Identification of Relevant Predictors of Loan Default Using the Elastic Net Model

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LIST OF ABBREVIATION

AUC	The area under receiver operating characteristic curves analysis
EN MDA	Multivariate discriminant model employing the predictor variables identified via the application of the Elastic Net
EN Logit	Logistic regression model employing the predictor variables identified via the application of the Elastic Net
FASB	The Financial Accounting Standards Board
IASB	The International Accounting Standards Board
LASSO	The least absolute shrinkage and selection operator
MDA	Multivariate discriminant analysis
ROC	Receiver Operating Characteristics

ABSTRACT

The timely prediction of loan default plays an important role in lending decisions and monitoring loans. However, there has been little development of models for the selection of relevant variables for the prediction of loan default. This study identifies financial and economic indicators for the forward-looking prediction of loan default by the application of a penalised regression approach, namely the Elastic Net model.

The study employs a sample of US firms with 162 loan default events in total between 1998 and 2013. The sample is sub-divided to form a Test sample and two holdout samples: one drawn from the same period as the Test sample; and one drawn from a subsequent period. The sample of non-defaulting firms is constructed using prior probabilities based on the bond default rate for each year.

The 278 potential variables, including the ten economic indicators and 268 financial ratios or summary indicators, are regularised with the application of the Elastic Net model. This process results in the extraction of the ten predictor variables, thus identified as relevant to distinguishing between defaulting and non-defaulting firms. Only one economic indicator, the interest rate, is identified as relevant to the prediction of loan default.

The prediction-usefulness of identified predictor variables are tested using the two most widely used conventional prediction models, multiple discriminant analysis (MDA) and logistic regression (Logit). The resulting MDA and Logit models are

compared with Altman’s Z-score model and Ohlson’s O-score model, respectively. Both the Elastic Net prediction models provide more logical explanations of the distinctive characteristics of loan defaulting firms than the Altman’s Z-score and Ohlson’s O-score models. The Elastic Net prediction models outperform the Altman’s Z-score and Ohlson’s O-score models in the accuracy of the Type I, the Type II and the overall classification. When applied to a holdout samples within and outside the same periods, the prediction accuracy of the Elastic Net models is maintained for both defaulting and non-defaulting firms.

This thesis contributes to the loan default literature by introducing the Elastic Net model for variable selection which enhances the predictive ability of the loan default prediction model. The findings of this thesis are potentially useful to financial institutions. Identification of financial and economic predictor variables of loan default can also facilitate assessment of the credit risk of loan applicants. The findings of this thesis may also facilitate better loan default prediction for purposes of monitoring loans. Lastly, the identification of relevant predictor variables may be useful for the classification of loans in the application of the expected loss model in the preparation of financial statements.

DECLARATION

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university of other tertiary institution without the prior approval of the University of Adelaide.

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CHAPTER 1

INTRODUCTION

1.1 MOTIVATION AND RESEARCH OBJECTIVES

The financial crisis of 2007-2008 highlighted the importance of the management of credit risk. In 2009, the global default rates on loans reached 13%, close to the previous peak of 15.4% set in 1933 (Bhamra, Fisher & Kuehn, 2011).

As the recent financial crisis demonstrates, credit losses related to loans can have a significant detrimental impact on the broader economy. Considering the impact of loan defaults on macro-financial vulnerabilities, a large increase in loan defaults could lead to the onset of a financial crisis (Kaminsky & Reinhart, 1999; Nkusu, 2011). Thus the timely or early detection of changes in loan quality is critical for social and financial conditions (Cicchetti & Dubin, 1994; Crotty, 2009; Baixauli, Alvarez & Módica, 2012).

The evaluation and management of credit risk is particularly important to financial institutions. The banking industry indicates that managing the credit risk of loan customers is the most important aspect of the banking business model (ABA, 2010). The assessment of the credit worthiness of existing and potential borrowers is critical for granting decisions and monitoring the performance of loans.

The evaluation of the credit risk of loans is also important for financial reporting. In response to the Global Financial Crisis, the International Accounting Standards Board (IASB) introduced an expected loss model for accounting for the impairment of loans and similar financial assets (IFRS 9, para.5.5.1). In the event of a significant increase in the credit risk of a loan the *lifetime expected credit loss* must be recognised (IFRS 9, para. 5.5.3). In assessing credit risk, the Standard requires the entity to go beyond reliance on belated indicators and to take into account more forward-looking criteria, including 'current conditions and forecasts of future economic conditions' (IFRS 9, para. 5.5.17). Information produced under the expected loss model is expected to reflect the changed quality of a loan more quickly (Hlawatsch & Ostrowski, 2010). However, the proposed approaches to the classification of loans did not receive broad support in the consultative processes in the development of the Standard. The majority (82%) of respondents to the *Request for Information* (2009) showed their concern for the operational feasibility of the expected loss model, especially in relation to the determination of relevant information. The responses to the IASB's request are analysed and summarised in Appendix A. Banks also expressed concerns regarding the identification of information that needs to be incorporated into the assessment of loan quality in response to a survey by Deloitte. An extract from the report (Deloitte, 2011) is provided in Appendix B.

Loan default and the broader financial distress prediction literature has not reached consensus on the relevance of various financial indicators for discriminating between defaulting and non-defaulting firms. Prior studies vary in terms of the predictor variables used and mixed results are found for the usefulness of the selected variables. Moreover, the direction of the association with the likelihood of default for some of financial variables in prediction models is counterintuitive, such as a positive association between liquidity measures and the default (e.g., Altman 1968). A further limitation of the literature is the reduction in prediction accuracy in attempts to validate the model using samples from different periods (Ball & Foster, 1982; Platt & Platt, 1990).

The identification of relevant predictor variables is critical to the usefulness of a prediction model in explaining the characteristics of defaulting firms and discriminating between defaulting and non-defaulting firms. However, the method of selecting relevant predictor variables has received insufficient attention in the literature[1]. Most prior studies have focused on the increase of prediction accuracy through the application of diverse prediction models and have not provided a proper explanation on why certain variables are selected for any prediction model (Baesens, Setiono, Mues & Vanthienen, 2003).

This thesis aims to address the methodological limitations in the loan default prediction literature in the selection of predictor variables and to identify variables that are relevant and useful for the prediction of loan default. Accordingly, the primary research objective of this thesis is to introduce an innovative model for the systematic selection of variables that are relevant to the prediction of loan default.

There has been limited investigation of the relevance of forward-looking economic indicators to the prediction of loan default or other forms of financial distress. A secondary objective of this study is to investigate whether economic indicators are relevant to the prediction of loan default.

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[1] Though factor analysis has been applied in the bankruptcy prediction literature by Pinches, Mingo, Caruther (1973), it has limitations, as discussed in Chapter 3.

Considering the criticality of the early and timely detection of the deterioration of loan quality, it is imperative to identify both financial and economic information that is useful to distinguish between defaulting and non-defaulting firms before the actual loan default. Thus, the identification of relevant variables for the prediction of loan default can provide a basis for more informed credit risk assessment, for lending decisions, monitoring loans and the application of the expected loss model in the preparation of financial statements.

1.2 SUMMARY OF MAJOR FINDINGS

The Elastic Net Model (Zou & Hastie, 2005) (hereafter the Elastic Net) is employed in this thesis to identify the relevant financial and economic variables for the prediction of loan default. The Elastic Net is widely used in various fields, especially in medical research, for simultaneous variable selection and coefficient estimation. The Elastic Net performs well as a valuable tool for model fitting and feature extraction (Yuan & Lin, 2006). It is particularly useful when predictor variables are more than the sample size and are extracted from groups sharing the same pathway (Zou & Hastie, 2005; Yuan & Lin, 2006). This feature is particularly relevant to the application to loan default prediction studies, which are characterised by relatively small samples of defaulting firms and may involve large sets of potential predictor variables. The Elastic Net combines the strengths of both ridge regression and least absolute shrinkage and selection operator (LASSO)[2] with

[2] The ridge regression and the LASSO are the shrinkage methods using penalised regression techniques. The ridge regression (Hoerl & Kennard, 1970) estimates the regression coefficients through an L_2-norm penalised least squares criterion. L_2 penalty minimises the sum of the square of

fewer restrictions to provide effective classification performance, while employing a minimal number of predictor variables (Hans, 2011; Shen et al., 2011). To the best of the researcher's knowledge, the Elastic Net has not been used in any other financial distress prediction studies. With the application of the Elastic Net, this thesis seeks to identify financial and economic variables that are relevant to distinguishing between defaulting and non-defaulting firms and to the prediction of loan default.

A sample of US loan defaulting firms from 1998-2013 is used. The yearly bond default rates are employed as a proxy of each year's loan default rates to determine the appropriate proportion of non-defaulted firms.

Ten predictor variables are extracted from a set of 278 potential variables including financial ratios, other firm-specific financial information and economic information. The interest rate is the only economic indicator selected from 10 potential economic indicators.

