M (2006). Bayesian kernel based classification for financial distress detection. *European Journal of Operational Research*, 172(3), 979–1003.

Gilbert, L.R. Menon, K. Schwartz K.B., (1990), Predicting bankruptcy for firms in financial distress, *Journal of Business Finance and Accounting*, 17 (1), 161–171

Gilson, S. C. and Vetsuypens, M. R., (1993), CEO compensation in financially distressed firms, *Journal of Finance*, 48, 425–458.

Gini, C. (1909). "Concentration and dependency ratios" (in Italian). English translation in Rivista di Politica Economica, 87 (1997), 769–789.

Glennon, D., and Nigro, P. (2005). Measuring the default risk of small business loans: A survival analysis approach. *Journal of Money, Credit and Banking*, 923-947.

Gompers, P., Ishii, J., and Metrick, A. (2003). Corporate governance and equity prices. *Quarterly Journal of Economics*, 118, 107−155.

Grada, C.O. (2010), *Famine: A Short History*, Princeton University Press

Greenland, S. (1989). Modeling and variable selection in epidemiologic analysis. *American Journal of Public Health*, 79(3), 340-349.

Grice, J. S., and Dugan, M. T. (2001). The limitations of bankruptcy prediction models: Some cautions for the researcher. *Review of Quantitative Finance and Accounting*, 17(2), 151-166.

Grunert, J., Norden, L., and Weber, M. (2005). The role of non-financial factors in internal credit ratings. *Journal of Banking and Finance*, 29(2), 509-531.

Hambrick, D. C, and D'Aveni R. A. (1992). Top team deterioration as part of the downward spiral of large corporate bankruptcies. *Management Science*, 38, 1445-1446.

Han, J, (2012), *A Study of Financial Distress and RandD in Chinese Enterprises*, PhD thesis, St. Andrews University

Hand, D. J. (2005). Good practice in retail credit scorecard assessment. *Journal of the Operational Research Society*, 56(9), 1109-1117.

Hand, D. J. (2009). Measuring classifier performance: a coherent alternative to the area under the ROC curve. *Machine Learning*, 77(1), 103-123.

Hand, D. J. and Henley, W. E. (1997). Statistical classification methods in consumer credit scoring: a review. *Journal of the Royal Statistical Society: Series A* (Statistics in Society), 160(3), 523-541.

Hand, D.J. and Anagnostopoulos, C. (2013). A better Beta for the H measure of classification performance. Preprint submitted to Pattern Recognition Letters, arXiv preprint arXiv:1202.2564.

Hermalin, B. E. and Weisbach M. S. (2003). Boards of directors as an endogenously determined institution: A survey of the economic literature. *Economic Policy Review*, April: 7-26

Hernandez Tinoco, M., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis*, *30*, 394-419.

Hillegeist, S. A., Keating, E. K., Cram, D. P., and Lundstedt, K. G. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies*, 9(1), 5-34.

Hovey, M., Li, L., and Naughton, T. (2003). The relationship between valuation and ownership of listed firms in China. *Corporate Governance: An International Review*, 11(2), 112-122.

Hsu, HH. and Wu, YH. (2009), Board composition, audit committee structure, 'grey directors' and the incidence of corporate failure in the UK, *Finance and Corporate Governance Conference 2010 Paper*.

Hu, Y. C., and Ansell, J. (2007). Measuring retail company performance using credit scoring techniques. *European Journal of Operational Research*, 183(3), 1595-1606.

Hua, Z., Wang, Y., Xu, X., Zhang, B., and Liang, L. (2007). Predicting corporate financial distress based on integration of support vector machine and logistic regression. *Expert Systems with Applications*, 33(2), 434-440.

Hwang, R. C., Siao, J. S., Chung, H., and Chu, C. K. (2011). Assessing bankruptcy prediction models via information content of technical inefficiency. *Journal of Productivity Analysis*, 36(3), 263-273.

Hwang, S. N., and Chang, T. Y. (2003). Using data envelopment analysis to measure hotel managerial efficiency change in Taiwan. *Tourism Management*, 24(4), 357-369.

Izan, H. Y. (1984). Corporate distress in Australia. *Journal of Banking and Finance*, 8(2), 303-320.
Jacobson, T., Lindé, J., and Roszbach, K. (2005). Credit risk versus capital requirements under Basel II: are SME loans and retail credit really different?. *Journal of Financial Services Research*, 28(1-3), 43-75.
Jensen, M. C., and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4), 305-360.
Jensen, M., (1993), The modern industrial revolution, exit and the failure of internal control systems, *Journal of Finance*, 48, 831-880
Jingu, T. (2007). Corporate Governance for Listed Companies in China-Recent Moves to Improve the Quality of Listed Companies. *Nomura Capital Market Review*, 10(2), 36-52.
Jo, H., and Han, I. (1996). Integration of case-based forecasting, neural network, and discriminant analysis for bankruptcy prediction. *Expert Systems with Applications*, 11(4), 415-422.
Johnsen, T., and Melicher, R. W. (1994). Predicting corporate bankruptcy and financial distress: information value added by multinomial logit models. *Journal of Economics and Business*, 46(4), 269-286.
Jones, S., and Hensher, D. A. (2004). Predicting firm financial distress: a mixed logit model. *The Accounting Review*, 79(4), 1011-1038.
Jones, S., and Hensher, D. A. (2007). Modelling corporate failure: A multinomial nested logit analysis for unordered outcomes. *The British Accounting Review*,39(1), 89-107.
Joy, O.M., Tollefson, J.O., (1975). On the financial applications of discriminant analysis. *Journal of Financial and Quantitative Analysis*, 10 (5), 723–739.
Joy, O.M., Tollefson, J.O., (1978). Some clarifying comments on discriminant analysis. *Journal of Financial and Quantitative Analysis*, 13(1), 197–200.
Kao, C., and Hwang, S. N. (2010). Efficiency measurement for network systems: IT impact on firm performance. *Decision Support Systems*, 48(3), 437-446.
Kaski, S., Sinkkonen, J., and Peltonen, J. (2001). Bankruptcy analysis with self-organizing maps in learning metrics. *Neural Networks, IEEE Transactions on*,*12*(4), 936-947.
Kattan, M. W., Adams, D. A., and Parks, M. S. (1993). A comparison of machine learning with human judgment. *Journal of Management Information Systems*, *9*(4), 37-57.
Keasey, K., and Watson, R. (1987). Non-Financial Symptoms and the Prediction of Small Company Failure: A Test of Argenti's Hypotheses. *Journal of Business Finance and Accounting*, 14(3), 335-354.
Keasey, K., and Watson, R. (1991). Financial Distress Prediction Models: A Review of Their Usefulness. *British journal of Management*, 2(2), 89-102.
Keasey, K., McGuinness, P., and Short, H. (1990). Multilogit approach to predicting corporate failure—further analysis and the issue of signal consistency. *Omega*, 18(1), 85-94.
Kim, H. S., and Sohn, S. Y. (2010). Support vector machines for default prediction of SMEs based on technology credit. *European Journal of Operational Research*, 201(3), 838-846.

Kim, S. Y. (2011). Prediction of hotel bankruptcy using support vector machine, artificial neural network, logistic regression, and multivariate discriminant analysis. *The Service Industries Journal*, *31*(3), 441-468.

Kiviluoto, K. (1998). Predicting bankruptcies with the self-organizing map. *Neurocomputing*, 21(1), 191-201.

Koh, H.C., (1992). The sensitivity of optimal cutoff points to misclassification costs of Type I and Type II errors in the going-concern prediction context. *Journal of Business Finance and Accounting*, 19 (2), 187–197.

Kornai J., (1986). The Soft Budget Constraint. Kyklos: *International Review for Social Sciences*, 39(1), 3-30.

Koyuncugil, A. S., and Ozgulbas, N. (2012). Financial early warning system model and data mining application for risk detection. *Expert Systems with Applications*, 39(6), 6238-6253.

Kumar P and Ravi V (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques-A review. *European Journal of Operational Research*, 180(1): 1–28.

Kumbhakar, S. C., and Lovell, C. K. (2003). *Stochastic frontier analysis*. Cambridge University Press.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., and Vishny, R. W. (1998). *Law and Finance* (pp. 26-68). Springer Berlin Heidelberg.

Lacher, R. C., Coats, P. K., Sharma, S. C., and Fant, L. F. (1995). A neural network for classifying the financial health of a firm. *European Journal of Operational Research*, 85(1), 53-65.

Laitinen, E. K. (1993). Financial predictors for different phases of the failure process. *Omega*, 21(2), 215-228.

Lane, W. R., Looney, S. W., and Wansley, J. W. (1986). An application of the Cox proportional hazards model to bank failure. *Journal of Banking and Finance*,10(4), 511-531.

Lau, A. H. L. (1987). A five-state financial distress prediction model. *Journal of Accounting Research*, 25(1), 127-138.

Lee, ST., Yeh, YH., (2004), Corporate Governance and Financial Distress: evidence from Taiwan, *Corporate governance*, 12(3), 378-388

Lemmon, M. L., and Lins, K. V. (2003). Ownership structure, corporate governance, and firm value: Evidence from the East Asian financial crisis. *Journal Of Finance*, 58(4), 1445-1468.

Lennox, C. (1999). Identifying failing companies: a re-evaluation of the logit, probit and DA approaches. *Journal of Economics and Business*, 51(4), 347-364.

Leshno, M., and Spector, Y. (1996). Neural network prediction analysis: The bankruptcy case. *Neurocomputing*, 10(2), 125-147.

Lev, B. (1969). Industry averages as targets for financial ratios. *Journal of Accounting Research*, 290-299.

Li D. and Liu J, (2009), Determinants of Financial Distress of ST and PT Companies: A panel analysis of Chinese Listed Companies, working paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1341795

Li Z, Crook J and Andreeva G (2014). Chinese companies distress prediction: An application of data envelopment analysis. *Journal of the Operational Research Society*, 65(3), 466–479

Li, H, Wang Z., and Deng X. (2008). Ownership, independent directors, agency costs and financial distress: Evidence from Chinese listed companies. *Corporate Governance*, 8, 622-636

Li, H., and Sun, J. (2009a). Majority voting combination of multiple case-based reasoning for financial distress prediction. *Expert Systems with Applications*, 36(3), 4363-4373.

Li, H., and Sun, J. (2009b). Hybridizing principles of the Electre method with case-based reasoning for data mining: Electre-CBR-I and Electre-CBR-II. *European Journal of Operational Research*, 197(1), 214-224.

Li, H., and Sun, J. (2010). Forecasting business failure in China using case-based reasoning with hybrid case respresentation. *Journal of Forecasting*, 29(5), 486-501.

Li, H., and Sun, J. (2011). Predicting business failure using forward ranking-order case-based reasoning. *Expert Systems with Applications*, 38(4), 3075-3084.

Li, H., and Sun, J. (2013). Predicting Business Failure Using an RSF-based Case-Based Reasoning Ensemble Forecasting Method. *Journal of Forecasting*, 32(2), 180-192.

Li, H., Sun, J., and Sun, B. L. (2009). Financial distress prediction based on OR-CBR in the principle of k-nearest neighbors. *Expert Systems with Applications*, 36(1), 643-659.

Li, L., Naughton, T., and Hovey, M. (2008). *A review of corporate governance in China*. Available at SSRN 1233070.

Liebman, B. L., and Milhaupt, C. J. (2008). Reputational Sanctions in China's Securities Market. *Columbia Law Review*, 929-983.

Lin, F. Y., and McClean, S. (2001). A data mining approach to the prediction of corporate failure. *Knowledge-Based Systems*, *14*(3), 189-195.

Lin, R. H., Wang, Y. T., Wu, C. H., and Chuang, C. L. (2009). Developing a business failure prediction model via RST, GRA and CBR. *Expert Systems with Applications*, 36(2), 1593-1600.

Lin, S. M., Ansell, J., and Andreeva, G. (2012). Predicting default of a small business using different definitions of financial distress. *Journal of the Operational Research Society*, *63*(4), 539-548.

Lipton, L., Lorsch, J., (1992). A modest proposal for improved corporate governance. *The Business Lawyer*, 48, 59-77.

Liu, J. S., and Lu, W. M. (2010). DEA and ranking with the network-based approach: a case of RandD performance. *Omega*, 38(6), 453-464.

Liu, Q. (2006). Corporate governance in China: Current practices, economic effects and institutional determinants. *CESifo Economic Studies*, 52(2), 415-453.

Liu, S., Sun, P., and Liu, N. (2003). The Ultimate Ownership and Its Shareholding Structures: Does It Matter for Corporate Performance?. *Economic Research Journal*, 4, 51-62.

Lizal, L. (2002). Determinants of financial distress: What drives bankruptcy in a transition economy? The Czech Republic case. William Davidson Institute (WDI) - Working Papers

Lovell, C. A., and Pastor, J. T. (1995). Units invariant and translation invariant DEA models. *Operations Research Letters*, 18(3), 147-151.

Lu, W. M., Wang, W. K., and Kweh, Q. L. (2014). Intellectual capital and performance in the Chinese life insurance industry. *Omega*, *42*(1), 65-74.

Lugovskaya, L. (2010). Predicting default of Russian SMEs on the basis of financial and non-financial variables. *Journal of Financial Services Marketing*, 14(4), 301-313.

Luo, X. (2003). Evaluating the profitability and marketability efficiency of large banks: An application of data envelopment analysis. *Journal of Business research*, 56(8), 627-635.

Mahmood, M. A., and Lawrence, E. C. (1987). A performance analysis of parametric and nonparametric discriminant approaches to business decision making. *Decision Sciences*, 18(2), 308-326.

Malmquist, S., 1953. Index numbers and indifference surfaces. *Trabajos de Estatistica*, 4, 209–242.

Mangasarian, O. L. (1965). Linear and nonlinear separation of patterns by linear programming. *Operations Research*, 13(3), 444-452.