Significant differences are observed between defaulting and non-defaulting firms for eight of the nine financial variables one year before default. Divergence between the performance of defaulting and non-defaulting firms was evident from three or

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the differences between the targe value and the estimated value. The ridge regression shrinks the coefficients of correlated predictor variables toward each other (Friedman, Hastie & Tibshirani, 2000). Tibshirani (1996) proposed the LASSO estimator which estimates the regression coefficients through an L_1-norm penalised least squares criterion. L_1-penalty minimises the sum of the absolute differences between the target value and the estimated value. While demonstrating promising performance, the LASSO estimator has some shortcomings (Zou & Hastie, 2005). First, the LASSO estimator selects only one predictor from a group while ignoring others. Second, the LASSO method cannot select more predictor variables than the sample size. However, the extent of shrinkage in the Ridge and the LASSO is dependent on sample size. Detailed explanation is provided in Chapter 3.

four years before default for most financial variables. Changes in the loan default rate lagged changes in the interest rate, reflecting the forward-looking nature of this indicator and its relevance to distinguishing between defaulting and non-defaulting firms.

The prediction accuracy of variables selected by applying Elastic Net is tested in the multiple discriminant analysis and logistic regression models, EN MDA and EN Logit, respectively. The direction of the coefficients for the selected predictor variables is more intuitive in terms of the expected association of firms' financial characteristics with the likelihood of loan default compared with the Altman's (1968) Z-model and Ohlson's (1980) O-model.

The inclusion of the economic variable, the interest rate, enhances the prediction results of both prediction models. The observed differences in the Type I classification of EN MDA and EN Logit imply that the defaulting firms are more sensitive to changes in the interest rate than the non-defaulting firms and are more likely to default on their loans when the interest rate increases.

The EN MDA and EN Logit models outperform the Altman (1968)'s Z-score model and Ohlson (1980)'s O-score model in the accuracy of the Type I, the Type II and the overall classification. When tested over five years before loan default, EN MDA and EN Logit show consistent superiority over the benchmark models. Further, the classification accuracy is maintained for both defaulting and non-defaulting firms in EN MDA and EN Logit when tested on hold-out samples within and outside the period of the sample, from which the variables were extracted using Elastic Net.

The tests and analyses demonstrate the efficacy of the predictor variables extracted using the Elastic Net in capturing the characteristics of loan defaulting firms and the forward-looking prediction of loan default.

1.3 CONTRIBUTIONS OF RESEARCH

A conceptually richer and more accurate classification model to predict loan default is important to academics, regulators and banks (Shumway, 2001; Jones & Hensher, 2004). The aims of this study are to identify the most significant variables and to evaluate the relevance of economic indicators in the prediction of loan default.

The thesis contributes to the literature by introducing an innovative technique, the Elastic Net (Zou & Hastie, 2005), to address a methodological limitation in the selection of variables for the prediction of loan default. Further, this thesis identifies financial and economic variables that are useful in the prediction of loan default and in describing the characteristics of defaulting firms.

The central argument of this thesis is that a primary reason for the poor performance of prior predictive models is that they are subject to the choice of predictor variables used in the statistical models and the model to identify predictor variables has not been sufficiently developed. The variable selection methods employed thus far in the loan default and bankruptcy prediction studies have been criticised because they are often arbitrary and subjective, resulting in inconsistencies and limited usefulness in the prediction of loan default. This thesis introduces and demonstrates the efficacy of the Elastic Net to address the identified limitation in the loan default prediction literature.

With the application of the Elastic Net, this thesis identifies nine firm specific financial variables and one economic indicator, the interest rate, as relevant to the prediction of loan default. The identification of the distinguishing features of defaulting firms provides a basis for further investigation of the trajectory of loan default.

A further contribution of this thesis is the insight that the expansion of loan default prediction models to include the interest rate increases their prediction accuracy. This may enable the prediction model to capture current economic conditions under which the users make their decisions (Barth, 2006).

Finally, this thesis demonstrates that improvement in the variable selection methodology is effective in addressing the inconsistency in the composition and performance of previous loan default prediction models and their reduced prediction accuracy outside the period from which they were derived.

1.4 IMPLICATIONS OF THE RESEARCH

This thesis has the potential to facilitate better prediction and classification of loans and loan applicants. The thesis findings are potentially relevant to the assessment of credit in multiple contexts including bank lending decisions, monitoring loans and in the application of the expected loss model in the preparation of financial statements.

The identification of the characteristics of defaulting firms in this study can potentially facilitate more informed assessment of commercial loan applicants by financial institutions. The findings may assist financial institutions in determining what information should be collected for the assessment of the creditworthiness of borrowers. More accurate classification of applicants as defaulting or non-defaulting enables financial institutions to reduce the risk of granting loans to defaulting firms and the opportunity cost of denying loans to non-defaulting firms.

The timely detection of changes in the credit quality of loans is critical for financial institutions (Cicchetti & Dubin, 1994; Crotty, 2009; Baixauli, Alvarez & Módica, 2012). The identification of forward-looking variables for the prediction of loan default may enable better monitoring of loans. For instance, the identification of defaulting firms before the actual default may enable financial institutions to act to reduce their credit exposure, or to obtain compensation for the higher credit risk.

As discussed in Section 1.1, concerns were expressed about the uncertainty of information and indicators required for the application of the expected loss model to account for the impairment of loans. In particular, preparers need to consider forward-looking information in the assessment of credit risk. The forward-looking variables identified in this thesis as relevant to loan default may be useful for detecting change in the credit risk of loans. Thus, financial and economic variables can be used to make an accurate classification of loans for both monitoring purposes and in the application of the expected loss model. This thesis provides empirical evidence of the relevance of identified variables, thus mitigating reliance on ad hoc estimation that could be subject to sample properties of prior studies.

Lastly, the findings of this thesis may have implications for more quantitative portfolio credit risk analysis in bank capital regulations, arising under the proposed Basel II accord on regulatory capital (Allen & Saunders, 2003; Gordy, 2003; Kashyap & Stein, 2004). Within that framework regulators allow banks the discretion to calculate capital requirements for their banking books using "internal assessments" of key risk drivers, rather than the alternative regulatory standardised model[3]. Thus, where banks rely on their own assessment of a borrower's credit risk, accurate prediction of default and classification of loans is critical to the measurement method of expected credit losses. Thus, the findings of this thesis may help banks and regulators determine the capital requirements for banks based on the credit risk of loans issued.

1.5 THESIS STRUCTURE

The remainder of this thesis is structured as follows. Chapter 2 reviews the literature on the prediction of loan default and bankruptcy studies. Considering the limited number of loan default prediction studies, and their tendency to use ratios identified

[3] Under the 1988 Basel Accord, the regulatory standardised model is used to determine the capital charge on commercial bank lending by applying a uniform 8% of loan face value, regardless of the financial strength of the borrower or the quality of collateral (Gordy, 2003). However, under Basel II, the risk weights and capital charge are determined through the combination of quantitative inputs provided by the bank and formulas specified by the Basel Committee on Banking Supervision.

from bankruptcy prediction models, the literature review is extended to include the bankruptcy prediction studies. Chapter 2 also provides an overview of the variable selection methods employed in the loan default and bankruptcy literature. By identifying underlying issues associated with the literature, this extended literature review underpins the research question of the thesis.

Chapter 3 discusses the methodological limitations of variable selection models utilised in the bankruptcy and the medical research for the identification of the relevant predictors or indicators from a pool of potential variables. The chapter explains the Elastic Net as an alternative and less restrictive model for the extraction of relevant predictors.

Chapter 4 presents an overview of the research design of this thesis. It details the sample selection and the data collection procedures employed in this thesis. It also provides a detailed description of the loan default sample and the list of potential predictors. Further, it discusses the multivariate approaches that are used in this thesis to evaluate the performance of the selected predictor variables.

The empirical analyses and findings of this thesis are provided in Chapters 5 and 6. Chapter 5 reports the selected predictor variables and their predictive ability. It presents the descriptive statistics and the relative contribution of the 10 predictor variables selected via application of the Elastic Net. Chapter 6 tests and reports the usefulness of the predictor variables in relation to the *ex ante* prediction of loan default.

Finally, Chapter 7 provides the summaries and concludes the thesis. The contribution to the literature and potential implications for practice are discussed, followed by avenues of possible future research.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

A large number of studies present models using competing statistical techniques, such as multiple discriminant analysis, logistic regression and the mixed logit model, to predict a firm's failure to meet their financial obligation or to estimate the probability of bankruptcy. The objective of this chapter is to provide a broad overview of the variable selection methods employed in loan default prediction and the related bankruptcy prediction literature in order to develop an understanding of the prediction of loan default and to identify opportunities for further development or enhancement.

Most studies focus on more extreme events, such as bankruptcy, with much less attention devoted to the prediction of loan default. Further, many of the studies that investigate loans and credit risk focus on the granting of credit (e.g. Danos, Holt & Imhoff, 1989). While loan default may increase the likelihood of bankruptcy, bankruptcy is not necessarily preceded by loan default, and loan default is not necessarily followed by bankruptcy (Payne & Hogg, 1994). However, insights from the broader financial distress prediction literature are relevant to the development of a model for the prediction of loan default because the methodology is similar. Further, loan default studies often rely on variables factored into bankruptcy prediction models. Accordingly, the scope of this literature review is not limited to loan default prediction studies, but extends to bankruptcy prediction studies[4].