Mangena, M. and Chamisa, E. (2008). Corporate governance and incidences of listing suspension by the JSE Securities Exchange of South Africa: An empirical analysis. *The International Journal of Accounting*, 43, 28-44.

Mann, (2005), Compensation and credit risk, Moody's report, Special comment.

Marais, M. L., Patell, J. M., and Wolfson, M. A. (1984). The experimental design of classification models: An application of recursive partitioning and bootstrapping to commercial bank loan classifications. *Journal of Accounting Research,* 22, 87-114.

Martin, D. (1977). Early warning of bank failure: A logit regression approach. *Journal of Banking and Finance*, 1(3), 249-276.

Martin, E.A. (2003). Oxford Dictionary of Law (7th ed. ed.). Oxford: Oxford University Press.

McKee, T. E., and Lensberg, T. (2002). Genetic programming and rough sets: A hybrid approach to bankruptcy classification. *European Journal of Operational Research*, 138(2), 436-451.

Mensah, Y. M. (1984). An examination of the stationarity of multivariate bankruptcy prediction models: a methodological study. *Journal of Accounting Research*, 22(1), 380-395.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance,* 29(2), 449-470.

Messier, W. F., and Hansen, J. V. (1988). Inducing rules for expert system development: an example using default and bankruptcy data. *Management Science*, 34(12), 1403-1415.

Meyer, P. A., and Pifer, H. W. (1970). Prediction of bank failures. The Journal of Finance, 25(4), 853-868.

Min, J.H. and Lee YC (2008). A practical approach to credit scoring. *Expert Systems with Applications*, 35(4): 1762–1770.

Min, J. H., and Lee, Y. C. (2005). Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters. *Expert Systems with Applications*, 28(4), 603-614.

Min, S. H., Lee, J., and Han, I. (2006). Hybrid genetic algorithms and support vector machines for bankruptcy prediction. *Expert Systems with Applications*, 31(3), 652-660.

Mossman, C. E., Bell, G. G., Swartz, L. M., and Turtle, H. (1998). An empirical comparison of bankruptcy models. *Financial Review, 33*(2), 35-54.

Nam, C. W., Kim, T. S., Park, N. J., and Lee, H. K. (2008). Bankruptcy prediction using a discrete-time duration model incorporating temporal and macroeconomic dependencies. *Journal of Forecasting*, 27(6), 493-506.

New York Times, (1998), China's Paragon of Corruption; Meet Mr. Chu, a Hero to Some, an Embezzler to Others, http://www.nytimes.com/1998/03/06/business/china-s-paragon-of-corruption-meet-mr-chu-a-hero-to-some-an-embezzler-to-others.html?pagewanted=allandsrc=pm

Nwogugu, M. (2007). Decision-making, risk and corporate governance: A critique of methodological issues in bankruptcy/recovery prediction models. *Applied Mathematics and Computation*, 185(1), 178-196.

O'Brien, Robert M. (2007). "A Caution Regarding Rules of Thumb for Variance Inflation Factors," *Quality and Quantity*, 41(5), 673-690.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 109-131.

Olson, D.L., Delen, D. and Meng, Y., (2012), Comparative analysis of data mining methods for bankruptcy prediction, *Decision Support Systems*, 52(2), 464–473

Oral, M. and Yolalan R. (1990). An empirical study on measuring operating efficiency and profitability of bank branches. *European Journal of Operational Research*, 46(3), 282–294.

Organisation for Economic Cooperation and Development (OECD), (2004), *OECD Principles of Corporate Governance*, http://www.oecd.org/corporate/ca/corporategovernanceprinciples/31557724.pdf

Paradi, JC, Asmild M and Simak PC, (2004). Using DEA and worst practice DEA in credit risk evaluation. *Journal of Productivity Analysis*, 21(2), 153–165.

Park, C. S., and Han, I. (2002). A case-based reasoning with the feature weights derived by analytic hierarchy process for bankruptcy prediction. *Expert Systems with Applications*, 23(3), 255-264.

Parkan, C., (1987). Measuring the efficiency of service operations: An application to bank branches. *Engineering Costs and Production Economics*, 12(1), 237–242.

Parker, S., Peters, G.F. and Turetsky, H.F., (2002), Corporate governance and corporate failure: A survival analysis, *Corporate Governance*, 2(2), 4-12

Pastor, J. T., and Lovell, C. A. (2005). A global Malmquist productivity index. *Economics Letters*, 88(2), 266-271.

Pawlak, Z. (1982). Rough sets. *International Journal of Computer and Information Sciences*, 11(5), 341-356.

Pederzoli, C., and Torricelli, C. (2005). Capital requirements and business cycle regimes: forward-looking modelling of default probabilities. *Journal of Banking and Finance*, 29(12), 3121-3140.

Peel, M. J., and Peel, D. A. (1988). A multilogit approach to predicting corporate failure-some evidence for the UK corporate sector. *Omega*, 16(4), 309-318.

Perry, S. C. (2001). The relationship between written business plans and the failure of small businesses in the US. *Journal of small business management*, 39(3), 201-208.

Pindado, J., Rodrigues, L., and de la Torre, C. (2008). Estimating financial distress likelihood. *Journal of Business Research, 61*(9), 995-1003.

Platt, H. and Platt, M., (2012), Corporate Board Attributes and Bankruptcy, *Journal of Business Research*, 65, 1139-1143

Platt, H. D., and Platt, M. B. (1990). Development of a class of stable predictive variables: the case of bankruptcy prediction. *Journal of Business Finance and Accounting*, 17(1), 31-51.

Polsiri P., and Sookhanaphibarn K., (2009), Corporate Distress Prediction Models Using Governance and Financial Variables: Evidence from Thai Listed Firms during the East Asian Economic Crisis, *Journal of Economics and Management*, 5(2), 273-304

Portela, MCAS, Thanassoulis E and Simpson G (2004). Negative data in DEA: A directional distance approach applied to bank branches. *Journal of the Operational Research Society*, 55(10), 1111–1121.

Premachandra IM, Bhabra GS and Sueyoshi T (2009). DEA as a tool for bankruptcy assessment: A comparative study with logistic regression technique. *European Journal of Operational Research*, 193(2), 412–424.

Premachandra IM, Chen Y and Watson J (2011). DEA as a tool for predicting corporate failure and success: A case of bankruptcy assessment. *Omega*, 39(6), 620–626.

Psillaki M, Tsolas IE and Margaritis D (2010). Evaluation of credit risk based on firm performance. *European Journal of Operational Research*, 201(3), 873–881.

Pulina, M., Detotto, C., and Paba, A. (2010). An investigation into the relationship between size and efficiency of the Italian hospitality sector: A window DEA approach. *European Journal of Operational Research*, 204(3), 613-620.

Quinlan, J.R. (1983), "Learning efficient classification procedures and their application to chess and games", in: R.S. Michalski, J.G. Carbonell and T.M. Mitchell (eds.), *Machine Learning: An Artificial Intelligence Approach*, Tioga, Palo Alto, CA.

Roe, M. (2002). Corporate law's limits. Journal of Legal Studies, 31, 233– 271.

Rosenberg, E., and Gleit, A. (1994). Quantitative methods in credit management: a survey. *Operations Research*, 42(4), 589-613.

Ross, S.A., Westerfield RW and Jaffe J (1999). *Corporate Finance*. Irwin/McGraw-Hill Press: New York.

Roy, B., and Słowiński, R. (2008). Handling effects of reinforced preference and counter-veto in credibility of outranking. *European Journal of Operational Research*, 188(1), 185-190.

Roy, B., and Vincke, P. (1984). Relational systems of preference with one or more pseudo-criteria: Some new concepts and results. *Management Science*, 1323-1335.

Ruigrok, W., S. Peck, and S. Tacheva, (2007), Nationality and gender diversity on Swiss Corporate Boards, *Corporate Governance,* 15, 546-557.

Salchenberger, L. M., Cinar, E., and Lash, N. A. (1992). Neural Networks: A New Tool for Predicting Thrift Failures. *Decision Sciences*, 23(4), 899-916.

Salloum, C.C., Azoury N. and Azzi T.M, (2013), Board of directors' effects on financial distress evidence of family owned business in Lebanon, *International Entrepreneurship and Management Journal*, 9(1), 59-75

Sánchez-Lasheras, F., de Andrés, J., Lorca, P., and de Cos Juez, F. J. (2012). A hybrid device for the solution of sampling bias problems in the forecasting of firms' bankruptcy. *Expert Systems with Applications*, 39(8), 7512-7523.

Santen, B.P.A. and Soppe, A., (2009), Financial Distress, Board Structure and NED Characteristics in the Netherlands, *Corporate Ownership and Control*, 7(1), Sarkar, S., and Sriram, R. S. (2001). Bayesian models for early warning of bank failures. *Management Science*, 47(11), 1457-1475.

Schlimmer, J. C., and Granger Jr, R. H. (1986). Incremental learning from noisy data. *Machine Learning*, 1(3), 317-354.

Shanghai Stock Exchange (2008). *Rules Governing the Listing of Stocks on Shanghai Stock Exchange*. Shanghai Stock Exchange: Shanghai, p 90.

Shanghai Stock Exchange, (2013), Guidelines of Election and Behaviour of Directors in listed companies http://www.sse.com.cn/lawandrules/sserules/listing/stock/c/c_20130613_3720551.shtml

Sharp, J.A., Meng, W. and Liu, W. (2006). A modified slacks-based measure model for data envelopment analysis with 'natural' negative outputs and inputs. *Journal of the Operational Research Society*, 58(12): 1672–1677.

Sheskin, D. J. (2003). *Handbook of Parametric and Nonparametric Statistical Procedures*. CRC Press.

Shetty U, Pakkala TPM and Mallikarjunappa T (2012). A modified directional distance formulation of DEA to assess bankruptcy: An application to IT/ITES companies in India. *Expert Systems with Applications*, 39(2), 1988–1997.

Shi, C. (2007). Protecting investors in china through multiple regulatory mechanisms and effective enforcement. *Arizona Journal of International and Comparative Law*, 24(2), 451

Shin, K. S., and Lee, Y. J. (2002). A genetic algorithm application in bankruptcy prediction modeling. *Expert Systems with Applications*, 23(3), 321-328.

Shin, K. S., Lee, T. S., and Kim, H. J. (2005). An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications*, 28(1), 127-135.

Shleifer, A., and Vishny, R. W. (1997). A survey of corporate governance. *Journal of Finance*, 52(2), 737-783.

Shumway, T. (2001). Forecasting bankruptcy more accurately: a simple hazard model. *Journal of Business*, 74(1), 101–124.

Simpson, W. G., and Gleason, A. E. (1999). Board structure, ownership, and financial distress in banking firms. *International Review of Economics and Finance*,8(3), 281-292.

Stiglitz, J.E .(1972). Some aspects of the pure theory of corporate finance: Bankruptcies and take-overs. *The Bell Journal of Economics and Management Science*, 3(2), 458–482.

Sueyoshi, T (1999). DEA-discriminant analysis in the view of goal programming. *European Journal of Operational Research*, 115(3): 564–582.

Sueyoshi, T (2001). Extended DEA-discriminant analysis. *European Journal of Operational Research*, 131(2), 324–351.

Sueyoshi, T (2006). DEA-discriminant analysis: Methodological comparison among eight discriminant analysis approaches. *European Journal of Operational Research*, 169(1): 247–272.

Sueyoshi T and Goto M (2009). Methodological comparison between DEA (data envelopment analysis) and DEA-DA (discriminant analysis) from the perspective of bankruptcy assessment. *European Journal of Operational Research*, 199(2), 561–575.

Sun, J, Jia MY and Li H (2011). AdaBoost ensemble for financial distress prediction: An empirical comparison with data from Chinese listed companies. *Expert Systems with Applications*, 38(8), 9305–9312.
Sun, J., and Li, H. (2008). Listed companies' financial distress prediction based on weighted majority voting combination of multiple classifiers. *Expert Systems with Applications*, *35*(3), 818-827.
Sun, J., and Li, H. (2011). Dynamic financial distress prediction using instance selection for the disposal of concept drift. *Expert Systems with Applications*, 38(3), 2566-2576.
Sun, L., and Shenoy, P. P. (2007). Using Bayesian networks for bankruptcy prediction: Some methodological issues. *European Journal of Operational Research*, 180(2), 738-753.
Sun, W., and Cui, K. (2013). Linking corporate social responsibility to firm default risk. *European Management Journal*.
Taffler, R.J., (1982). Forecasting company failure in the UK using discriminant analysis and financial ratio data. *Journal of the Royal Statistical Society*, 145, 342–358 (Part 3).
Takahashi, K., Kurokawa, Y., and Watase, K. (1984). Corporate bankruptcy prediction in Japan. *Journal of Banking and Finance*, *8*(2), 229-247.
Tam, K. Y. (1991). Neural network models and the prediction of bank bankruptcy. *Omega*, 19(5), 429-445.
Tam, O. K. (2000). Models of corporate governance for Chinese companies. *Corporate Governance: An International Review*, 8(1), 52-64.
Tam, O. K. (2002). Ethical Issues in the Evolution of Corporate Governance in China. Journal of Business Ethics, 37(3), 303-320.
Tam, O.K.(1999), *The Development of Corporate Governance in China*, Edward Elgar Publishing Ltd
Tan, L. H., and Wang, J. (2004). Proposing a Model for Corporate Governance in China's Listed Companies: Problems and Prospects. Available at SSRN 526942.
Tay, F. E., and Shen, L. (2002). Economic and financial prediction using rough sets model. *European Journal of Operational Research*, 141(3), 641-659.
Tennyson, B. M., Ingram, R. W., and Dugan, M. T. (1990). Assessing the information content of narrative disclosures in explaining bankruptcy. *Journal of Business Finance and Accounting*, *17*(3), 391-410.
The Company Law of the People's Republic of China, (2006), http://www.gov.cn/flfg/2005-10/28/content_85478.htm
Thomas, L.C., Edelman, D.E. and Crook, J.N., (2002). *Credit Scoring and Its Applications.* SIAM: Philadelphia.
Thomas, L. C. (2000). A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers. *International Journal of Forecasting*,16(2), 149-172.
Thomas, L. C. (2009). *Consumer Credit Models: Pricing, Profit and Portfolios: Pricing, Profit and Portfolios*. Oxford University Press.
Ting, W., Yen, S. H., and Chiu, C. L. (2008). The influence of qualified foreign institutional investors on the association between default risk and audit opinions: Evidence from the Chinese Stock Market. *Corporate Governance: An International Review*, *16*(5), 400-415.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130(3), 498-509.

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research*, 143, 32-41.

Tone, K., and Tsutsui, M. (2009). Network DEA: a slacks-based measure approach. *European Journal of Operational Research*, 197(1), 243-252.

Tsai, MC, Lin SP, Cheng CC and Lin YP (2009). The consumer loan default predicting model-An application of DEA-DA. *Expert Systems with Applications*, 36(9): 11682–11690.

Tsai, C. F., and Wu, J. W. (2008). Using neural network ensembles for bankruptcy prediction and credit scoring. *Expert Systems with Applications*, 34(4), 2639-2649.

Tseng, F. M., and Hu, Y. C. (2010). Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. *Expert Systems with Applications*, 37(3), 1846-1853.

Tsoukas, S., and Mizon, P. (2012). Forecasting US bond default ratings allowing for previous and initial state persistence. *International Journal of Forecasting*, 28(1), 273-287.

Vapnik, V. N. (1998). Statistical learning theory. Adaptive and learning systems for signal processing, communications, and control. *Simon Haykin*.

Verikas A, Kalsyte Z, Bacauskiene M and Gelzinis A (2010). Hybrid and ensemble-based soft computing techniques in bankruptcy prediction: a survey. *Soft Computing*, 14(9), 995–1010.

Wang, Z., Deng, X., (2006), Corporate Governance and Financial Distress: Evidence from Chinese Listed Companies, *The Chinese Economy*, 39(5), 5–27

Whitaker, R. B. (1999). The early stages of financial distress. *Journal of Economics and Finance*, 23(2), 123-132.

Wilcox, J. W. (1973). A prediction of business failure using accounting data. *Journal of Accounting Research*, 163-179.

Wilson, N., and Altanlar, A. (2011). Director characteristics, gender balance and insolvency risk: an empirical study. *Gender Balance and Insolvency Risk: An Empirical Study*, (September 22, 2009).

Wilson, N., Wright, M., & Scholes, L. (2013). Family business survival and the role of boards. *Entrepreneurship Theory and Practice*, *37*(6), 1369-1389.

Wilson, N., and Altanlar, A. (2014). Company failure prediction with limited information: newly incorporated companies. *Journal of the Operational Research Society*, *65*(2), 252-264.

Wilson, R. L., and Sharda, R. (1994). Bankruptcy prediction using neural networks. *Decision Support Systems*, 11(5), 545-557.

Worthington, A. C., and Lee, B. L. (2008). Efficiency, technology and productivity change in Australian universities, 1998–2003. *Economics of Education Review*, 27(3), 285-298.

Wu, C. H., Tzeng, G. H., Goo, Y. J., and Fang, W. C. (2007). A real-valued genetic algorithm to optimize the parameters of support vector machine for predicting bankruptcy. *Expert Systems with Applications*, 32(2), 397-408.

Wu, W. W. (2010). Beyond business failure prediction. *Expert Systems with Applications*, 37(3), 2371-2376.

Xiao, Z, Yang X, Pang Y and Dang X (2012). The prediction for listed companies' financial distress by using multiple prediction models with rough set and Dempster-Shafer evidence theory. *Knowledge Based Systems*, 26, 196–206.

Xu, X and Wang Y (2009). Financial failure prediction using efficiency as a predictor. *Expert Systems with Applications*, 36(1), 366–373.

Xu, X., and Wang, Y. (1999). Ownership structure and corporate governance in Chinese stock companies. *China Economic Review*, 10(1), 75-98.

Yang, Z. R., Platt, M. B., and Platt, H. D. (1999). Probabilistic neural networks in bankruptcy prediction. *Journal of Business Research*, 44(2), 67-74.

Yang, Z., You, W., and Ji, G. (2011). Using partial least squares and support vector machines for bankruptcy prediction. *Expert Systems with Applications*, 38(7), 8336-8342.

Yeh, CC, Chi DJ and Hsu MF (2010). A hybrid approach of DEA, rough set and support vector machines for business failure prediction. *Expert Systems with Applications*, 37(2), 1535–1541.

Yeh, QJ (1996). The application of data envelopment analysis in conjunction with financial ratios for bank performance evaluation. *Journal of the Operational Research Society*, 47(8), 980–988.

Yermack, D. (1995). Do corporations award CEO stock options effectively? *Journal of Financial Economics*, 39, 237-269.

Zahra, S. A. and Pearce, J. A. (1989). Boards of Directors and Corporate Financial Performance - A Review and Integrative Model. *Journal of Management*, 15, 291-334.

Zavgren, C.V., (1985). Assessing the vulnerability to failure of American industrial firms: a logistic analysis. *Journal of Business Finance and Accounting*, 12 (1), 19–45.

Zeitun, R and Tian G.G., (2007), Does ownership affect a firm's performance and default risk in Jordan?, *Corporate Governance*, 7(1), pp. 66 – 82

Zhou, L., Lai, K. K., and Yen, J. (2012). Empirical models based on features ranking techniques for corporate financial distress prediction. *Computers and Mathematics with Applications*, 64(8), 2484-2496.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. Journal of Accounting Research, 22, 59-82.

Appendices

Appendix A Codes in R to calculate H, AUC, Gini and KS

```
inp<-read.table(file.choose(),header=TRUE)

#   DAVID J. HAND, DEPARTMENT OF MATHEMATICS, IMPERIAL COLLEGE,
LONDON
#   d.j.hand@imperial.ac.uk

# This is R code for H, AUC, AUCH, GINI, and KS statistic
# In addition to these statistics, the output includes
#       - the kernel smoothed score distributions of the two classes
#       - the ROC curve and convex hull
#       - a plot of the minimum loss produced for each value of c
#       - the weight function implicitly used by the AUC, as a
function of score
#       - the weight function implicitly used by the AUC, as a
function of c
#       - the weight function used by the AUC measure

# data is in a matrix called ‘inp’ with two columns
# column 1: classes, labelled 0 or 1
# column 2: classifier scores

n0n1 <- nrow(inp)

x <- t(inp)

# alpha and betad are the parameters in the beta
# cost distribution ~ c^alpha * (1-c)^betad

alpha <- 2
betad <- 2

par(mfrow=c(3,2))

# Smoothed histograms
class0 <- x[,x[1,]==0]
class1 <- x[,x[1,]==1]

xmin <- min(x[2,])
xmax <- max(x[2,])
plot(density(class0[2,]),xlim=c(xmin,xmax),main= "Kernel smoothed
score distributions ",xlab= "Score ")
lines(density(class1[2,]),lty=4)

# order data into increasing scores
zord <- order(x[2,])

sc <- x[,zord]

n1 <- sum(sc[1,])
n0 <- n0n1 - n1
pi0 <- n0/n0n1
pi1 <- n1/n0n1

# Calculate the raw ROC, replacing any tied
# sequences by a ‘diagonal’ in the ROC curve.

# The raw ROC starts at F0[1]=0, F1[1]=0, and ends at
# F0[K1]=n0, F1[K1]=n1.

F0 <- c(0:n0n1)
```

```
F1 <- c(0:n0n1)

sc <- cbind(sc,sc[,n0n1])

K1 <- 1
k <- 2
for (i in 1:n0n1)
{
F0[k] <- F0[K1]+(1-sc[1,i])
F1[k] <- F1[K1]+sc[1,i]
K1 <- k
k <- if (sc[2,i+1] == sc[2,i]) (k) else (k+1)
}

F0 <- F0[1:K1]
F1 <- F1[1:K1]

# Plot the ROC
plot(F1/n1,F0/n0, xlab= "F1 ",ylab= "F0 ",type= "l", main= "ROC
curve and convex hull ")
lines(c(0,1),c(0,1),type= "l")

# Compute KS statistic
KS <- max((F0/n0) - (F1/n1))

# Find the upper concave hull

G0 <- c(0:(K1-1))
G1 <- c(0:(K1-1))


i <- 1
hc <- 1
while (i < K1)
{
c1 <- c((i+1):K1)
for (j in (i+1):K1)
{
u1 <- (F1[j]-F1[i])
u0 <- (F0[j]-F0[i])
c1[j] <- u1/(u1+u0)
}

argmin <- i+1
c1min <- c1[i+1]
for (k in (i+1):K1)
{
argmin <- if (c1[k] <= c1min) (k) else (argmin)
c1min <- c1[argmin]
}
hc <- hc+1
G0[hc] <- F0[argmin]
G1[hc] <- F1[argmin]
i <- argmin
}
G0 <- G0[1:hc]/n0
G1 <- G1[1:hc]/n1

# Draw hull
lines(G1,G0,type= "l",lty=2)

# Calculate the LHalpha value

cost <- c(1:(hc+1))
b0 <- c(1:hc+1)
b1 <- c(1:hc+1)
```

```
cost[1] <- 0
cost[hc+1] <- 1

b0[1] <-
  pbeta(cost[1],shape1=(1+alpha), shape2=betad)*
  beta((1+alpha), betad)/   beta(alpha, betad)

b1[1] <-
  pbeta(cost[1],shape1=alpha, shape2=(1+betad))*
  beta(alpha, (1+betad))/   beta(alpha, betad)

b0[hc+1] <-
  pbeta(cost[hc+1],shape1=(1+alpha), shape2=betad)*
  beta((1+alpha), betad)/ beta(alpha, betad)

b1[hc+1] <-
  pbeta(cost[hc+1],shape1=alpha, shape2=(1+betad))*
  beta(alpha, (1+betad))/ beta(alpha, betad)

for (i in 2:hc)
{
cost[i] <- pi1*(G1[i]-G1[i-1]) /
   (pi0*(G0[i]-G0[i-1]) + pi1*(G1[i]-G1[i-1]))

b0[i] <-
  pbeta(cost[i],shape1=(1+alpha), shape2=betad)*
  beta((1+alpha), betad)/ beta(alpha, betad)

b1[i] <-
  pbeta(cost[i],shape1=alpha, shape2=(1+betad))*
  beta(alpha, (1+betad))/ beta(alpha, betad)
}


LHalpha <- 0
for (i in 1:hc)
{LHalpha <- LHalpha + pi0*(1-G0[i])*(b0[(i+1)]-b0[i]) +
pi1*G1[i]*(b1[(i+1)]-b1[i])
}

B0 <-
  pbeta(pi1,shape1=(1+alpha), shape2=betad)*
  beta((1+alpha), betad)/ beta(alpha, betad)

B1 <-
  pbeta(1,shape1=alpha, shape2=(1+betad))*
  beta(alpha, (1+betad))/ beta(alpha, betad) -

  pbeta(pi1,shape1=alpha, shape2=(1+betad))*
  beta(alpha, (1+betad))/ beta(alpha, betad)

H <- 1 - LHalpha/(pi0*B0 + pi1*B1)


# Calculate the area under the ROC curve, AUC

K11 <- K1+1

F0[K11] <- n0
F1[K11] <- n1

F0 <- F0[1:K11]
F1 <- F1[1:K11]

F0A <- F0[2:K11]
F0B <- F0[1:K1]
```

```
F1A <- F1[2:K11]
F1B <- F1[1:K1]

AUC <- sum((F0A-F0B)*(n1-(F1A+F1B)/2))/(n0*n1)
Gini <- 2*AUC - 1

# CALCULATE THE AREA UNDER THE CONVEX HULL, AUCH

AUCH <- 0
for (i in 1:(hc-1))
{
AUCH <- AUCH + G0[i]*(G1[i+1]-G1[i]) + 0.5*(G0[i+1]-G0[i])*(G1[i+1]-
G1[i])
}

# CALCULATE THE MINIMUM LOSS VS c CURVE

Q <- c(1:(hc+1))

for (i in 1:hc)
{
Q[i] <- cost[i]*pi0*(1-G0[i]) + (1-cost[i])*pi1*G1[i]
}
Q[(hc+1)] <- 0

plot(cost,Q,type= "l", main= "Minimum loss by cost ",xlab= "cost
",ylab= "Minimum achievable loss ")

# PLOT THE AUC MIXTURE WEIGHT FUNCTION IN TERMS
# OF THE SCORE

plot(density(x[2,]),lty=1,xlab= "Score ",main= " AUC measure weight
function of T", ylab= "W(t)")

# PLOT THE AUC MIXTURE WEIGHT FUNCTION IN TERMS
# OF THE COST

aucd <- c((n0*G0 + n1*G1),1)
aucd2 <- c(1, (n0*G0 + n1*G1))
aucf <- (aucd-aucd2)/n0n1

plot(cost[2:hc],aucf[2:hc],type= "h", xlim=c(0,1), ylim=c(0,1),main=
"AUC measure weight function of c",xlab= "Cost",ylab= "w(c)")

# PLOT THE BETA WEIGHT FUNCTION IN TERMS OF THE COST

b <- c(1:100)/100
y <- dbeta(b,alpha,betad)
plot(b,y,type= "l",xlab= "Cost ", main= "H measure weight function
of c",ylab= "w(c) ")

H
AUC
Gini
AUCH
KS
```

Appendix B Description of Malmquist DEA inputs and outputs

Values are in million CNY except the number of employees.