[4] The review of the literature does not include studies that develop structural or contingent claims analysis such as The Black-Scholes-Merton, KMV-Merton and hazard models. These models rely

Section 2.2 discusses several limitations of the financial distress prediction literature, including underdeveloped variable selection methods, inconsistencies in the relevance of predictor variables, counterintuitive or illogical performance of predictor variables and lower prediction accuracy outside the sample period. The section also discusses empirical investigations of the role of economic indicators in the prediction of loan default. Section 2.3 summarises the key findings of the literature review and identifies gaps that inform the research questions and method of this study.

2.2 REVIEW OF VARIABLE SELECTION METHODS

2.2.1 UNDERDEVELOPMENT OF VARIABLE SELECTION METHODS

Ever since Beaver (1966) pioneered empirical research in financial distress prediction using a univariate analysis, the literature on default and credit risk modelling has been growing and is now extensive (Carling, Jacobson, Lindé &

on estimates of firm value and its volatility. Though contingent claims analysis has a strong theoretical basis in corporate bankruptcy prediction, the practical implementation of these models is subject to some limitations. First, one of the key variables required for this analysis is the volatility of the firm's value. As volatility is not directly observable, the volatility needs to be approximated, which may introduce errors on estimation and biased probabilities of default (Crosbie & Bohn, 2003; Saunders & Allen, 2010; Bauer & Agarwal, 2014). Second, Saunders and Allen (2010) and Bauer and Agarwal (2014) argue that such models are unable to differentiate between the duration of loans since they assume a zero-coupon bond for all liabilities. Although the contingent claims analysis postulates that option maturity time, T, is the weighted-average time-to-default maturity, for simplicity most studies use a forecasting horizon of one year, i.e., $T = 1$ (Hillegeist, Keating, Cram & Lundstedt, 2004; Vassalou & Xing, 2004; Bharath & Shumway, 2008). Since firms typically have debt payment obligations at intermediate times before debt maturity T and loans normally extend over several years, the use of $T = 1$ for maturity is a mismatch via-à-vis actual debt maturity.

Roszbach, 2007). However, developments in the method of selecting variables have not kept pace with the development of prediction models (Carling et al., 2007).

Table 2.1 Variable Selection Methods Used in Previous Prediction Studies

Study	*Prior Studies*	*Statistical Relevance*	*Statistical Model (Factor Analysis)*	*Suggestion by Bankers*	*Judgement of Researcher*
Beaver[1)]	√				
Altman[2)]	√	√		√	√
P, M & C[3)]			√		
A, H & N[4)]	√	√			√
K & K[5)]	√			√	
Zavgren[6)]	√				
H, Mc & M[7)]	√				
J & H[8)]	√	√			
Roszbach[9)]		√			

1) Beaver (1966)
2) Altman (1968)
3) Pinches, Mingo and Caruthers (1973)
4) Altman, Haldeman and Narayanan (1977)
5) Kietrich and Kaplan (1982)
6) Zavgren (1985)
7) Hopwood, McKeown and Mutchler (1988, 1989)
8) Jones and Hensher (2004, 2007)
9) Roszbach (2004)

Table 2.1 presents the methods adopted for the selection of predictor variables of studies that disclosed the basis on which variables were selected for consideration. As presented in Table 2.1, popularity or frequent appearance in prior studies is the most common reason for selecting predictor variables. Selection based on the statistical significance and relevance is the next common method and the researcher's subjective discretion and practitioners' advice come next. The study by Pinches, Mingo and Caruthers (1973) employed the factor analysis to extract the relevant predictors from the large number of potential variables. Variables identified in Pinches et al. (1973) were later adopted by Zavgren (1985) and Hopwood, McKeown and Mutchler (1988, 1989). However, they adopted the same variables without testing their statistical significance or the relevance to their sample (Zhang, Hu, Patuwo & Indro, 1999).

2.2.2 RELEVANCE OF FINANCIAL VARIABLES FOR THE PREDICTION OF LOAN DEFAULT AND BANKRUPTCY

This study reviewed 120 loan default and bankruptcy prediction studies, among which 31 studies are frequently cited by other studies for the selection of financial predictor variables. There are 47 financial variables that are considered useful and are incorporated into the final set of predictor variables set by one or more of the 31 studies. The current ratio, the ratio of total liabilities to total Assets and total assets turnover are frequently included in prediction models, whereas other variables, such as the ratio of cash to expenses, are included in prediction models by only one study.

Table 2.2 Financial Ratios Incorporated in Loan Default and Bankruptcy Prediction Studies

	Cash/TA	Cash/S	Cash/Exp	Cash/MTA	WC/TA	WC/S	CA/TA	CA/CL	CA/TL	QA/CL	QA/TA	QA/S	CL/TE	CL/TL	NCL/TA	TL/TE	TL/TC	TL/TA	RE/TA	M/BL	ME/TC	S/TA	S/CA	S/CFO	EBT/TE	EBT/TA	EBIT/TA	EBITA/TA	EBIT/Int	NI/TA	NI/TE	NI/MTA	CFO/TL	CFO/TA	CFO/NCF	CFO/Int	CFI/NCF	CFF/NCF	WC/NCF	TL/NCF	Div/NCF	Int/NCF	Inv/S	Inv/Recv	Nor_STE	Size	CHIN
Altman (1968)					√														√	√		√					√																				
Edmister (1973)						√		√	√	√			√			√						√			√	√	√																√				
Pinches et al (1973)			√					√									√					√									√												√	√			
Deakin (1976)					√	√		√		√		√						√					√																	√							
Altman et al (1977)								√											√		√						√		√																√	√	
Kaplan & Urwitz (1979)																√		√												√			√			√										√	
Dambolena, Khoury(1980)								√											√		√						√		√																√	√	
Ohlson (1980)					√			√										√												√			√													√	√
Dietrich & Kaplan (1982)					√			√		√								√				√														√										√	√
Hamer (1983)					√			√										√		√	√	√					√		√	√			√												√	√	√
Izan (1984)								√								√				√							√		√																		
Lincoln (1984)							√			√				√				√	√				√																	√							

	Cash/TA	Cash/S	Cash/Exp	Cash/MTA	WC/TA	WC/S	CA/TA	CA/CL	CA/TL	QA/CL	QA/TA	QA/S	CL/TE	CL/TL	NCL/TA	TL/TE	TL/TC	TL/TA	RE/TA	M/BL	ME/TC	S/TA	S/CA	S/CFO	EBT/TE	EBT/TA	EBIT/TA	EBITA/TA	EBIT/Int	NI/TA	NI/TE	NI/MTA	CFO/TL	CFO/TA	CFO/NCF	CFO/Int	CFI/NCF	CFF/NCF	WC/NCF	TL/NCF	Div/NCF	Int/NCF	Inv/S	Inv/Recv	Nor_STE	Size	CHIN
Mensah (1984)																																															
Zmijewski (1984)								√										√									√																				
Frydman et al. (1985)	√	√			√	√	√	√		√	√	√						√	√		√	√	√				√		√	√										√						√	
Gentry et al. (1985, 1987)																																			√		√	√	√		√	√					
Zavgren (1985)	√									√						√	√					√																					√	√			
Betts and Behoul (1987)																																															
Hopwood et al (1988, 1989)	√						√	√		√						√						√	√							√																	
Platt & Platt (1990)							√							√				√						√																							
Foster et al. (1998)	√	√					√	√							√															√																	
Shumway (2001)																		√												√																	
Chava & Jarrow(2004)					√			√										√	√	√		√					√			√																√	
Jones & Hensher(2004)	√				√											√						√											√	√		√											
Gharghori et al. (2006)					√			√										√	√	√		√					√		√				√													√	
Carling et al (2007)																		√										√															√				

	Cash/TA	Cash/S	Cash/Exp	Cash/MTA	WC/TA	WC/S	CA/TA	CA/CL	CA/TL	QA/CL	QA/TA	QA/S	CL/TE	CL/TL	NCL/TA	TL/TE	TL/TC	TL/TA	RE/TA	M/BL	ME/TC	S/TA	S/CA	S/CFO	EBT/TE	EBT/TA	EBIT/TA	EBITA/TA	EBIT/Int	NI/TA	NI/TE	NI/MTA	CFO/TL	CFO/TA	CFO/NCF	CFO/Int	CFI/NCF	CFF/NCF	WC/NCF	TL/NCF	Div/NCF	Int/NCF	Inv/S	Inv/Recv	Nor_STE	Size	CHIN
Hensher & Jones (2007)	√				√											√																	√														
Angelini et al. (2008)					√														√													√											√				
Campbell et al. (2008)																		√												√																	
Wu et al. (2010)					√			√									√	√	√			√					√			√			√														√
Bauer & Agarwal (2014)				√														√														√														√	

This table reports the summary of the financial ratios employed as explanatory variables in the bankruptcy studies. When a study employs a market-driven information such as volatility, the variable is not included.