			employees	debts	costs	assets	capitals	profits	cash	sales
	1510	Mean	4207	1147	1491	2539	538	92	27	1581
		Max	45943	31752	25498	58042	12512	3710	872	29171
		Min	104	43	38	144	51	-1797	-3686	20
	2010	Mean	2866	824	972	1659	295	50	46	1009
2001		Max	33874	4810	19359	9908	1884	1012	883	19565
		Min	54	46	38	198	51	-1010	-686	24
	4040	Mean	1159	789	503	1573	288	41	47	530
		Max	5349	7381	4157	9690	1868	502	819	4455
		Min	36	6	30	168	65	-538	-330	12
	1510	Mean	4167	1290	1625	2730	539	121	19	1748
		Max	45766	33304	27784	61489	12512	5942	1937	33877
		Min	115	46	25	146	51	-1031	-729	17
	2010	Mean	2764	888	1129	1731	291	41	8	1211
2002		Max	37243	7567	28063	13493	1884	1220	791	28333
		Min	47	56	59	172	51	-577	-757	18
	4040	Mean	1137	944	563	1768	301	33	31	588
		Max	7119	6670	4063	8416	1868	603	577	4574
		Min	33	7	7	171	66	-690	-675	3
	1510	Mean	4209	1441	2050	3068	529	213	79	2266
		Max	45738	25227	34475	60918	12512	9929	2689	44460
		Min	173	22	25	248	60	-570	-1811	9
	2010	Mean	2804	1088	1458	2005	296	60	27	1559
2003		Max	40946	19022	51712	21288	1884	1655	1248	52123
		Min	42	70	68	153	51	-788	-618	1
	4040	Mean	1148	1192	664	2105	326	37	-1	696
		Max	9756	6696	5561	10561	1868	830	1383	6380
		Min	34	6	14	208	66	-642	-506	3
	1510	Mean	4359	1804	2930	3646	573	318	62	3245
		Max	44722	22242	45202	64255	12512	13586	2911	58638
		Min	179	35	61	260	60	-923	-881	16
	2010	Mean	2721	1235	1767	2196	312	78	47	1880
2004		Max	42783	15382	63680	18144	2690	2802	1709	64593
		Min	29	57	77	129	51	-524	-505	28
	4040	Mean	1171	1366	814	2361	349	42	37	858
		Max	13558	9230	6422	15534	2274	1260	2163	7667
		Min	33	5	17	202	55	-954	-600	14
	1510	Mean	4688	2331	3889	4493	635	317	-8	4198
		Max	44421	63097	108422	142024	17512	18311	1784	126608
		Min	173	23	49	164	60	-997	-2665	18
	2010	Mean	2757	1430	2102	2456	333	78	-10	2165
2005		Max	32755	24234	66058	27219	2690	3061	1342	66597
		Min	30	56	110	173	58	-696	-954	1
	4040	Mean	1180	1526	828	2572	381	57	-34	888
		Max	12568	13411	8529	21992	3723	1976	598	10559
		Min	21	7	12	200	63	-1142	-1100	11
	1510	Mean	4841	3040	4716	5483	659	377	101	5009
		Max	44104	78313	143657	164847	17512	19204	9263	162326
		Min	177	27	57	156	59	-1679	-2275	69
	2010	Mean	2789	1757	2646	2918	361	132	34	2748
2006		Max	46355	25348	75825	31430	3082	3187	3694	76491
		Min	30	50	46	223	59	-1376	-5237	105
	4040	Mean	1343	2449	1103	3897	475	148	178	1215
		Max	15174	32466	14664	49920	4370	3434	7495	17918
		Min	17	38	10	45	63	-866	-462	6

2007	1510	Mean	5373	3753	6169	6967	769	575	176	6697
		Max	94269	93735	173608	188336	17512	19308	6253	191559
		Min	158	56	52	312	50	-364	-2276	63
	2010	Mean	4280	2920	3951	4643	465	239	283	4118
		Max	266607	156283	177619	215213	21300	4329	26987	180507
		Min	136	32	78	219	50	-1048	-2099	94
	4040	Mean	1432	3955	1665	6368	608	364	310	1957
		Max	16464	66175	28059	100094	6872	7642	6303	35527
		Min	16	44	12	200	63	-933	-2674	4
2008	1510	Mean	5451	4197	7357	7568	814	198	60	7520
		Max	107887	102183	193014	200021	17512	8154	8356	200638
		Min	147	27	38	238	50	-8022	-8837	32
	2010	Mean	5742	4739	6130	7054	667	260	184	6331
		Max	267188	191001	233114	252096	21300	4569	26267	234619
		Min	165	49	58	222	59	-425	-9926	62
	4040	Mean	1417	4981	1734	8024	849	386	119	2066
		Max	16515	80418	34856	119237	10995	6322	5016	40992
		Min	18	38	16	182	87	-432	-1764	5
2009	1510	Mean	5948	4986	6507	8665	871	214	-60	6667
		Max	107831	99923	142118	201143	17512	7295	1996	148525
		Min	135	18	33	245	67	-5391	-8583	31
	2010	Mean	6047	5987	7566	8766	724	377	202	7855
		Max	276150	245422	347495	311781	21300	8645	5615	355521
		Min	146	39	70	230	59	-300	-1812	74
	4040	Mean	1643	7173	2206	11190	962	581	902	2694
		Max	17616	92200	41122	137609	10995	8617	9758	48881
		Min	18	43	11	192	87	-59	-1746	12
2010	1510	Mean	6248	5970	8897	10175	953	441	81	9269
		Max	108256	104723	186586	216065	17512	17076	3114	202413
		Min	124	19	53	204	75	-2537	-6261	8
	2010	Mean	6590	7692	10365	11225	849	541	335	10781
		Max	285054	315414	464434	389306	21300	10515	15319	473663
		Min	109	41	69	213	62	-848	-1568	70
	4040	Mean	1865	10576	2838	15218	1095	782	282	3508
		Max	22850	161051	39582	215638	10995	11941	13094	50714
		Min	18	36	14	192	87	-281	-2374	15

Appendix C Collinearity Diagnostics

Major variables in Chapter Four (ratios in initial abbreviations)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
Efficiency	2.59	1.61	0.3863	0.6137
CFOPS	3.28	1.81	0.3048	0.6952
ORPS	3.64	1.91	0.2750	0.7250
SCPS	1.59	1.26	0.6282	0.3718
SRPS	1.28	1.13	0.7838	0.2162
UPPS	2.07	1.44	0.4825	0.5175
CFPS	1.45	1.21	0.6874	0.3126
EBITPS	4.55	2.13	0.2200	0.7800
FCFFPS	2.25	1.50	0.4435	0.5565
FCFEPS	2.17	1.47	0.4613	0.5387
ROE	3.68	1.92	0.2721	0.7279
ROIC	5.02	2.24	0.1992	0.8008
GMS	2.36	1.54	0.4242	0.5758
OPS	2.64	1.62	0.3791	0.6209
OES	1.34	1.16	0.7479	0.2521
FES	1.83	1.35	0.5456	0.4544
EM	3.84	1.96	0.2602	0.7398
CAA	3.12	1.77	0.3205	0.6795
TAA	4.64	2.15	0.2156	0.7844
CLL	1.41	1.19	0.7104	0.2896
CUR	3.25	1.80	0.3075	0.6925
CR	2.30	1.52	0.4356	0.5644
EBITAL	1.92	1.39	0.5203	0.4797
CFOL	1.75	1.32	0.5701	0.4299
CFOIL	3.76	1.94	0.2662	0.7338
CFOCL	4.59	2.14	0.2178	0.7822
CCC	4.33	2.08	0.2310	0.7690
AIP	3.67	1.92	0.2722	0.7278
ARP	1.84	1.36	0.5437	0.4563
IT	2.29	1.51	0.4365	0.5635
RT	1.54	1.24	0.6480	0.3520
CAT	3.57	1.89	0.2800	0.7200
COR	1.22	1.11	0.8176	0.1824
CFOOR	2.70	1.64	0.3705	0.6295
CI	1.27	1.13	0.7883	0.2117
ORG	2.34	1.53	0.4272	0.5728
TPG	2.98	1.73	0.3360	0.6640
NPG	2.83	1.68	0.3528	0.6472
AG	1.77	1.33	0.5653	0.4347
Mean VIF	2.68			

Major variables in Chapter Five

Variable	VIF	SQRT VIF	Tolerance	R-Squared
TE	1.15	1.07	0.8679	0.1321
r1	1.07	1.03	0.9353	0.0647
r2	1.11	1.05	0.9007	0.0993
r3	1.19	1.09	0.8372	0.1628
r4	1.14	1.07	0.8743	0.1257
r5	1.04	1.02	0.9590	0.0410
r6	1.10	1.05	0.9097	0.0903
Mean VIF	1.12			

Variable	VIF	SQRT VIF	Tolerance	R-Squared
PTE	1.11	1.05	0.9006	0.0994
SE	1.10	1.05	0.9099	0.0901
r1	1.07	1.03	0.9359	0.0641
r2	1.11	1.06	0.8970	0.1030
r3	1.20	1.09	0.8367	0.1633
r4	1.13	1.06	0.8887	0.1113
r5	1.03	1.02	0.9683	0.0317
r6	1.09	1.04	0.9177	0.0823
Mean VIF	1.10			

Variable	VIF	SQRT VIF	Tolerance	R-Squared
GE	1.16	1.08	0.8652	0.1348
r1	1.06	1.03	0.9467	0.0533
r2	1.12	1.06	0.8921	0.1079
r3	1.20	1.09	0.8340	0.1660
r4	1.15	1.07	0.8731	0.1269
r5	1.04	1.02	0.9653	0.0347
r6	1.11	1.05	0.9006	0.0994
Mean VIF	1.12			

Variable	VIF	SQRT VIF	Tolerance	R-Squared
SPE	1.13	1.06	0.8833	0.1167
r1	1.07	1.03	0.9384	0.0616
r2	1.11	1.05	0.9007	0.0993
r3	1.20	1.09	0.8367	0.1633
r4	1.14	1.07	0.8777	0.1223
r5	1.04	1.02	0.9639	0.0361
r6	1.10	1.05	0.9128	0.0872
Mean VIF	1.11			

Variable	VIF	SQRT VIF	Tolerance	R-Squared
ME	1.14	1.07	0.8791	0.1209
r1	1.08	1.04	0.9273	0.0727
r2	1.11	1.05	0.9008	0.0992
r3	1.22	1.10	0.8198	0.1802
r4	1.12	1.06	0.8950	0.1050
r5	1.03	1.01	0.9733	0.0267
r6	1.10	1.05	0.9107	0.0893
Mean VIF	1.11			

Major variables in Chapter Five

Variable	VIF	SQRT VIF	Tolerance	R-Squared
Boardsize	1.45	1.21	0.6878	0.3122
IndependentDirector	1.16	1.08	0.8647	0.1353
Supervisor	1.33	1.15	0.7539	0.2461
SeniorManager	1.27	1.12	0.7904	0.2096
Duality_d	1.24	1.11	0.8057	0.1943
WorkLocation_d	1.05	1.02	0.9552	0.0448
StateShares	2.61	1.62	0.3833	0.6167
SOE_d	2.06	1.44	0.4855	0.5145
BoardShares	1.67	1.29	0.6004	0.3996
SupervisorShares	1.22	1.1	0.8216	0.1784
Top10Shares	1.53	1.24	0.6539	0.3461
InstitutionShares	2.08	1.44	0.4799	0.5201
AverageShares	2.09	1.44	0.479	0.521
OtherListing_d	1.12	1.06	0.8926	0.1074
CapitalChange_d	1.26	1.12	0.7959	0.2041
ConnectedShareholder_d	1.09	1.04	0.9169	0.0831
ManagementSalary	1.68	1.3	0.5944	0.4056
DirectorSalary	1.4	1.18	0.7164	0.2836
IndependentDirectorSalary	1.68	1.29	0.5966	0.4034
SeniorSalary	1.62	1.27	0.6183	0.3817
NonpaidSeniorStaff	1.96	1.4	0.51	0.49
ChairAge	1.05	1.02	0.955	0.045
ChairGender_d	1.27	1.12	0.7903	0.2097
ChairCollege_d	1.91	1.38	0.5237	0.4763
ChairUndergraduate_d	2.57	1.6	0.3885	0.6115
ChairMasters_d	3	1.73	0.3335	0.6665
ChairDoctorate_d	1.5	1.22	0.6674	0.3326
ChairQualification_d	2.46	1.57	0.406	0.594
ChairNationality_d	1.24	1.11	0.8096	0.1904
ChairPaid_d	1.7	1.3	0.5898	0.4102
ChairConpost_d	1.77	1.33	0.5658	0.4342
CEOAge	1.05	1.03	0.9508	0.0492
CEOGender_d	1.26	1.12	0.7935	0.2065
CEOCollege_d	1.89	1.38	0.5289	0.4711
CEOUndergraduate_d	2.62	1.62	0.3818	0.6182
CEOMasters_d	2.97	1.72	0.3372	0.6628
CEODoctorate_d	1.45	1.2	0.6915	0.3085
CEOQualification_d	2.37	1.54	0.4216	0.5784
CEONationality_d	1.24	1.12	0.8041	0.1959
CEOPaid_d	1.07	1.03	0.9342	0.0658
CEOConpost_d	1.48	1.22	0.6763	0.3237
Ratio1	1.72	1.31	0.5806	0.4194
Ratio2	1.31	1.15	0.7619	0.2381
Ratio3	1.09	1.04	0.9212	0.0788
Ratio4	1.32	1.15	0.7565	0.2435
Ratio5	1.2	1.1	0.8326	0.1674
Ratio6	1.34	1.16	0.7465	0.2535
Macro1	17.5	4.18	0.0571	0.9429
Macro2	3.17	1.78	0.3155	0.6845
Macro3	10.79	3.29	0.0927	0.9073
Macro4	11.46	3.39	0.0873	0.9127
Mean	VIF	2.34		

Mean VIF 2.34

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Chinese companies distress prediction: an application of data envelopment analysis

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Bankruptcy prediction is a key part in corporate credit risk management. Traditional bankruptcy prediction models employ financial ratios or market prices to predict bankruptcy or financial distress prior to its occurrence. We investigate the predictive accuracy of corporate efficiency measures along with standard financial ratios in predicting corporate distress in Chinese companies. Data Envelopment Analysis (DEA) is used to measure corporate efficiency. In contrast to previous applications of DEA in credit risk modelling where it was used to generate a single efficiency—Technical Efficiency (TE), we assume Variable Returns to Scale, and decompose TE into Pure Technical Efficiency and Scale Efficiency. These measures are introduced into Logistic Regression to predict the probability of distress, along with the level of Returns to Scale. Effects of efficiency variables are allowed to vary across industries through the use of interaction terms, while the financial ratios are assumed to have the same effects across all sectors. The results show that the predictive power of the model is improved by this corporate efficiency information.