BL	Book value of liabilities
CA	Current assets
CFO	Cash flow from operating activities
CFI	Cash flow from investing activities
CFF	Cash flow from financing activities
CHIN	Change Net Income over two years
CL	Current liabilities
Div	Dividend payment
EBIT	Earnings before interest and taxes
EBITA	Earnings before interest, taxes and amortisation
EBT	Earnings before tax
Exp	Total expenses
Int	Interest expenses
Inv	Inventory
ME	Market value of equity
MTA	Total assets plus market value of common equity
NCF	Net cash flow
NCL	Noncurrent liabilities
NI	Net income
Nor STE	Stability of earnings
QA	Quick assets
RE	Retained earnings
RECV	Accounts receivable
S	Sales revenue
Size	Assets
TA	Total assets
TC	Total capital
TE	Total equity
TL	Total liabilities
WC	Working capital

Table 2.2 shows the financial variables employed by each of the 31 studies. In general, ratios reflecting profitability, liquidity and solvency prevail as the most commonly used indicators. However, the literature does not provide unequivocal evidence of the importance of individual variables or categories of variables, as discussed below.

In some studies the variables incorporated into the prediction model differ between prediction periods, such as one year and five years before failure. For example, Betts and Behoul (1987) select five to eight variables from a pool of 58 potential predictor variables for the classification of failed and non-failed firms over three years prior to bankruptcy. Each year, different variables are incorporated into their prediction model. However, the authors do not explain this inconsistency in the composition of their prediction models.

While many ad hoc classification systems exist for financial ratios, most of the systems observed in the literature fail to take account of the empirical relationships existing between and among financial ratios[5]. Thus, although over 100 predictor variables are employed in the diverse prediction studies of loan default and bankruptcy, it is unclear whether the predictor variables employed in the prediction

[5] One exception is factor analysis, which was employed by Pinches et al. (1973), Mensah (1983), Zavgren (1985), Platt & Platt (1990), Mutchler, Hopwood and McKeown (1997) and Ravi Kumar and Ravi (2007) to reduce the subjectivity of variable selection. Factor analysis is an analytic technique used to identify a reduced set of latent variables, called factors, which explain or account for the covariance of a set of related observed variables (Walter, Tellegen, McDonald & Lykken, 1996). In factor analysis, the aim is to establish the minimum number of latent variables that can adequately explain the covariance among the observed variables. Factor analysis is discussed in more depth on Chapter 3.

models capture the comprehensive dimensions of loan defaulting or bankrupt firms (Fan & Li, 2002; Brookhart et al., 2006; Meinshausen & Bühlmann, 2006).

Some studies find that profitability ratios are relevant to the prediction of bankruptcy. Firms with higher values for profitability variables are expected to be less likely to experience bankruptcy because a firm's continuing existence is ultimately based on the earning power of its assets (Altman, 1968; Agarwal & Taffler, 2008; Sarlija, Bensic & Zekic-Susac, 2009). Both the decline in sales and the deviation between firms' actual earnings and forecasts of their earnings are found to indicate that the distressed firms lost both earnings and sales (Altman, 1984).

While there is both intuitive appeal and empirical evidence that more profitable firms are less likely to fail, some studies find no association between profitability and bankruptcy. For example, Zavgren (1985) find that the profitability measure is insignificant and does not distinguish failing firms from healthy firms in any sample year between 1972 and 1978, whereas the turnover ratios are found to be significant over the five-year period prior to bankruptcy. Similarly, Wu, Gaunt and Gray (2010) find that the profitability variable is not useful for the prediction of financial distress. Their analysis reveals that the book value of total assets for the bankrupt firms decreases by 9.8% over the year prior to bankruptcy, suggesting that the ratio of sales to total assets may be misleading.

Mixed findings are observed for the role of liquidity measures for the prediction of failure. According to the findings of Zavgren (1985), a liquidity measure, such as liquid assets to current liability, is found to be significant for the prediction of financial distress, because the negative coefficient of this acid test ratio may indicate a weakened ability to meet current financial obligations of a failing firm, which increases the bankruptcy risk. Philosophov and Philosophov (2010) find that the use of ‘working capital to total assets (WC/TA)’ instead of ‘current liabilities to total assets (CL/TA)’ improves prediction accuracy. They claim that WC/TA is a better indicator because the deterioration of WC as a firm approaches bankruptcy is caused not only by an increased proportion of CL, but also by a decreased proportion of CA. Their finding is consistent with those of Grice and Ingram (2001) and Grice and Dugan (2003).

In contrast, Beaver (1966) finds that liquidity, measured by the current ratio is less effective in identifying corporate failure than other financial variable. He employed the six variables comprising ‘cash flow to total debt’, ‘net income to total assets’, ‘total debt to total assets’, ‘working capital to total assets’, ‘current assets to current liability’ and no-credit interval. Among those six variables, the cash flow to total debt is the strongest predictor followed by net income to total assets and the total debt to total assets. All three liquid assets and liquidity ratios perform lest well. Ohlson (1980) also reports the similar finding that among nine predictor variables, ‘working capital to total assets’, ‘current liability to current assets’ and ‘two years’ consecutive loss’ have the *t*-statistics less than two, while the other predictors are all statistically significant at a respectable level. Further, the deletion of the current ratio slightly increases the *t*-statistics of the working capital ratio.

Equivocal results are also found in relation to the usefulness of cash flow. Gentry, Newbold and Whitford (1985, 1987) find that net change in cash, but not operating cash flow, is useful for classifying failed and non-failed firms. However, Jones and Hensher (2004, 2007) find the opposite. Using a mixed logit model to classify three stages of corporate distress, they test predictor variables based on cash, operating cash flow (CFO), working capital, profitability and total debt to total equity. They find that CFO variables are significant in their models, improving prediction accuracy.

As discussed above, previous studies provide evidence of the relevance of financial information, but agreements cannot be reached on the relevant information for the prediction of loan default or bankruptcy. This can be explained partially because different sets of predictor variables are employed in the prior studies. Further, no consistent framework for the selection of predictor variables from data sets has emerged from the literature (Roszbach, 2004). Also, while there is evidence that these variables can be relevant to the prediction of bankruptcy, they might not be relevant to the prediction of loan default.

2.2.3 ILLOGICAL PERFORMANCE OF PREDICTION MODELS

As noted above in Section 2.2.2, most methods of identifying predictor variables observed in the literature fail to take account of empirical relationships existing between and among financial ratios. This limitation, coupled with a focus on the prediction accuracy of models rather than the identification of relevant predictors of default has contributed to the inclusion of predictor variables for which the direction of their effect on the likelihood of default is illogical. This issue is illustrated by Hillegeist, Keating, Cram and Lundstedt (2004), who develop modified discriminant functions based on two heavily cited bankruptcy prediction studies, Altman (1968) and Ohlson (1980). Hillegeist et al (2004) update the original coefficients to reflect the characteristics of the sample in a different period. The original coefficients of Altman (1968) and Ohlson (1980) and the modified coefficients of by Hillegeist et al (2004) are summarised in Table 2.3

The discriminant function[6] of Altman (1968) is given as

$$Z = 0.012\ X_1 + 0.014\ X_2 + 0.033\ X_3 + 0.006\ X_4 + 0.999\ X_5$$

where X_1 is WCTA (working capital to total assets), X_2 is RETA (retained earnings to total assets), X_3 is EBITTA (earnings before interest and taxes to total assets), X_4 is $E_{MV}TD_{BV}$ (market value of equity to book value of total debts) and X_5 is STA (sales to total assets).

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[6] Begley, Ming and Watts (1996) used an inconsistently modified discriminant function as $Z = 0.12\ X_1 + 0.014\ X_2 + 0.33\ X_3 + 0.006\ X_4 + 0.999\ X_5$. In relation to that, Shumway (2001) commented that Begley et al. (1996) contains two typographical errors. Because of its inconsistent presentation of coefficients, that study is not considered in this thesis.

Table 2.3 The Original and Updated Coefficients of Altman (1968) and Ohlson (1980)

Altman (1968)	WC/TA	RE/TA	EBIT/TA	V_E/TL_B	S/TA	C				
Original	*-1.20*	*-1.40*	*-3.30*	*-0.60*	*-0.99*					
Updated	*-0.08*	0.04	*-0.10*	*-0.22*	0.06	-4.34				
Ohlson (1980)	Size	TL/TA	WC/TA	CL/CA	NI/TA	FU/TL	INTWO	OENEG	CHIN	C
Original	-0.41	6.03	-1.43	0.08	-2.37	-1.83	0.29	*-1.72*	-0.52	-1.32
Updated	0.04	0.08	*0.01*	*-0.01*	*1.20*	0.18	0.01	1.59	-1.10	-5.9

The table summarises the original and the updated coefficients employed in Hillegeist et al. (2004), who compared the prediction performance of accounting-based models, Altman’s (1968) Z-score and Ohlson’s (1980) O-score, with that of the Black-Scholes-Merton option-pricing model, BSM-Prob. Considering the logical directions of coefficients and the changed economic conditions, they changed the directions of original coefficients of Altman (1968) to be negative and updated the coefficients of both the Z-score model and O-score model based on the financial characteristics of their sample.