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Introduction

The recent financial crisis indicates the importance of credit risk management and the necessity of recognising early indicators of corporate financial distress in order to prevent potential losses. Credit scoring models are such tools to generate early signals of corporate bankruptcy, which have received academic attention since at least 1950s and are still widely used.

One of the main problems in failure prediction models is variable selection. Financial ratios that are the quotient of two items in financial statements are the most popular variables that have been considered in the literature. Beaver (1966) was the first author to introduce financial ratios into bankruptcy prediction. In recent decades there have been a great number of bankruptcy prediction studies based on financial ratios using different statistical and machine-learning techniques. They are reviewed in Altman (1993), Balcaen and Ooghe (2006), Kumar and Ravi (2007), Bahrammirzaee (2010) and Verikas *et al* (2010). Recent papers (eg Wang and Ma, 2011) also demonstrate that financial ratios are still dominating the variable selection. However, it is widely recognised that the main cause of the company's financial failure is its poor management (Gestel *et al*, 2006). The quality of management can be measured by the company's efficiency that compares outputs to inputs.

One way to assess the efficiency of an organisation relative to the most efficient one is to use Data Envelopment Analysis (DEA). A number of papers have used DEA efficiencies in corporate bankruptcy modelling (see next section). In this paper we use DEA to compute various measures of corporate efficiency that we then input as a variable in a standard classifier to see how well this enables one to predict financial distress. The paper makes a number of contributions. First, unlike previous papers on corporate failure modelling that simply use a single efficiency measure, we decompose this measure—Technical Efficiency (TE) into Pure Technical Efficiency (PTE), which indicates the ability to improve efficiency by wisely allocating resources and applying new technology and Scale Efficiency (SE), which measures the ability to achieve better efficiency by adjusting to its optimal scale, and examine how each of these separately contributes to predicting financial distress. Second, in contrast to most applications of DEA in financial distress prediction we assume variable rather than Constant Returns to Scale (CRS). Third, DEA can only meaningfully be carried out for a sample of firms that use the same or similar technology (Dyson *et al*, 2001) and our study is the first to meet this requirement in the context of mixed-industry bankruptcy prediction. While this reduces our sample size, by modifying the second stage logistic regression we are

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able to determine the effects of variables that are common across industries. Fourth, we add corroboratory evidence to the very few studies that, regardless of country, have explored the corporate efficiency as a predictive variable in a financial distress model.

The paper is organised as follows. The next section provides a comprehensive review of the application of DEA in corporate distress prediction models. In the third section the methodology adopted in this research is presented. This is followed by the description of the data used in the empirical analysis and the subsequent section reports the results. The paper finishes with conclusions and recommendations.

Literature review

DEA is an optimising technique that measures the relative efficiencies of a group of companies or Decision Making Units (DMUs) that use multiple inputs and produce multiple outputs. An efficient company uses less inputs to produce more outputs. Such efficiency is evaluated by the distance of a particular DMU to the efficient frontier (ideal position), which is based on its peers (other DMUs in the sample). The main idea and notation will be introduced in the next section, for more comprehensive explanation of DEA see Cooper *et al* (2000).

DEA has been incorporated into the prediction of corporate distress (or bankruptcy) in two different ways. First, DEA has been used to derive a classification algorithm to separate distressed firms from non-distressed firms (Emel *et al*, 2003; Cielen *et al*, 2004; Paradi *et al*, 2004). Second, the relative efficiency of firms has been computed using DEA and this relative efficiency has been used as a feature of each firm in a subsequently developed classification rule (Xu and Wang, 2009; Psillaki *et al*, 2010; Yeh *et al*, 2010). We consider the former first.

As a classifier DEA has a number of advantages compared with statistical methods. For example it is non-parametric and so does not require any distributional assumptions about error terms or about covariance matrices. DEA also has some inherent disadvantages such as sensitivity to the selection of inputs and outputs, and issues when dealing with negative values. When the number of variables are close to or larger than the number of companies, efficiency scores tend to be 1 so discriminative power is lost.

It is logical to assume that efficiency is associated with the probability of failure. Barr *et al* (1993) found there are significant differences of scores in a sample of banks between the surviving and failing and the difference increases as the date of failure approaches. Paradi *et al* (2004) used an additive DEA model to compute a worst performance boundary. Output variables are those that reflect poor financial performance such as bad debt, warranty claims etc and input variables represent the opposite, for example profits, sales etc. For each DMU, an inefficiency score is computed. Paradi *et al* (2004) then use the layer technique (or tiered DEA, Barr *et al*, 2000) of removing inefficient companies to find a new boundary, each lower boundary indicating a lower chance of bankruptcy. A similar method is followed by Cielen *et al* (2004) who apply a cut-off to the estimated efficiency of each DMU (rather than the layer technique). They find, in a comparison of classification accuracy, that the DEA method outperformed decision trees and a linear programming method (Freed and Glover, 1981). However, they used the ratio form of the DEA model, which is problematic when negative financial ratios are incorporated. Min and Lee (2008) estimated a Charnes, Cooper and Rhodes (CCR) model (defined in the next section) with CRS and applied a cut-off to the efficiency score for each firm. The DEA score method performed less well than a linear discriminant function. Premachandra *et al* (2009) estimated an additive DEA, which is invariant to data translation (and so can deal with negative data) with varying Returns to Scale (RTS). On the training sample DEA had an inferior predictive performance whereas out of sample it was superior. Unfortunately they could not compare the performance of both techniques using the same test dataset. More recently Premachandra *et al* (2011) estimate an additive DEA model to derive efficiency and a bankruptcy frontier and derive a prediction index for each firm from these two. They find the use of a two frontier method improves predictive performance compared to a single bankruptcy frontier. Sueyoshi (1999) proposed a two-stage method labelled 'DEA-DA'. In the first stage a linear program is used to predict class membership of each case and to identify cases where the predicted class is ambiguous (since two discriminating functions are computed). In the second stage a model that classifies cases that could fit into either group is estimated. Subsequent work has compared the performance of the two-stage classifier with that of other standard methods (Sueyoshi, 2001 and 2006; Sueyoshi and Goto, 2009; Tsai *et al*, 2009) with the conclusion that DEA-DA performs at least as well as other techniques for corporate bankruptcy prediction and better in the case of consumer loans.

As the second way of incorporating DEA into distress prediction, many researchers have carried out experiments to incorporate a DEA efficiency score (or TE) as a predictor into other classification models. Xu and Wang (2009) put efficiency score obtained by DEA into Support Vector Machines (SVMs), logistic regression and linear discriminant analysis (MDA). Yeh *et al* (2010) also use efficiency scores into SVMs and neural networks. Both studies found that the inclusion of efficiency scores increased predictive performance of failed companies.

A limitation of many studies that have used DEA efficiency in bankruptcy prediction is that they have estimated TE across a range of industries that use heterogeneous technologies (Cielen *et al*, 2004; Premachandra *et al*, 2009; Premachandra *et al*, 2011). If the technology used by the DMUs in the sample is different, then the weights on the inputs and outputs will be different and the concept of efficiency will be somewhat meaningless. Otherwise, the analysis has to use a single industry, which obviously limits the sample size (eg Shetty *et al*, 2012).

The use of a DEA classifier or an efficiency score computes the relative efficiency of firms in a sample and can be used for in-sample prediction. However, if we wish to predict the failure probability for a case out of the sample, difficulties arise because the addition of a new case may alter the relative efficiencies of all of the firms currently included in the model possibly changing the optimal weights on the inputs and the outputs and so altering the efficient frontier. In principle the addition of a new case would necessitate the re-estimation of the DEA model. Both Emel *et al* (2003) and Min and Lee (2008) estimated a statistical model to predict DEA efficiency using the input and output financial ratios that could be used to classify out of sample cases.

While a large number of papers have estimated models to predict financial distress for Chinese listed companies using financial ratios (for example see Ding *et al*, 2008; Sun *et al*, 2011 and Xiao *et al*, 2012), as far as we are aware only one (Xu and Wang, 2009) has considered DEA efficiency as an explanatory variable.

Stiglitz (1972) emphasised that RTS impacts on the probability of bankruptcy. In practice RTS are typically increasing, or decreasing so it is surprising to see most of applications of DEA in corporate failure prediction have an assumption of CRS. Examples of papers that assume CRS are Xu and Wang (2009) and Yeh *et al* (2010). The paper of Psillaki *et al* (2010) is one of the few cases that assume Variable Returns to Scale (VRS) to evaluate credit risk. They use the Banker, Charnes and Cooper (BCC) model named by Banker *et al* (1984) but with only one output and two inputs.

The contributions of this research are first, to assume a VRS technology rather than CRS, which is not common in reality, and second, under the assumption of VRS, to include four additional variables in a model to predict financial distress.

These variables are the TE (CRS efficiency), PTE (VRS efficiency), SE and an RTS parameter (defined in the next section). By incorporating these four variables, our prediction models include variables that are economically directly related to the probability of distress. Unlike most European companies that are relatively small in size, Chinese companies are often much larger and their largest number of employees exceeds 100 thousand and total revenue exceeds £20 billion. Therefore, cases of decreasing RTS are often observed and it is expected to have some causality for financial difficulty.

Methodology

DEA

Consider a set of DMUs, each denoted as DMU_j ($j = 1, \ldots, n$), each producing several outputs $y_r (r = 1, \ldots,$ s) by using several inputs $x_i (i = 1, \ldots, m)$. For any DMU, DMU_0, we wish to find the weight on each output and on each input that maximises efficiency defined as the ratio of weighted outputs to weighted inputs, subject to the ratio being not greater than 1 for any DMU. This fractional programming problem can be converted into a linear program (Cooper *et al*, 2000) and for convenience the dual program is usually considered:

$$\max \quad v = \mathbf{u}^T \mathbf{y}_0 - u_0 \tag{1}$$

$$\text{s.t.} \quad \mathbf{v}^T \mathbf{x}_0 = 1 \tag{2}$$

$$-\mathbf{v}^T X + \mathbf{u}^T Y - u_0 \mathbf{e}^T \leqslant 0 \tag{3}$$

$$\mathbf{v} \geqslant 0, \mathbf{u} \geqslant 0$$

where $\mathbf{u}$ and $\mathbf{v}$ are column vectors of weights to be estimated. If (x_0, y_0) is on the efficient frontier then at this point $u_0^* > 0$, $u_0^* = 0$, and $u_0^* < 0$ implies and is implied by increasing, constant and decreasing RTS, respectively (Banker and Thrall, 1992). In a one input one output context the u_0 term would be the intercept for the line referred to above. Furthermore, if θ_C^* and θ_B^* denote CCR and BCC efficiency scores of a particular DMU then SE is defined as (Charnes *et al*, 1978)

$$SE = \frac{\theta_C^*}{\theta_B^*} \tag{4}$$

Intuitively, the BCC model finds the optimal efficiency for a DMU when RTS are not necessarily constant. Dividing the efficiency of a DMU when estimated with CRS by the efficiency when VRS are assumed isolates the SE of the DMU. Thus we can write:

$$\text{TE} = \text{PTE} \times \text{SE}$$

Selecting inputs and outputs

Choosing the most appropriate inputs and outputs is of crucial importance when conducting all DEA studies, but so far, there is no generally agreed method for the selection. Different DEA studies have used different inputs and outputs, which is a shortcoming of DEA (Premachandra *et al*, 2009). First of all, inputs and outputs have to be meaningful within the framework of the competitive environment (Oral and Yolalan, 1990). One disadvantage of DEA is that it computes relative efficiency with more discrimination between DMUs when the number of variables is significantly smaller than the number of DMUs (Parkan, 1987). This is normally the case in recent research. It is desirable that the number of input variables is larger than or equal to the number of output variables (Yeh, 1996).

In the few studies that use DEA to model default risk, input variables are selected from, for example, Capital, Liability, Human Resources, Technology and Real Estate etc, and the output variables are profits and sales. Psillaki *et al* (2010) used one output (Value Added) and two inputs, Capital Shares and Number of Fulltime Employees. Similarly, Yeh *et al* (2010) selected R&D expenses, R&D designers, and the number of patents and trademarks as input variables and the output variables included Gross Profit and Market Share.

When empirically modelling bankruptcy, to eliminate scale or size and unit effects in the values, it is common to use financial ratios rather than physical or monetary items. Min and Lee (2008) include three input ratios, which are Financial Expenses to Sales, Current Liabilities Ratio, Bond Payable to Total Assets, an ordinal variable (Total Borrowings) and three output ratios: Capital Adequacy Ratio, Current Ratio and Interest Coverage Ratio. Cielen *et al* (2004) argue that financial ratios with a positive correlation can be used as inputs while those with a negative correlation are output. Premachandra *et al* (2009) propose that the smaller (inferior) values in the financial ratios, which could possibly cause financial distress, are considered to be inputs whereas the larger (superior) values in those ratios, which could cause financial distress, are considered as outputs. Xu and Wang (2009) in a Chinese case study go back to the original definition of efficiency for variable selection. They use Total Assets, Total Liabilities and Costs of Sales as the inputs, with Income from Sales as the sole output.

Our choice of variables has been influenced by the following considerations. Since financial ratios are going to be used in a second stage logistic regression we do not employ them in the first stage so as to reduce possible collinearity. We follow the original idea of DEA that inputs and outputs are measured as absolute amounts rather than as ratios. Thus we have chosen five inputs (Number of Employees, Share Capital, Total Cost, Total Assets and Total Liabilities) and three outputs (Total Sales, Total Profit and Cash Accrued), which are main items in all financial reports.

A key issue regarding DEA is how to deal with negative values in inputs and outputs such as for growth or profits. There are three popular methods that have been used: the Range Directional Measure proposed by Portela *et al* (2004), the Modified Slack-Based Measure proposed by Sharp *et al* (2006), and the Semi-Oriented Radial Measure proposed by Emrouznejad *et al* (2010). Recently a fourth method, Variant of Radial Measure, has been introduced by Cheng *et al* (2013).

Our data output matrix, **Y** has negative values and we wish to assume VRS, which is both unit invariant and translation invariant and can handle positive and negative mixed data. A suitable model is the slacks-based efficiency model, which in input orientation can be expressed as (from Cooper *et al*, 2000):

$$\min \quad \rho = 1 - \frac{1}{\mathrm{m}} \sum_{i=1}^{m} \frac{s_i^-}{x_{i0}} \tag{5}$$

$$\text{s.t.} \quad \mathbf{x}_0 - X\lambda - \mathbf{s}^- = \mathbf{0} \tag{6}$$

$$\mathbf{y}_0 - Y\lambda + \mathbf{s}^+ = \mathbf{0} \tag{7}$$

$$\lambda \geqslant \mathbf{0}, \mathbf{s}^- \geqslant \mathbf{0}, \mathbf{s}^+ \geqslant \mathbf{0}$$

MaxDEA is used to solve the programs for each industry separately.

We deduce a score for each DMU for each type of efficiency and relate these to the probability of distress using logistic regression. However, DEA scores assume a common technology across the DMUs. When we include the four types of efficiency variables we ensure that only DMUs within the same industry sector are accorded the same parameters while the financial ratios are assumed to have the same parameters across all sectors. Therefore the specification of the logistic regression is amended to be

$$\mathrm{logit}(p_q) = \alpha + \sum_{l=1}^{L} \sum_{p=1}^{P} \delta_{pl} D_p e_{plq} + \beta_1 w_{1q} + \beta_2 w_{2q} + \cdots + \beta_K w_{Kq} \tag{8}$$

where p_q denotes the probability of suffering distress for company q; e_{pql} denotes efficiency score type l for sector p for company q; w_{1q} denotes financial variable 1 for company q and so on; $D_p = 1$ if company q is a member of industry p, 0 otherwise; δ_{pl} denotes a parameter for industry p for efficiency score type l to be estimated; β_1 denotes a parameter for covariate 1 to be estimated, and K denotes the number of covariates.

We compared alternative specifications of Equation 8: with only efficiency variables, with only financial variables and with combinations of both.

Data

The data used in this research are from two Chinese security markets, the Shanghai Stock Exchange and the Shenzhen Stock exchange and sourced from the Wind database. The database provides information for those companies listed in both markets (note that no cross-listing is allowed) and covers the historic records from 1991. The sample contains the annual data of 2104 listed companies in China between 1998 and 2010. Since one of the important input variables in the DEA models is Number of Employees and it was not until 2001 that the companies started to report this information in their statements, the reports prior to 2001 are excluded from the sample. A few companies with extreme outlying values of input or output variables (mainly caused by unusual or abnormal value changes and rare events) were also excluded because the efficient frontier is very sensitive to outlying values and so their inclusion may have resulted in inaccurate estimates of relative efficiencies. 'Special Treatment' (ST) is the status imposed by the government to give notice of a bad performance to investors and so it is an indicator of financial distress used in this research. A company is ascribed ST status if any of the following conditions holds (Shanghai Stock Exchange, 2008):

- Negative profit in the most recent two consecutive years or if the correction of errors yields this result.
- Failure to disclose its annual interim report.
- Likelihood of being dissolved.
- Reorganisation, settlement or bankruptcy liquidation.
- Other characteristics determined by the Stock Exchange.

The majority of companies (84.3%) receive ST because of losses in two successive fiscal years.

Since DEA models are estimated from homogeneous production processes (Dyson *et al*, 2001), we solve DEA programs to compute efficiency scores for separate industry sectors and within the same year to ensure that the companies in the sample share the same productivity process and a similar business environment. To keep as many distressed companies as possible in the sample for modelling, all industries were examined and the second level industrial sectors Raw Materials (code 1510 in Wind), Industrial Equipment (2010) and Real Estate (4040) were found to have the highest frequency of ST cases. In 2002, 2003, 2006 and 2007, there are more ST cases than in other years. Therefore the STs in 2002 or 2003 are grouped together as the training sample and the STs in 2006 or 2007 are grouped into the hold-out sample to test the predictive performance of the logistic regression. Thus efficiency scores and financial covariate data for 2001 with ST/non-ST status taken from 2002 and 2003 were used to train the model, which then was then applied to the data in 2005 to predict the probability of becoming ST in 2006 and 2007. The numbers of ST and non-ST companies are displayed in Table 1. Some companies were delisted and some new companies entered the sample during the study period. There are 429 cases common in both samples. The predictive accuracy is tested by an out-of-time rather than an out of sample validation, which is in line with the literature (eg Shumway, 2001).

Descriptive statistics for the financial variables used in the DEA analysis are shown in Table 2. The occasional negative values for profits and cash flows are apparent. The financial ratios collected from the database contain six groups of measures relating to profitability, operation capacity, growth rates, capital composition, liquidity, cash flow. Those variables with too many missing values were deleted. Variables that were highly correlated (VIF > 5) were also excluded. For those variables where only a few values were missing, the missing values were replaced by the means in that year. The final list of ratios selected for inclusion in the logistic regression and represented by w_q in Equation 8 is in Table 3.

Results

DEA

There are four types of efficiency scores of importance to this paper: TE, PTE, SE and RTS levels. The first three are all continuous scores whereas RTS is a categorical ordinal variable with three levels: decreasing, constant and increasing.

First, we consider aggregate results. One of the objectives of this paper is to test whether the probability of distress is associated with low efficiency. We consider various efficiency measures where following previous literature (Xu and Wang, 2009) we do not treat each sector separately and then second when we do treat each sector separately. Descriptive statistics of efficiency scores are shown in Table 4. As a preliminary analysis we computed two-way ANOVA and found that for each of the three types of efficiency score, there is a significant difference between the mean score for the ST group and the mean score for the non-ST group. But there is a significant difference in the mean efficiency scores between the industry sectors in 2001 only in terms of TE and SE, and for 2005 only in SE.

From Table 5 we can see that both in 2001 and 2005 there are relatively low numbers of companies with decreasing or constant RTS. We therefore classified the RTS values into two values: decreasing or constant on the

Table 1 Sample sizes

Sector code	*Training sample* (2001–2003)				*Test sample* (2005–2007)			
	1510	2010	4040	*Total*	1510	2010	4040	*Total*
Non-ST	181	144	95	420	218	185	92	495
ST	17	14	19	50	18	20	22	60
Total	198	158	114	470	236	205	114	555
ST/Non-ST (%)	9.40	9.70	20.00	11.90	8.30	10.80	23.90	12.10
ST rate (%)	8.59	8.86	16.67	10.64	7.63	9.76	19.30	10.81

Table 2 Statistics of DEA variables

	Sector	2001					2005				
		N	*Mean*	*SD*	*Min*	*Max*	*N*	*Mean*	*SD*	*Min*	*Max*
Inputs											
	1510	198	3925	5388.8	104	45943	236	4240.6	5622.1	140	44421
employees	2010	158	2498.2	2353	102	15000	205	2281.4	2312.9	129	19676
	4040	114	1252.9	1594.5	56	13319	114	1038.9	1742.2	34	12568
	1510	198	524.5	1182.4	51	12512	236	604.1	1434.3	60.4	17512
capitals(mCNY)	2010	158	291.7	224.7	80.2	1884.4	205	323.7	296.7	57.6	2689.6
	4040	114	298.3	234.3	66	1867.7	114	369.7	410.9	53.5	3722.7
	1510	198	1410.6	2935	37.6	25497.9	236	3620.3	9098.1	49.3	108422.4
costs(mCNY)	2010	158	995.1	1820.5	50	19358.6	205	1656.7	2563.9	110.4	19459.7
	4040	114	506.5	607.9	48	4157.4	114	774.4	964.3	12.2	8528.6
	1510	198	2478.9	4881.2	154.6	58042.1	236	4269.4	10471.3	164.4	142024.2
assets(mCNY)	2010	158	1671.7	1436.8	198.1	9907.9	205	2273.6	2330.4	172.9	18033.6
	4040	114	1659.2	1507	287	9690.3	114	2428.5	2747.5	27.3	21992.4
	1510	198	1120.2	2561.6	43	31752	236	2248.9	4926	22.6	63097.3
debts(mCNY)	2010	158	805.8	810.5	45.9	4810	205	1318	1491.5	55.6	9517.7
	4040	114	834.4	978.2	6.5	7380.5	114	1459.5	1675.6	7	13411.2
Outputs											
	1510	198	88.5	355.4	−1797.4	3709.6	236	281.4	1334.9	−997.2	18310.8
profits(mCNY)	2010	158	54.9	160.9	−1009.8	1011.8	205	60.4	238.2	−696	2057.1
	4040	114	44.1	126.1	−537.6	501.9	114	40.9	293.6	−1142.2	1976.2
	1510	198	16.7	336.9	−3686.2	872.5	236	−6.6	334.4	−2664.6	1784.3
cash(mCNY)	2010	158	50.1	208.1	−686.4	882.7	205	−15.6	160.9	−953.8	661.3
	4040	114	45.9	150.8	−329.9	585.2	114	−22.9	216.3	−1100.2	597.9
	1510	198	1499.3	3142.1	20.1	29170.8	236	3895.2	10297.5	17.9	126608.4
sales(mCNY)	2010	158	1037.8	1858.1	51.6	19565.1	205	1706.5	2657.2	0.9	19474.2
	4040	114	536.1	663.6	12.2	4455.1	114	825.4	1154.4	3.5	10558.9

Table 3 List of eligible financial ratios

Group	*Ratio*	*Group*	*Ratio*
Profitability (10)	Operating revenue per share	Capital composition (4)	Book value per share (BPS)
	Return on equity (ROE)		Equity multiplier
	Return on assets (ROA)		Current assets/total assets
	Return on invested capital (ROIC)		Tangible assets/total assets
	Gross margin/total sales		
	Operating profit/total sales	Cash flow (6)	Net cash flow from operating per share
	Operating expenses/total sales		Net cash flow per share
	Financial expenses/total sales		Net cash flow from operating/operating revenue
	Undistributed profits per share		Net cash flow from operating/total liabilities
	EBIT per share(EBITPS)		Net cash flow from operating/interest bearing liabilities
			Net cash flow from operating/current liabilities
Liquidity and liability (7)	Current liabilities/total liabilities		
	Current ratio	Operation capacity (4)	Inventory turnover
	Quick ratio		Receivables turnover
	Cash ratio		Current assets turnover
	EBITDA/total liabilities		Total assets turnover
	Surplus capital per share		
	Surplus reserve per share	Growth rates (4)	Operating revenue growth
			Total profit growth
			Net profit growth
			Total assets growth

Table 4 Means and standard deviations of efficiency scores

Sector code	*ST*	*N*	*Training sample*						*N*	*Test sample*					
			TE		*PTE*		*SE*			*TE*		*PTE*		*SE*	
			Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*		*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
1510	0	181	0.557	0.209	0.628	0.214	0.886	0.117	218	0.493	0.219	0.597	0.214	0.824	0.163
	1	17	0.323	0.180	0.533	0.277	0.647	0.247	18	0.237	0.086	0.439	0.199	0.614	0.233
	All	198	0.537	0.216	0.620	0.221	0.866	0.148	236	0.474	0.222	0.585	0.216	0.808	0.178
2010	0	144	0.556	0.239	0.694	0.214	0.792	0.171	185	0.493	0.242	0.615	0.227	0.796	0.198
	1	14	0.231	0.082	0.473	0.243	0.545	0.188	20	0.201	0.084	0.439	0.182	0.497	0.194
	All	158	0.527	0.248	0.675	0.225	0.770	0.186	205	0.465	0.247	0.598	0.229	0.767	0.216
4040	0	95	0.632	0.251	0.728	0.232	0.864	0.154	92	0.578	0.285	0.706	0.269	0.824	0.221
	1	19	0.368	0.271	0.574	0.264	0.665	0.300	22	0.207	0.092	0.394	0.218	0.610	0.278
	All	114	0.588	0.272	0.702	0.244	0.831	0.199	114	0.506	0.298	0.646	0.287	0.782	0.247
Total	0	420	0.574	0.231	0.673	0.222	0.849	0.151	495	0.509	0.243	0.624	0.233	0.813	0.188
	1	50	0.314	0.206	0.532	0.261	0.625	0.255	60	0.214	0.087	0.422	0.199	0.574	0.241
	All	470	0.546	0.242	0.658	0.230	0.825	0.179	555	0.477	0.249	0.602	0.238	0.788	0.208

Table 5 Levels of returns to scale

	RTS 2001				*RTS* 2005			
	Decreasing	*Constant*	*Increasing*	*Total*	*Decreasing*	*Constant*	*Increasing*	*Total*
ST	69	69	282	420	58	66	371	495
Non-ST	5	0	45	50	0	0	60	60
Total	74	69	327	470	58	66	431	55

one hand and increasing (IRS) on the other and included a dummy variable to represent the existence of IRS in the logistic regressions.

Logistic regression

We have two objectives. First, to investigate the statistical significance of efficiency measures in explaining the probability of suffering financial distress and second, to evaluate the predictive performance of including efficiency variables in such posterior probability models.

Pre-analysis showed that if efficiency variables and financial ratios are entered together into a stepwise logistic regression, nearly all of the efficiency variables are excluded. However, we are interested in the role specifically of efficiency variables and so we adopted the following procedure. Since values of the efficiency variables were derived from a DEA model where the objective function consisted of financial variables, collinearity is possible between some financial ratios and some efficiency scores. Conscious of this potential collinearity we considered three model specifications. First we have models with only efficiency variables (Models 1–6). Models 1–4 contain only industry-specific efficiency variables to try to reduce the heterogeneity in technologies that would otherwise be present. Models 5 and 6 are included simply to show the parameter estimates if, as in previous literature, in the DEA analysis all industrial sectors were assumed to be homogeneous.