The discriminant function of Altman (1968) can be read that all five variables are positively related to bankruptcy and thus, a firm with higher profitability and more equity and assets is likely to bankrupt. However, Hillegeist et al. (2004) pose that this is illogical and contrary to general expectation. They change the signs of the original coefficients of Altman (1968)'s Z-score to negative as presented in Table 2.3. Hillegeist et al. (2004) also updated the coefficients to reflect the changed economic conditions in the different period. However, the updated Z-score also results in counterintuitive directions on coefficients. For example, a firm with a higher ratio of retained earnings to total assets or higher ratio of sales to total assets is more likely to be classified as bankrupt.

The logistic regression function of Ohlson (1980) is given as

$$O = -1.32 - 0.407\ X_1 + 6.03\ X_2 - 1.43\ X_3 + 0.0757\ X_4 - 2.37\ X_5 - 1.83\ X_6 \\ + 0.285\ X_7 - 1.72\ X_8 - 0.521\ X_9$$

where X_1 is size; X_2 is total liabilities to total assets (TL/TA); X_3 is working capital to total assets (WC/TA); X_4 is current liabilities to current assets (CL/CA); X_5 is net income to total assets (NI/TA); X_6 is cash flow from operation to total liabilities (FU/TL); X_7 is negative income for two year (INTWO); X_8 is negative equity (OENEG) and X_9 is change in net income (CHIN).

The original and the updated coefficients of Ohlson (1980) are presented in Table 2.3. In contrast to Altman (1968), most coefficients for variables in the regression function of Ohlson (1980) have logical signs. The exception is OENEG, which is a dummy variable assigned a value of ‘one’ if total liabilities exceed total assets and ‘zero’ otherwise. As noted by Ohlson (1980), OENEG is expected to be positively related to the probability of bankruptcy, but has a negative coefficient.

Hillegeist et al. (2004) update the O-score of Ohlson (1980), but do not arbitrarily change the sign of OENEG. The updated O-score of Hillegeist et al. (2004) also shows illogical signs on the coefficients. For example, the probability of bankruptcy is given as a positive function of WCTA and NITA and a negative function of CLCA.

As discussed, the variables employed in the Z-score and O-score models, the most popular prediction models, do not yield logically defensible characteristics of failing firms. This discussion further supports the main argument of this thesis that a model should predict the loan default accurately and also that predictor variables should be useful for understanding the characteristics of default.

2.2.4 Limited Prediction Accuracy Beyond the Sample Period

The limited development of variable selection methods has contributed to empirical prediction models that tend to be sample-specific and incapable of indicating the most likely predictors of financial distress (Ball & Foster, 1982). Corporate failure prediction models typically are highly accurate *ex post* prediction, that is, classification within the sample from which the model is developed (Platt & Platt, 1990). Further, many models maintain similar prediction accuracy when applied to a hold-out sample within the same period. However, *ex ante* (out-of-sample period) classification accuracy measures are reported to be ten or more percentage points lower than that of the model's *ex post* classification accuracy. A comparison of within-sample and out-of-sample prediction accuracy of prior studies is presented in Table 2.4.

Table 2.4 A Comparison of Financial Distress Prediction Accuracy Within and Outside Sample Period

	Sample Period			*Outside Sample Period*		
Model	*Failed*	*Non-Failed*	*All*	*Failed*	*Non-Failed*	*All*
Altman (1968)	94%	97%	95%	96%	79%	84%
Deakin (1972)	97%	97%	97%	82%	77%	79%
Altman et al (1977)	96.2%(L)* 94.3% (Q)	89.7% (L) 91.4% (Q)	92.8% (L) 92.8% (Q)	92.5%	91.4%	91%
Zmijewski (1984)	52% (E)** 42% (W)	100% (E) 100% (W)	76% (E) 97% (W)	54% (E) 44% (W)	99.8% (E) 100% (W)	76% (E) 96% (W)
Gentry et al. (1985)	78.79%	87.88%	83.33%	69.57%	73.91%	71.74%
Platt and Platt (1990)	93 %(A)*** 78% (U)	86% (A) 67% (U)	90% (A) 78% (U)	93% (A) 86% (U)	88% (A) 86% (U)	90% (A) 87% (U)

* (L) represents the results using a linear model and (Q) represents the results using a quadratic model.
** (E) represents even weight and (Q) represents 20:1 weights.
*** (A) represent adjusted with industry effects and (U) represents unadjusted with industry effects.
† (F) represents outright failure and (I) represents insolvent stage prior to failure.

As presented in Table 2.4, prediction accuracy decreased when the models are tested on a sample drawn from a different period. The results of Altman, Haldeman and Narayanan (1977) maintain considerably high accuracy of when the model is tested on a validation sample. However, their validation sample is from the same time period. Platt and Platt (1990) show similar *ex pos*t and *ex ante* prediction accuracy. Their estimation (test) samples are from 1972 to 1986 and the validation samples are from 1986 to 1987. Thus the validation period is similar to testing prediction accuracy of a model using variables of one or two year before bankruptcy. As noted by Shumway (2001), estimating the probability of bankruptcy over a short horizon introduces biases and overestimates the impact of the predictor variables. Further, Campbell, Hilscher and Szilyagyi (2008) suggest that the prediction of corporate failure needs to be explored using long horizons in order to capture economic changes over time.

The disparity between *ex post* and *ex ante* classification results is perhaps the most pertinent issue in the field of failed classification (Platt & Platt, 1990). Mensah (1984) and Wood and Piesse (1987) suggest that data instability because of changes in inflation, interest rates and/or phases of the business cycle may be responsible for differences in classification results between estimation and forecast periods. Also, Pinches et al. (1973) find substantial changes in some financial ratios over time. This suggests that period-specific characteristics of predictor variables may contribute to weaker *ex post* prediction accuracy.

In summary, models have been developed to predict loan default and bankruptcy with a high degree of accuracy. However, their accuracy decreases when the models are tested on samples drawn from different periods. This implies that the predictor variables employed in the models are of limited usefulness for forward-looking prediction of loan default under different economic conditions.

2.2.5 CONSIDERATION OF ECONOMIC VARIABLES

Much of the financial distress prediction literature is focused on using financial statement data to predict default. As discussed in Section 1.2, the Boards have advocated the use of forward-looking information, such as 'current conditions and forecasts of future economic conditions' by banks in implanting the expected loss model (IFRS 9, para 5.5.17). The Boards also recommend that banks take into account more of forward-looking criteria for the assessment of credit quality over the life of loans, which is also recommended by the BASEL (1999). Accordingly, this section reviews the literature on the role of economic indicators in the prediction of loan default.

The previous literature demonstrates that economic factors can impact credit rating transition (Figlewski, Frydman & Liang, 2012) and the likelihood of corporate failure (Koopman, Kräussl, Lucas & Monteiro, 2009; Koopman, Lucas & Schwaab, 2012; Johnstone, Jones, Jose & Peat, 2013). General economic indicators include inflation, the level of employment and recession indicators (Figlewski, Frydman & Liang, 2012; Koopman, Lucas & Schwaab, 2012). Credit risks increases under adverse economic conditions (Anderson & Sundaresan, 2000; Collin-Dufresne & Goldstein, 2001).

The direction of economic indicators, such as real GDP, GNP, leading index and public debt to GDP, represents the strength of an economy (Figlewski et al., 2012; Koopman et al., 2012). Economic growth is considered a positive indication of economic strength, compared with stagnation or decline. Changes in the general conditions can impact firms by increasing costs, such as the costs of production and marketing. Entities are unable to fully pass on increased costs to customers to the extent that higher prices result in lower demand. The impact of declining economic conditions may spread default over large sectors of the economy because of contagion effect occurring along supplier-customer relationships (Stiglitz & Greenwald, 2003). For example, a firm may itself face increased risk if one of its major customer defaults (McNeil & Wendin, 2007). Lando and Nielson (2010) also note that financial, legal or other business relationships between firms can act as a conduit for the spread of risk.

Glennon and Nigro (2005) provide evidence of a relationship between economic conditions and loan default. They find that loan default is time-sensitive and particularly affected by a changing economic climate during the term of the loan.

Lev (1989) suggests that the use of financial information in isolation from economic variables may impede the validity and reliability of prediction models. Similarly, Roszbach (2004) notes that firms with identical financial statements may have a different bankruptcy risk depending on the economic conditions prevailing at the time of evaluation. The consideration of economic factors is of particular relevance in the prediction of loan default since loans typically extend over multiple periods with potentially varying economic conditions. However, there has been limited empirical investigation of the usefulness of economic indicators in the prediction of loan default.

Carling, Jacobson, Linde and Roszbach (2007) incorporated economic variables, such as real GDP and households' expectations, for the prediction of consumers' loan default. However, there was little diversity in the economic variables considered. Further, they did not test the usefulness of the economic variables for *ex ante* prediction of loan default.

Patel and Pereira (2008) develop separate models for the prediction of loan default using accounting-based variables and economic variables. They find that default risk is closely linked to economic factors. The classification accuracy of the accounting-based model is only 70%, compared with 92% for the prediction model with economic variables. However, they do not develop a model using both accounting and economic variables.