Second, we estimated models that included combinations of the industry-specific efficiency variables and subsequently uncorrelated financial ratios were entered using a stepwise routine (Models 7–9). Third, we estimated models that included significant financial variables selected from all those available using a forward stepwise routine together with combinations of efficiency scores. Thus the efficiency score was 'force' entered in each model, except Model 10. All of the models were parameterised across all industries with industry-specific dummies interacted with each efficiency variable to yield industry-specific parameters and the efficiency scores. We therefore assume the marginal effects of the efficiency variables are specific to each industry sector but the marginal effects are the same for each financial variable for all industries. The models are specified in Table 6.

DEA allows one to compute the efficiency of an organisation relative to the most efficient organisations in the dataset. To compute the relative efficiency scores for a new case requires us to solve the program for a different set of DMUs and so could alter the efficiency boundary and thus the efficiencies of the original cases relative to the new efficiency boundary. To assess the discriminatory power of including efficiency variables we computed the relative efficiency for each member of the holdout sample in 2005. We assume that the marginal effects of relative TE, PTE and SE, and so the logistic regression parameters that were estimated for 2001–2003, remained constant over time. We argue that in competitive markets it is relative efficiency rather than absolute efficiency that determines the chance of financial success or, as in our case, financial distress. This is consistent with the approach used in the literature (see Xu and Wang 2009). We then predicted the probability of a new case becoming distressed in 2006–2007 using the 2005 efficiencies and 2001–2003 parameters.

Table 6 Models to be compared

A Efficiency variables only	
Model 1	Industry-specific TE only
Model 2	Industry-specific PTE and SE
Model 3	Industry-specific TE and RTS
Model 4	Industry-specific PTE, SE and RTS
Model 5	Pooled TE
Model 6	Pooled PTE and SE
B Efficiency variables forced entry, financial ratio variables selected by stepwise routine	
Model 7	Industry-specific TE forced entry, financial ratios selected by forward stepwise routine.
Model 8	Industry-specific PTE and SE forced entry, financial ratios selected by forward stepwise routine
Model 9	Industry-specific PTE, SE and RTS forced entry, financial ratios selected by forward stepwise routine
C Financial variables selected by stepwise and then forced entry with efficiency variables	
Model 10	Financial variable selected by forward stepwise routine.
Model 11	Industry-specific TE, financial ratios from Model 10
Model 12	Industry-specific PTE and SE, financial ratios from Model 10
Model 13	Industry-specific PTE, SE and RTS financial ratios from Model 10

Parameters and significance levels

Table 7 shows that when included alone each of the efficiency variables had the expected sign: an increase in efficiency is associated with a decrease in the probability of distress. This is true when we consider TE alone or PTE and SE together. The effect of a marginal change in relative TE score for Real Estate has a smaller effect on the probability of distress than in the Industrial Equipment industry. Generally an increase in relative PTE has a smaller marginal effect on distress likelihood that does an increase in relative SE. RTS (either constant-decreasing or increasing) have no detectable effect of the probability of distress. A failure to compute relative efficiency for each industry sector separately and so to assume homogeneity

Table 7 Coefficient estimates from efficiency only logistic regressions A

Variable	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Technical efficiency score					−10.52**	
Raw materials	−11.89**		−12.34**			
Industrial equipment	−14.23**		−24.41**			
Real estate	−9.40**		−8.56**			
Pure technical efficiency score						−4.95**
Raw materials		−3.82**		−4.39**		
Industrial equipment		−6.93**		−9.53**		
Real estate		−5.89**		−5.77**		
Scale efficiency score						−7.33**
Raw materials		−9.79**		−10.16**		
Industrial equipment		−9.02**		−12.27**		
Real estate		−7.26**		−6.90**		
Returns to scale						
Raw materials			−0.97	−5.77		
Industrial equipment			2.08	3.32		
Real estate			1.39	−1.54		
Constant	2.58**	7.56**	3.47**	8.59**	2.13**	6.20**

** indicates the figures are significant at 5% level of significance.

of technology across all three sectors not only yields incorrect efficiency scores but if such scores are used masks considerable differences in the effects of each type of efficiency between the industry sectors.

Table 8 shows that when we force the efficiency scores into each logistic regression, and then select financial variables in a stepwise fashion the SE variables remain significant with the expected signs while the RTS variables are never significant. In all sectors improving relative PTE has a smaller effect of the chance of distress than an improvement in relative scale.

The parameters of most of the financial ratios have the expected signs. For example, higher net cash flow per share or higher return on equity or return on assets is associated with a lower chance of distress. In Table 9 we see that if we include the efficiency variables and the financial ratios that would be included if the efficiency variables were not, then only the SE scores remain significant. Again their parameters have the expected signs.

Table 8 Coefficient estimates from logistic regressions B

Variable	*Model 7*	*Model 8*	*Model 9*
Technical efficiency score			
Raw materials	−8.35**		
Industrial equipment	−10.67**		
Real estate	−7.12**		
Pure technical efficiency score			
Raw materials		−2.81	−1.82
Industrial equipment		−6.19**	−9.75
Real estate		−6.24**	−5.25*
Scale efficiency score			
Raw materials		−10.82**	−11.08**
Industrial equipment		−9.66**	−16.17**
Real estate		−8.21**	−7.93**
Returns to scale			
Raw materials			−1.68
Industrial equipment			5.24
Real estate			−2.09
Net cash flow from operating per share	−5.43**	−6.12**	−4.82**
Return on equity	−0.09*	−0.20**	−0.25**
Return on assets	−0.18**		
Undistributed profit per share			
Gross margin/total sales	−0.07**		
Operating profit/total sales	0.03*		
Financial expenses/total sales	0.13*	0.12*	0.15*
Tangible assets/total assets	−0.04*	−0.05**	−0.06**
Current ratio		3.22**	
Quick ratio			3.31**
Cash ratio		−6.37**	−7.77**
Net cash flow/current liabilities			−5.53*
Inventory turnover	0.36**	0.66**	0.72**
Total profit growth			
Total assets growth	−0.08**	−0.09**	−0.09**
Constant	3.47**	10.16**	11.74**

Models 7, 8 and 9: Efficiency variables forced entry, financial variables selected by forward stepwise routine.
* and ** indicate the figures are significant at 10% and 5% levels of significance.

Predictive performance

The statistical significance of a covariate does not necessarily imply that predictive performance is increased if the variable is included in a model. We now examine the predictive performance of all of our models. First we compare the predictive performance of using overall efficiency (TE) *versus* decomposed efficiency (PTE and SE), second we compare models with RTS levels *versus* models without RTS levels and third we compare models with and without financial ratios. The Area Under ROC curve (AUROC), the Gini coefficient and Error Rates are reported (Table 10 and Figure 1). For Error Rate calculation the proportion of STs that are predicted to be STs is the proportion of the observed STs in the training sample.

In the first comparison (Model 1 *versus* 2 and Model 5 *versus* 6) both pairs show that decomposition of efficiency scores reduces the classification accuracy in the test samples by a noticeable amount. The Gini decreases from 0.841 to 0.797 and from 0.833 to 0.781 if TE is decomposed into PTE and SE. In the second comparison (Models 1 *versus* 3 and Model 2 *versus* 4) we see that inclusion of RTS decreases predictive performance slightly. For example, without RTS Model 1 has a Gini of 0.841 while with RTS this is 0.829 in the test set and the corresponding figures for Models 2 and 4 are 0.797 and 0.791, respectively.

One might notice that for Models 1–6 (with only efficiency variables) the Gini for the test set exceeds that for the training set. We explain this unusual observation with reference to a particular model. Consider Table 4 and industry 4040 (Real Estate). Model 1 consists only of the TE variable. Notice that the difference in the mean TE between the ST and not-ST groups in the training set (0.632–0.368 = 0.264) is less than that in the test set (0.578–0.207 = 0.371). In a Kolmogorov–Smirnov diagram (Figure 2) the increase in the difference in the mean TE between the two groups will move the P_{non-ST} (s) line further from the P_{ST} (s) line in the test set than in the training set, where P_{non-ST} (s) and P_{ST} (s) denote the cumulative proportions at and below each score, *s*, of non-STs and STs, respectively. Therefore plotting P_{non-ST} (s) against P_{ST} (s) in a ROC curve graph will result in a more accentuated curve and so the greater difference in means will result in a larger Gini (see Thomas *et al*, 2002).

Turning to the inclusion of financial ratios, we see that they outperform the first six models that contain only efficiency variables. For each performance measure we highlight the model with the greatest predictive power. Generally, in the training sample the models of efficiency

Table 9 Coefficient estimates from logistic regressions C

Variable	*Model* 10	*Model* 11	*Model* 12	*Model* 13
Technical efficiency score				
Raw materials		−3.39*		
Industrial equipment		−4.43		
Real estate		−2.26		
Pure technical efficiency score				
Raw materials			−1.12	−1.85
Industrial equipment			−1.16	−2.74
Real estate			−1.72	−2.45
Scale efficiency score				
Raw materials			−4.28**	−4.56*
Industrial equipment			−4.89**	−6.89*
Real estate			−2.9*	−3.59*
Returns to scale				
Raw materials				−1.52
Industrial equipment				0.4
Real estate				−0.95
Net cash flow from operating per share	−4.32**	−4.03**	−3.85**	−4.32**
Return on equity	−0.11**	−0.11**	−0.12**	−0.12**
Return on assets				
Undistributed profit per share	−1.58**	−1.41**	−1.17**	−1.19**
Gross margin/total sales	−0.06**	−0.07**	−0.08**	−0.07**
Operating profit/total sales				
Financial expenses/total sales	0.12**	0.09**	0.11**	0.12**
Tangible assets/total assets				
Current ratio	−0.71*	−0.54**	−0.75*	−0.81*
Quick ratio				
Cash ratio				
Net cash flow/current liabilities				
Inventory turnover				
Total profit growth	−0.006**	−0.005**	−0.004**	−0.004*
Total assets growth	−0.05**	−0.04**	−0.04**	−0.04**
Constant	0.07	1.39	4.11*	5.84**

Model 10: All variables selected by forward stepwise routine.
Model 11, 12 and 13: Efficiency variables forced entry, financial variables from Model 10.
* and ** indicate the figures are significant at 10% and 5% levels of significance.

variables assisted by ratios are better in predictive accuracy than the models of ratios assisted by efficiency variables. But in the test sample, it is the other way around. In the test sample the highest classification accuracy and the highest discriminatory power is gained by Model 11 that includes industry-specific TE together with the most significant of all financial ratios. However, the difference between the performance of this model and Models 12 and 13, which have the same financial ratios but decompose TE and include RTS (Model 13), is inconsequential.

Conclusions and recommendations

DEA is a useful method to measure relative corporate efficiency and corporate efficiency is found to be helpful in credit scoring in previous literature and this paper as well. Rather than assuming CRS, this paper adopts a more realistic assumption, VRS. It allows the model to decompose overall TE into PTE and SE, which actually provides more information for analysis. Practically, these measures indicate that an inefficient company should improve its efficiency of use of inputs or adjust its operating scale to the optimum level to achieve better performance. Our results show not only those less technically efficient firms are at greater risk of becoming financially distressed than more technically efficient firms but that improvements in both pure technical and SE would reduce the risk. Of these two what really matters is how relatively scale efficient, rather than how pure technically efficient, firms are. This indicates that a firm that wants to perform better, in practice, should pay more attention to optimising its scale of business rather than optimising resources or applying new technology. Increasing scale of operation is likely to

Table 10 Model results

	Training sample					Test sample				
	Type I error (%)	*Type II error (%)*	*Overall accuracy (%)*	*AUROC*	*GINI*	*Type I error (%)*	*Type II error (%)*	*Overall accuracy (%)*	*AUROC*	*GINI*
Model 1	40.0	4.8	91.5	0.869	0.738	41.7	4.8	91.2	0.921	0.841
Model 2	52.0	6.2	88.9	0.881	0.761	46.7	5.5	90.1	0.898	0.797
Model 3	42.0	5.0	91.1	0.882	0.765	46.7	5.5	90.1	0.915	0.829
Model 4	52.0	6.2	88.9	0.887	0.775	45.0	5.3	90.5	0.895	0.791
Model 5	42.0	5.0	91.1	0.844	0.687	43.3	5.1	90.8	0.917	0.833
Model 6	50.0	6.0	89.4	0.843	0.686	46.7	5.5	90.1	0.891	0.781
Model 7	20.0	2.4	**95.7**	0.97	0.94	36.7	4.2	92.3	0.952	0.904
Model 8	30.0	3.6	93.6	0.979	0.957	40.0	4.6	91.5	0.935	0.869
Model 9	24.0	2.9	94.9	**0.983**	**0.965**	40.0	4.6	91.5	0.935	0.87
Model 10	22.0	2.7	95.4	0.964	0.927	30.6	3.9	93.4	0.952	0.903
Model 11	22.0	2.7	95.4	0.967	0.933	30.6	3.9	**93.4**	**0.955**	**0.909**
Model 12	22.0	2.7	95.4	0.968	0.936	32.3	4.1	93.0	0.955	0.909
Model 13	24.0	2.9	94.9	0.971	0.941	32.3	4.1	93.0	0.955	0.909

Type I error occurs when a distressed company is wrongly classified as a non-distressed company.
Type II error occurs when a non-distressed is wrongly classified as a distressed company.
Figures in bold indicate the best performance in the column across all models.

have a great effect on reducing risk of distress than moving on an efficiency frontier.

These results are consistent with those of Psillaki *et al* (2010) who found that TE was significantly negatively related to the probability of business failure for a sample of French firms in each of three industries. But because no study that models financial distress has decomposed TE no further comparison can be made.

However, in the prediction of financial distress, decomposition of efficiency variables has little help on prediction accuracy. A simpler model using TE only to assist financial ratios in logistic regression is just as effective as including PTE and SE as separate variables as found in the out-of-time validation. We also found that the inclusion of RTS had no detectable effect on the predictive accuracy of the model.

In terms of using efficiency as the only predictor, our results show that a group of financial ratios does outperform efficiency scores as they can cover many aspects of business while a DEA score is only based on a limited number on inputs and outputs. That is also the reason why financial ratios have dominated the corporate credit prediction for decades. However, to gain greatest predictive accuracy, financial ratio and efficiency variables should both be included. This is consistent with the findings of Yeh *et al* (2010) and Xu and Wang (2009).

Nevertheless, although predictive accuracy is the main concern in credit risk management, there is also the necessity to understand risk drivers that may give early indications of potential problems. In this respect, decomposed efficiency measures, in particular SE, can provide useful information to a credit analyst interested in relative performance of companies in a credit portfolio.

This paper has also introduced a modified logistic regression model, particularly for DEA variables. This is the first application of DEA in credit scoring to use the dummy variables for different industries to overcome the dilemma that a large sample size and homogeneity of DMUs cannot be achieved at the same time. Industry specification slightly improves prediction accuracy and remarkably increases discriminative power. More importantly, the proposed logistic regression properly handles the assumption of DEA methodology, which should be kept all the time when applying for it. Such methodology allows employing a large data set with a mixture of industries, but it needs to be noted that the more industries are involved, the more dummy variables are needed, and the number of companies in each category should still be large enough.

Finally, it has to be mentioned that the data analysed in this paper cover two time periods. It would be beneficial if more years of data are found to be supportive with the above conclusion in cross-sectional analysis. Moreover, the recent development of DEA actually can give estimation of time serial efficiency scores, which allow panel analysis

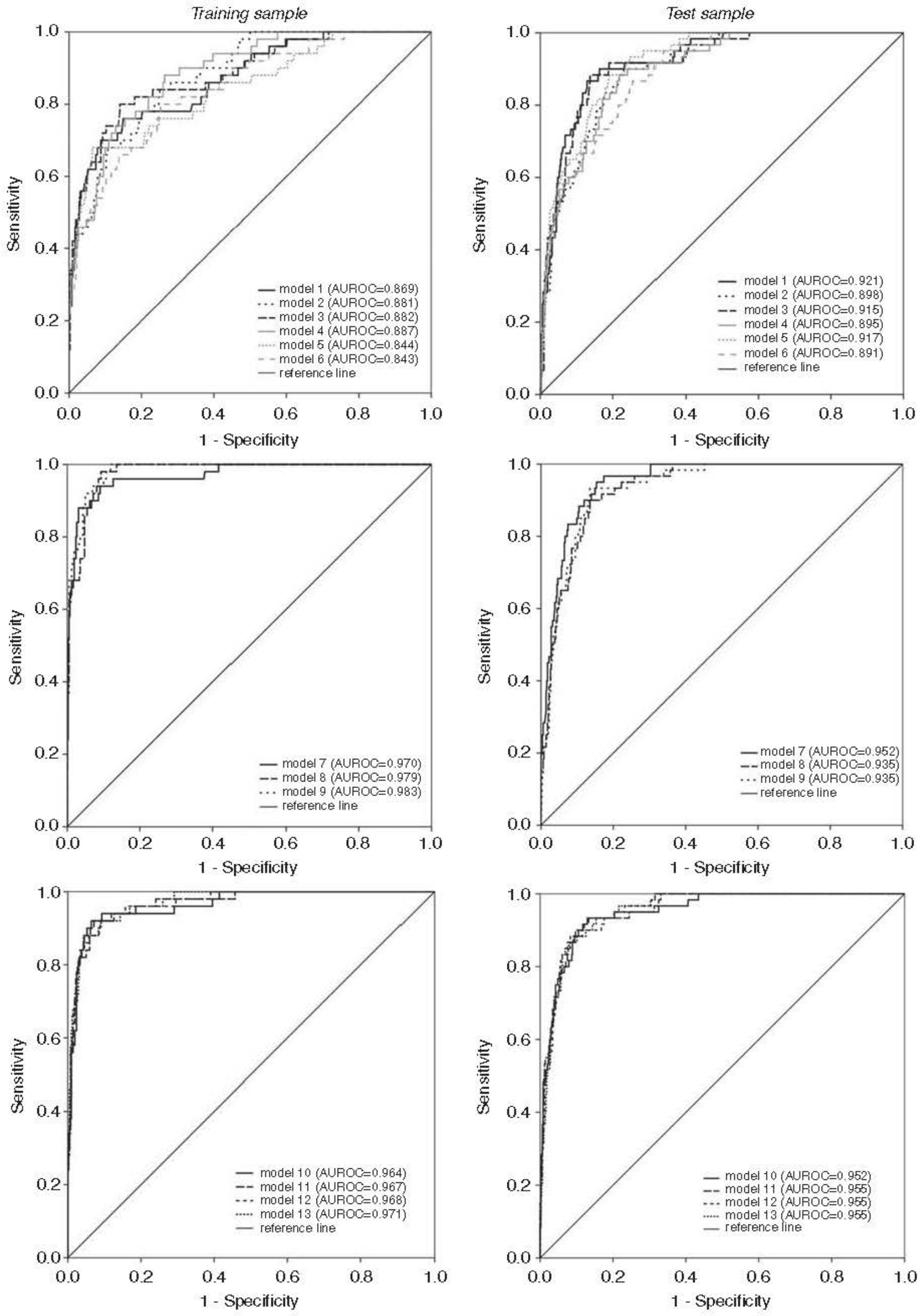

Figure 1 ROC curves.

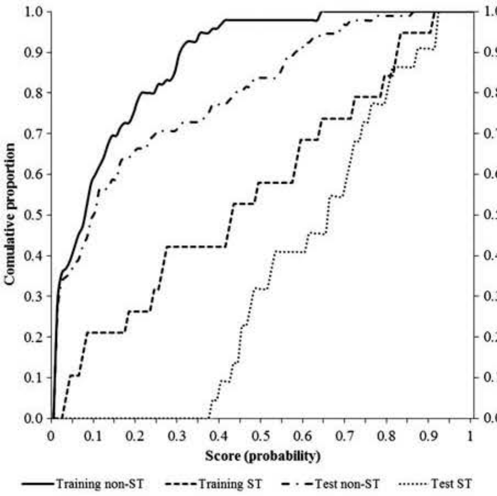

Figure 2 Kolmogorov–Smirnov plots.

across a period of time. The panel models and Malmquist DEA scores are the next step in future work.

References

Altman EI (1993). *Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting from Bankruptcy*. Wiley: New York.

Bahrammirzaee A (2010). A comparative survey of artificial intelligence applications in finance: Artificial neural networks, expert systems and hybrid intelligent systems. *Neural Computing and Applications* **19**(8): 1165–1195.

Balcaen S and Ooghe H (2006). 35 years of studies on business failure: An overview of the classical statistical methodologies and their related problems. *The British Accounting Review* **38**(1): 63–93.

Banker RD and Thrall RM (1992). Estimation of returns to scale using Data Envelopment Analysis. *European Journal of Operational Research* **62**(1): 74–84.

Banker RD, Charnes A and Cooper WW (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* **30**(9): 1078–1092.

Barr RS, Durchholz ML and Seiford LM (2000). Peeling the DEA onion: Layering and rank-ordering DMUs using tiered DEA. Southern Methodist University technical report.

Barr RS, Seiford LM and Siems TF (1993). An envelopment-analysis approach to measuring the managerial efficiency of banks. *Annals of Operations Research* **45**(1): 1–19.

Beaver BH (1966). Financial ratios as predictors of failure. *Journal of Accounting Research* **4**: 71–111.

Charnes A, Cooper WW and Rhodes EL (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research* **2**(6): 429–444.

Cheng G, Zervopoulos P and Qian Z (2013). A variant of radial measure capable of dealing with negative inputs and outputs in data envelopment analysis. *European Journal of Operational Research* **225**(1): 100–105.

Cielen A, Peeters L and Vanhoof K (2004). Bankruptcy prediction using a data envelopment analysis. *European Journal of Operational Research* **154**(2): 526–532.

Cooper WW, Seiford LM and Tone K (2000). *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-solver Software*. Kluwer Academic Publishers: Boston.

Ding Y, Song X and Zen Y (2008). Forecasting financial condition of Chinese listed companies based on support vector machine. *Expert Systems with Applications* **34**(4): 3081–3089.

Dyson RG, Allen R, Camanho AS, Podinovski VV, Sarrico CS and Shale EA (2001). Pitfalls and protocols in DEA. *European Journal of Operational Research* **132**(2): 245–259.

Emel AB, Oral M, Reisman A and Yolalan R (2003). A credit scoring approach for the commercial banking sector. *Socio-economic Planning Sciences* **37**(2): 103–123.

Emrouznejad A, Anouze AL and Thanassoulis E (2010). A semi-oriented radial measure for measuring the efficiency of decision making units with negative data, using DEA. *European Journal of Operational Research* **200**(1): 297–304.

Freed N and Glover F (1981). A linear programming approach to the discriminant problem. *Decision Sciences* **12**(1): 68–73.

Gestel TV, Baesens B, Suykens J, Poel DV, Baestaens DE and Willekens M (2006). Bayesian kernel based classification for financial distress detection. *European Journal of Operational Research* **172**(3): 979–1003.

Kumar P and Ravi V (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques—A review. *European Journal of Operational Research* **180**(1): 1–28.

Min JH and Lee YC (2008). A practical approach to credit scoring. *Expert Systems with Applications* **35**(4): 1762–1770.

Oral M and Yolalan R (1990). An empirical study on measuring operating efficiency and profitability of bank branches. *European Journal of Operational Research* **46**(3): 282–294.

Paradi JC, Asmild M and Simak PC (2004). Using DEA and worst practice DEA in credit risk evaluation. *Journal of Productivity Analysis* **21**(2): 153–165.

Parkan C (1987). Measuring the efficiency of service operations: An application to bank branches. *Engineering Costs and Production Economics* **12**(1): 237–242.

Portela MCAS, Thanassoulis E and Simpson G (2004). Negative data in DEA: A directional distance approach applied to bank branches. *Journal of the Operational Research Society* **55**(10): 1111–1121.

Premachandra IM, Bhabra GS and Sueyoshi T (2009). DEA as a tool for bankruptcy assessment: A comparative study with logistic regression technique. *European Journal of Operational Research* **193**(2): 412–424.

Premachandra IM, Chen Y and Watson J (2011). DEA as a tool for predicting corporate failure and success: A case of bankruptcy assessment. *Omega* **39**(6): 620–626.

Psillaki M, Tsolas IE and Margaritis D (2010). Evaluation of credit risk based on firm performance. *European Journal of Operational Research* **201**(3): 873–881.

Shanghai Stock Exchange (2008). *Rules Governing the Listing of Stocks on Shanghai Stock Exchange*. Shanghai Stock Exchange: Shanghai, p 90.

Sharp JA, Meng W and Liu W (2006). A modified slacks-based measure model for data envelopment analysis with 'natural' negative outputs and inputs. *Journal of the Operational Research Society* **58**(12): 1672–1677.

Shetty U, Pakkala TPM and Mallikarjunappa T (2012). A modified directional distance formulation of DEA to assess bankruptcy: An application to IT/ITES companies in India. *Expert Systems with Applications* **39**(2): 1988–1997.

Shumway T (2001). Forecasting bankruptcy more accurately: a simple hazard model. *The Journal of Business* **74**(1): 101–124.

Stiglitz JE (1972). Some aspects of the pure theory of corporate finance: Bankruptcies and take-overs. *The Bell Journal of Economics and Management Science* **3**(2): 458 482.
Sueyoshi T (1999). DEA-discriminant analysis in the view of goal programming. *European Journal of Operational Research* **115**(3): 564 582.
Sueyoshi T (2001). Extended DEA-discriminant analysis. *European Journal of Operational Research* **131**(2): 324 351.
Sueyoshi T (2006). DEA-discriminant analysis: Methodological comparison among eight discriminant analysis approaches. *European Journal of Operational Research* **169**(1): 247 272.
Sueyoshi T and Goto M (2009). Methodological comparison between DEA (data envelopment analysis) and DEA-DA (discriminant analysis) from the perspective of bankruptcy assessment. *European Journal of Operational Research* **199**(2): 561 575.
Sun J, Jia MY and Li H (2011). AdaBoost ensemble for financial distress prediction: An empirical comparison with data from Chinese listed companies. *Expert Systems with Applications* **38**(8): 9305 9312.
Thomas LC, Edelman DE and Crook JN (2002). *Credit Scoring and Its Applications*. SIAM: Philadelphia.
Tsai MC, Lin SP, Cheng CC and Lin YP (2009). The consumer loan default predicting model An application of DEA-DA. *Expert Systems with Applications* **36**(9): 11682 11690.
Verikas A, Kalsyte Z, Bacauskiene M and Gelzinis A (2010). Hybrid and ensemble-based soft computing techniques in bankruptcy prediction: a survey. *Soft Computing* **14**(9): 995 1010.
Wang G and Ma J (2011). Study of corporate credit risk prediction based on integrating boosting and random subspace. *Expert Systems with Applications* **38**(11): 13871 13878.
Xiao Z, Yang X, Pang Y and Dang X (2012). The prediction for listed companies' financial distress by using multiple prediction models with rough set and Dempster-Shafer evidence theory. *Knowledge based Systems* **26**: 196 206.
Xu X and Wang Y (2009). Financial failure prediction using efficiency as a predictor. *Expert Systems with Applications* **36**(1): 366 373.
Yeh CC, Chi DJ and Hsu MF (2010). A hybrid approach of DEA, rough set and support vector machines for business failure prediction. *Expert Systems with Applications* **37**(2): 1535 1541.
Yeh QJ (1996). The application of data envelopment analysis in conjunction with financial ratios for bank performance evaluation. *Journal of the Operational Research Society* **47**(8): 980 988.

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