2.3 CONCLUSION AND RESEARCH QUESTIONS

2.3.1 SUMMARY OF FINDINGS

The chapter has provided a broad overview of the literature on the prediction of financial distress, including loan default. Prediction models based on a sound conceptual underpinning can be effective for lending decisions and monitoring loans (Roszbach, 2004; Dermine & de Carvalho, 2006; Foos, Norden & Weber, 2010). However, there is little consensus regarding which variables are the best predictors of default (Lane, Looney & Wansley, 1986) and some models yield illogical relationships between financial variables and loan default. The chapter has identified several limitations in the methods employed in the selection of variables and testing models that contribute to the equivocal and sometimes counterintuitive findings.

The literature review reveals that the method of selecting explanatory variables is underdeveloped. The majority of studies provide very limited, if any, explanation about how variables are selected. The most common reason offered is the frequency of their inclusion in the prediction models of prior studies. Moreover, studies investigating the prediction of loan default also selected explanatory variables based on their use in bankruptcy prediction. However, variables that are useful for distinguishing bankrupt firms do not necessarily capture the characteristics of loan defaulting firms.

The relevance of an explanatory variable in the prediction model is to some extent a function of the set of variables considered by the researcher. A variable may be useful in one prediction model, but it is omitted from another model because of inferior performance relative to other variables. Differences between studies in the variables considered have contributed to the inconsistency of prediction models in the literature.

Most studies in the loan default and bankruptcy prediction literature are primarily focused on improving the predictive accuracy of a prediction model without explaining why their models incorporated certain variables (Baesens, Setiono, Mues & Vanthienen, 2003). However, the emphasis on prediction accuracy has often resulted in the inclusion of predictor variables even though the direction of their effect on the prediction of corporate failure is illogical. Though predictive accuracy may be enhanced it does not provide useful insights into useful indicators of impending loan default.

Most studies reviewed report high prediction accuracy when the model is tested on the sample from which it is drawn or a holdout sample from the same time period. However, the prediction accuracy decreases considerably when the model is tested on a sample drawn from a different time period. This suggests that the identified predictor variables and prediction models are not robust to alternative time periods and are thus of limited use for the prediction of loan default. A possible explanation is that the models are not robust to different economic conditions.

Lastly, though there is evidence that economic factors have an impact on credit ratings and the probability of bankruptcy, there has been limited investigation of the usefulness of economic variables in the prediction of loan default. Patel and Pereira (2008) find that a loan default prediction model using economic indicators has more classification accuracy than a model using accounting-based factors only. However, they do not investigate whether combining accounting and economic variables enhances the accuracy of prediction models.

2.3.2 RESEARCH GAP

The literature review has identified the need for further investigation that can provide insights into which variables are relevant to the prediction of loan default. As the accuracy of a prediction model largely depends on the selection of predictor variables incorporated in the model (Zou & Hastie, 2005; Yuan & Lin, 2006; Shah & Samworth, 2013), the focus should be placed on the development of a systematic approach to the selection of variables to use in a prediction model.

Starting with a comprehensive set of potential predictor variables mitigates the biases and subjectivity in the variable selection process. However, no consistent framework for the selection of predictor variables from large data sets has emerged from the literature. Thus the focus of the development of a loan default prediction model should be directed towards the isolation of variables bearing an explanatory relationship with evaluation of credit performance (Capon, 1982), rather than merely trying to develop scorecards that can distinguish defaulting firms from non-defaulting firms within a sample. Thus, the primary objective of this study is to introduce an innovative model for the systematic selection of variables that are relevant to the prediction of loan default. Though factor analysis has been applied in the bankruptcy prediction literature by Pinches et al. (1973), it has limitations, as discussed in chapter 3

As discussed in section 2.2.5, there has been limited empirical research on the relevance of economic factors to the prediction of loan default. A secondary objective of this study is to investigate whether economic indicators are relevant to the prediction of loan default.

The next chapter reviews alternative models for the selection of predictor variables. It is it necessary to look beyond financial distress prediction literature to investigate models used in other fields for the extraction of variables that are relevant to the classification or prediction of events.

CHAPTER 3

ELASTIC NET

3.1 INTRODUCTION

The methods to select variables for the prediction of loan default and bankruptcy are not well developed in the literature. Instead, predictor variables are often selected based on their popularity in other studies or researchers' subjective judgements. These practices may explain inconsistencies in the inclusion of predictor variables between models and in some instances, the illogical direction of their effect on the prediction of default or bankruptcy, as discussed in Sections 2.2.2 and 2.2.3.

An exception to the more subjective approaches is the use of factor analysis by Pinches, Mingo and Caruthers (1973) and Platt and Platt (1990) for the selection of variables in the prediction of bankruptcy. Other models for the selection of predictor variables are observed in other research fields. Shrinkage models, such as the ridge regression (hereafter, the Ridge) and the least absolute shrinkage and selection operator (hereafter, the LASSO), are used in medical research (e.g., Meinshausen & Bühlmann, 2006; Li & Jia, 2010). However, these models are not without operational restrictions and limitations, as discussed below. The Elastic Net Model (Zou & Hastie, 2005) has fewer operational restrictions, making it more appropriate for large pools of potential variables and small samples that characterises the prediction of loan default.

This chapter identifies and explains the limitations of variable selection models and explains how these limitations are addressed by the Elastic Net. The methodological limitations of factor analysis, Ridge and LASSO are discussed in Section 3.2. The Elastic Net is explained in Section 3.3. Section 3.4 summarises the chapter.

3.2 METHODOLOGICAL LIMITATIONS OF VARIABLE SELECTION MODELS

3.2.1 FACTOR ANALYSIS

Pinches et al. (1973) employed factor analysis to isolate independent patterns of financial ratios and successfully reduce the initial set of 48 potential financial and operating ratios to seven key sets of ratios: profitability; capital intensiveness; financial leverage; short-term liquidity; cash position; inventory intensiveness; and receivables intensiveness. The variables selected in Pinches et al. (1973) have been used in many other studies (e.g., Mensha, 1984; Zavgren, 1985; Platt & Platt 1990; Mutchler, Hopwook & McKeown; 1997; Ravi Kumar & Ravi, 2007).

Factor analysis is a multivariate statistical technique that identifies a reduced set of latent variables, called factors, which explain or account for the covariance of a larger set of related observed variables, and permits the reduction of the variable space under examination to form factor patterns (Walter, Tellegen, McDonald & Lykken, 1996). These factor patterns retain the maximum amount of information contained in the original data matrix. For example, Pinches et al (1973), produces factor patterns of the financial ratios in terms of industrial firms. The similarity of each variable in the reduced space with the factors is measured by its factor loading, which is the correlation of the variable with the corresponding factor.

The aim of factor analysis is to establish the minimum number of latent variables that can adequately explain the covariance among the observed variables. The meaning of a latent variable is typically determined by inspecting the content of the observed variables that have strong relations with it. If a factor has strong relations with observed variables that reflect the ability to solve a raised problem, it can be concluded that the factor represents the raised problem (Finch & West, 1997). However, factor analysis is based on assumptions regarding the number of latent variables, the meaning of the latent variables and how they relate to the observed variables.

The first assumption is that the input data are continuous and measured on an interval level. However, potential variables considered in loan default may include ordinal items that typically contain only a limited number of ordered categories. With ordinal variables the intervals between the scale points of items are likely to be fewer, larger and less equal than those of continuous scales (Little, Cunningham, Shahar & Wildaman, 2002). The lack of equal intervals violates the assumption that the input variables are learned and at least measured on an interval scale level if not continuous.

Secondly, factor analysis assumes that the data are normally distributed. However, the data distributions might be non-normal (Berstein & Teng, 1989; Bandalos, 2002). The problem with non-normality is reflected in significant univariate skewness and univariate kurtosis, where items with similar distributions tend to form clusters or factors irrespective of their content.

The third assumption of factor analysis is that the relationships between the dependent and independent variables are linear. However, in practice the relationships between items and the traits that underlie them can be non-linear (Bandalos, 2002; Little, Cunningham, Shahar & Wildaman, 2002).

In addition to the restrictive assumptions discussed above, factor analysis has methodological limitations. The fit of the model to the data can be improved through explicitly modelling shared unique variance by allowing the factors to be correlated. However, when large sets of items are analysed researchers are seldom able to specify such relations *a priori* (Little, Cunningham, Shahar & Wildaman, 2002). Researcher intervention to resolve these issues introduces biases that potentially influence the composition and performance of the resulting prediction model.

3.2.2 RIDGE AND LASSO

Penalised regression approaches, also called shrinkage or regularisation methods have been developed in various fields for the simultaneous selection of variables and estimation of coefficients. Penalised regression approaches that are widely used in medical research include the Ridge, the LASSO and the Elastic Net, which is based on the combined penalties of the Ridge and the LASSO.

Penalised regression approaches enable variable selection such that only the important predictor variables stay in the model. Regression coefficients are shrunk by adding a penalty function to the least-squares model. Although this process may result in biased estimates, the resulting regression coefficient estimates will have smaller variance that can result in enhanced prediction accuracy through a smaller mean square (Hastie, Tibshirani & Friedman, 2009).

The Ridge estimates the regression coefficients through an L_2-norm penalised least squares criterion (Hoerl & Kennard, 1970). It is similar to least squares but shrinks the estimated coefficients toward zero. The Ridge coefficients are defined in equation 3.1 as:

$$\hat{\beta}_{RIDGE} = \underbrace{argmin_{\beta} \sum_{i} (y_i - \beta' x_i)^2}_{\text{Loss Term}} + \underbrace{\lambda \sum_{k=1}^{K} \beta_k^2}_{\text{Penalty Term}} \qquad (3.1)$$

where, $\lambda \geq 0$ is a tuning parameter that controls the strength of the penalty term and the relative impact of the two terms, loss term and penalty term, on the regression coefficient estimates.

The Ridge shrinks the coefficients of correlated predictor variables toward each other, allowing them to borrow strength from each other (Friedman, Hastie & Tibshirani, 2010). However, the Ridge has several limitations. It depends on sample size and is thus less effective for smaller samples that are common in financial distress prediction modelling. As coefficients approach zero, the Ridge is more likely to apply shrinkage. A problem arises in the event of identical predictors. If there are k identical predictor variables, the Ridge assigns identical coefficients, each equal to $1/k$ of the coefficient that would be assigned if it were a unique predictor variable, that is, in the absence of k – 1 identical predictor variables. Thus, the Ridge penalty is more effective for larger samples and where there are many unique predictor variables with non-zero coefficients.

Tibshirani (1996) proposed the LASSO estimator which estimates the regression coefficients through an L_1-norm penalty. LASSO regression coefficients are defined in equation 3.2 as:

$$\hat{\beta}_{LASSO} = \underbrace{argmin_{\beta} \sum_{i} (y_i - \beta' x_i)^2}_{\text{Loss Term}} + \underbrace{\lambda \sum_{k=1}^{K} |\beta_k|}_{\text{Penalty Term}} \tag{3.2}$$

One important difference between the LASSO and the Ridge occurs for the predictor variables with the highest regression coefficients. In the Ridge, the L_2-norm penalty is the sum of the squares of the coefficients, whereas the L_1-norm penalty for the LASSO is the sum of the absolute values of the coefficients. The L_2-norm penalty pushes the regression coefficients toward zero with a force proportional to the value of the coefficient, whereas the L_1-norm penalty exerts the same force on all non-zero coefficients.

Though the Ridge is a useful technique for analysing multiple regression data that may suffer from multicollinearity (Hoerl & Kennard, 1970), the L_2-norm penalty of Ridge pushes the coefficients only close to zero, but not to zero, thus rendering it less useful for the selection of the relevant predictor variables. Conversely, the L_1-norm penalty causes the coefficients to be shrunk to zero. This feature makes the LASSO more useful than Ridge for the selection of variables in the linear model. As $\lambda \geq 0$ increases, more coefficients are set to zero, resulting in fewer variables being selected. However, the lasso estimator has some shortcomings (Zou & Hastie, 2005). First, the LASSO fails to do grouped selection. It tends to select only one variable from each group, thus potentially ignoring relevant predictor variables.

Second, the LASSO cannot select more predictor variables than the sample size. Where the number of potential predictor variables (*p*) exceeds, or is even moderately large compared with the sample size (*n*), the LASSO selects, at most, *n* variables. These limitations make the LASSO unsuitable for the selection variables for financial distress prediction models, where the set of potential variables is often larger than the sample size, and several variables within a group may be relevant.

3.3 ELASTIC NET

Zou and Hastie (2005) proposed the Elastic Net to overcome the limitations of the Ridge and the LASSO. The Elastic Net is based on the combined penalty of the LASSO and the Ridge. It combines the strengths of both the Ridge and the LASSO with fewer restrictions to provide a better classification performance, while extracting a minimal number of predictor variables (Hans, 2011; Shen et al., 2011). The Elastic Net performs well as a tool for model-fitting and feature-extraction (Yuan & Lin, 2006). The superiority of the Elastic Net over other statistical variable selection methods has been demonstrated in medical science literature (Mairal, Bach, Ponce & Sapiro, 2010; Meinshausen & Bühlmann, 2010; Barretina et al., 2012).

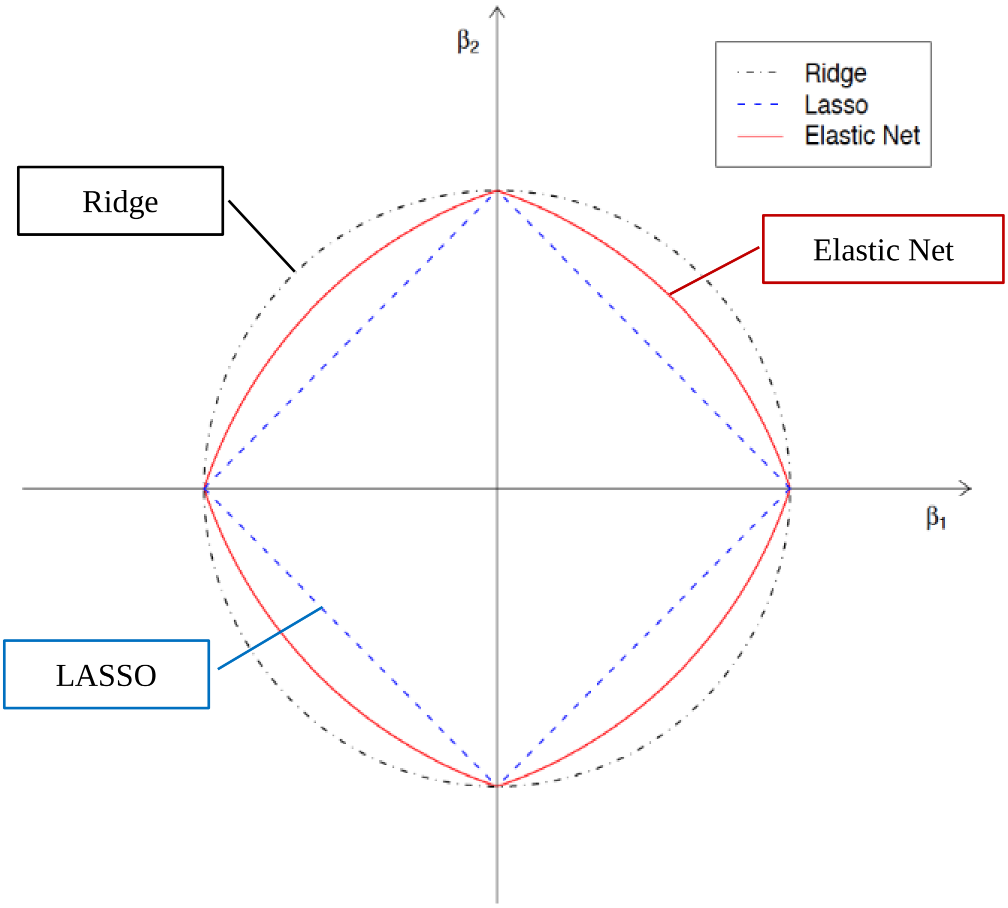
Drawing on Zou and Hastie (2005), for the purpose of explaining the Elastic Net, a data set that has *n* observations with *p* predictor variables is assumed. Let $\mathrm{y} = (\mathrm{y}_1, \mathrm{y}_2, \cdots, \mathrm{y}_\mathrm{n})^\mathrm{T}$ be the response and $\mathrm{X} = (\mathrm{X}_1 | \cdots | \mathrm{X}_\mathrm{p})$ be the model matrix, where $\mathrm{X}_\mathrm{j} = (\mathrm{X}_{1\mathrm{j}}, \mathrm{X}_{2\mathrm{j}}, \cdots, \mathrm{X}_{\mathrm{nj}})^\mathrm{T}, (\mathrm{j} = 1, 2, \cdots, \mathrm{p})$ are the predictors. The Elastic Net regression coefficients are defined in equation 3.3 as:

$$\hat{\beta}_{EN} = \underbrace{argmin_\beta \sum_i (y_i - \beta' x_i)^2}_{\text{Loss Term}} + \underbrace{\lambda_1 \sum_{k=1}^{K} |\beta_k| + \lambda_2 \sum_{k=1}^{K} \beta_k^2}_{\text{Penalty Terms}} \quad (3.3)$$

where, λ_1 and λ_2 are positive parameters and $\lambda_1 \, |\beta_k|_1 + \lambda_2 |\beta_k|^2$ is the penalties applied to the non-relevant variables to be deleted. $\lambda_1 \, |\beta_k|_1$ is an L_1-norm penalty that enforces the sparsity of the solution; and $\lambda_2 |\beta_k|^2$ is an L_2-norm penalty that ensures a similarity or a correlation among groups of correlated variables.

Figure 3.1 presents the geometric illustration of the Elastic Net, the Ridge and the LASSO.

Figure 3.1 Geometric Illustration of Elastic Net, Ridge and LASSO



The convex edges of the Elastic Net show that it is more lenient than the LASSO, but stricter than the Ridge. The singularities at the vertexes are generated from the L_1-norm penalty and are necessary for the sparse model. These semi-strict convex edges generated by L_2-norm penalty remove the limitation on the number of the selected variables and encourages the grouping effect.

The Elastic Net regularises the pool of potential variables by employing both the L_1-norm and L_2-norm penalties to yield a sparse solution. The L_1-norm and L_2-norm penalties shrink the estimates of the regression coefficients towards zero, relative to the maximum likelihood estimates. The purpose of this shrinkage is to prevent overfit arising from either multicollinearity of the covariates or high dimensionality. With the employment of the L_1-norm penalty, the Elastic Net's regularisation approach automatically selects the relevant variables and excludes non-relevant variables by shrinking their coefficients to zero. The L_2-norm penalty is expected to facilitate group selection and the selection of the subset of correlated potential variables in credit risk applications. This method allows the selection of groups of correlated features.

Rather than using least squares to find a subset of variables, the Elastic Net uses all variables in the dataset but constrains or regularises the coefficient estimates. The Elastic Net shrinks the coefficient estimates of unimportant variables to zero by imposing a penalty on their size, which is done by adding a penalty function to the least-squares model. This procedure enables variable selection such that only the important predictor variables stay in the prediction model (Hastie, Tibshirani & Friedman, 2009).

Shrinking the parameter estimates can significantly reduce their variance while having little effect on the basis of the classifier. Thus by shrinking the regression coefficient estimates, the Elastic Net can result in enhanced prediction accuracy because of a smaller mean squared error (Hastie, Tibshirani & Friedman, 2009).

The issues with the size of a set of predictor variables together with restrictive assumptions of linear relationships and a normal distribution can be resolved with the employment of the Elastic Net. It is particularly useful when the number of predictor variables exceeds the sample size, which often occurs when carrying out a multi-component analysis (Li & Jia, 2010; Shen et al., 2011). It does not treat "0" as a missing variable. Another important property of the Elastic Net is the grouping effect, as noted above. Unlike the LASSO which selects only one predictor variable from each group, the Elastic Net extracts the predictor variables from the groups sharing the same pathway (Zou & Hastie, 2005).

As noted by Hastie et al. (2009), one of the major practical benefits of the Elastic Net is that it involves relatively little researcher intervention. This technique is largely immune to monotonic transformation of input variables, the effects of outliers, missing values and other common data problems. It is not impaired by statistical problems such as multicollinearity or heteroscedasticity, which can seriously undermine the performance of parametric models. If an input variable is irrelevant, it is effectively omitted from the model. Hence, the Elastic Net is useful to produce a parsimonious model that may facilitate, with fewer predictor variables, more accurate prediction of events such as loan default.

3.4 CONCLUSION

This chapter discusses the limitations of factor analysis, the Ridge and the LASSO and introduces and explains the Elastic Net as a more efficient and effective model for simultaneous selection of variables and development of prediction models. The Elastic Net has fewer restrictions than the other penalised regression approaches. In particular, it does not assume linear relationships and continuous and normally distributed variables.

As discussed in Chapter 2, the financial distress prediction literature is characterised by limited development of methods for the selection of predictor variables. Accordingly, this study employs the Elastic Net to identify financial and economic predictor variables that are relevant to the prediction of loan default. The Elastic Net will be applied to a test sample of defaulted and non-defaulted firms to train and extract the predictor variables from a large pool of potential variables. The robustness of the Elastic Net to large pools of potential predictor variables and small samples makes it particularly well suited to the development of models for the prediction of loan default. The next chapter describes the research design.

CHAPTER 4

RESEARCH DESIGN:

DATA AND METHODS

4.1 INTRODUCTION

The objective of this chapter is to provide an overview of the data collection and sample selection procedures. Section 4.2 defines the scope of the loan default sample and presents the sample selection process for loan-default and non-default samples. Section 4.3 describes the characteristics and distribution of the test sample, from which the predictor variables are selected using the Elastic Net. The identification of, and data collection procedures for, potential predictor variables, including financial and economic variables, are presented in Section 4.4. Section 4.5 describes the statistical methods employed to derive models for the prediction of loan default, namely multiple discriminant analysis and logistic regression, followed by a description of the methods employed to evaluate the prediction models. Finally, Section 4.6 summarises the chapter.

4.2 SAMPLE SELECTION

4.2.1 SCOPE OF THE LOAN DEFAULT SAMPLE

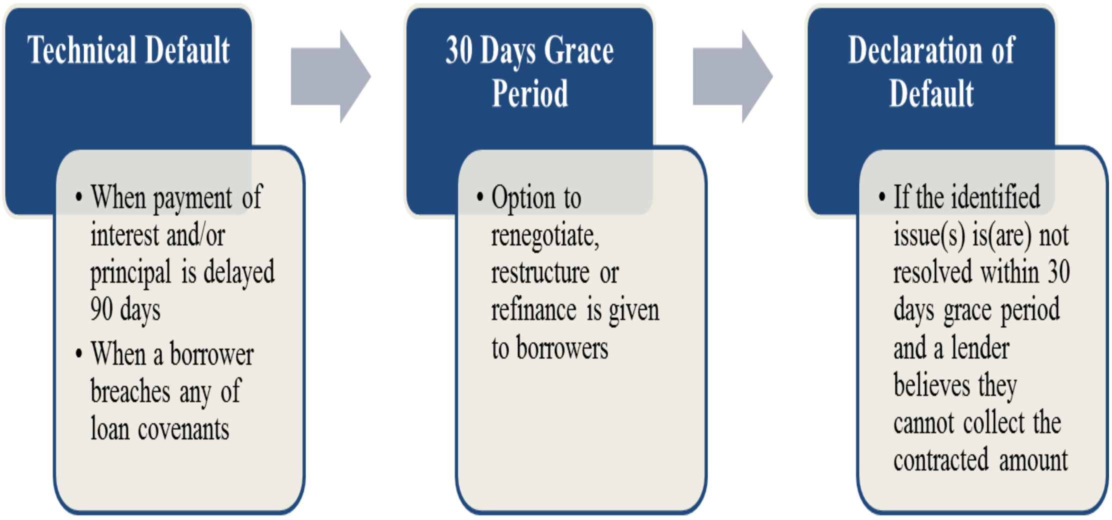
Various definitions of loan default are found in the literature including: 90 days missed payment of interest and principal (Gardner & Mills, 1989); the modification of indenture in association with a loan covenant violation (Beneish & Press, 1993); a voluntary or involuntary declaration of loan default by a firm or a financial institution (Foster, Ward & Woodroof, 1998; Foster & Zurada, 2013); and bankruptcy (Gharghori, Chan & Faff, 2006). Loan default is one of several financial distress events that may culminate in the insolvency of a firm (Jones & Hensher, 2004). Jones and Hensher (2004) classify financial distress into three states: State 0, non-failed firms; State 1, 'insolvent firms', comprising firms that have defaulted on a loan, failed to pay ASX annual listing fees as required by the ASX listing rules, undertaken capital raising specifically to generate sufficient working capital to finance continuing operations, or incurred a debt/total equity restructure because of a diminished capacity to make loan repayments; and State 2, firms that filed for bankruptcy followed by the appointment of liquidators, insolvency administrators, or receivers.

This study draws on the definition of loan default used by the Office of the Comptroller of the Currency[7] (OCC). A loan is considered to be defaulted if a borrower fails to resolve the identified issue within the grace period of 30 days, resulting in the declaration of the loan or the termination of the loan (OCC, 1998a) (see in Figure 4.1). This definition of loan default corresponds to one of the financial distress events included in State 1 of financial distress described by Jones and Hensher (2004), and is consistent with that used in prior studies including Foster, Ward and Woodroof (1998) and Foster and Zurada (2013).

[7] The Office of Comptroller of the Currency is an independent bureau within the Department of Treasury in the U.S. that regulates and supervises banks and savings associations.

Figure 4.1 Declaration Procedure of Loan Default

(sourced from the Comptroller's Handbook: Loan Portfolio Management (OCC, 1998b))



Though events such as delinquent payment or the breach of a loan covenant are treated as a technical default, they do not, by themselves, cause the loan to be classified as default (OCC, 1998b). Although related to loan default, a technical default does not always provide warning of a future actual loan default (Beneish & Press, 1993) because not all technical defaults result in loan default. If a financial institution expects to collect all amounts due, including interest accrued at the contractual interest rate for the period of delay, technical defaults arising from delinquency problems are often resolved via restructuring the loan terms (White, 1989; Senbet & Wang, 2012).

In addition, it is difficult to detect a technical default because most firms are reluctant to announce their delinquency in servicing a loan, resulting in a tendency to postpone the declaration of loan default until the borrower cannot avoid admitting it (Chen & Wei, 1993). Thus, a loan default is defined as occurring when the borrowing firm or the issuing financial institution declares that the borrower has defaulted on the loan, such that the information of loan default is made publicly available.

To identify the relevant predictor variables for the prediction of a loan default using Elastic Net and to construct a prediction model based on the identified predictor variables, samples of loan defaulted firms and non-default firms have been identified. The next section describes the sample selection criteria and procedures for the loan default sample, followed in Section 4.2.3 by a description of the selection of the sample of non-default firms.

4.2.2 SELECTION OF THE LOAN DEFAULT SAMPLE

The period after the late 1990s offers a powerful setting for this study because in 1994, the FASB amended FAS 114, 'Accounting by Creditors for Impairment of a Loan', which provides accounting rules for the impairment of loans. Thus, commencing the sample period from the late 1990s allows for the amended accounting rules to have been fully implemented in the years leading up to the earliest defaults. Arguably, the enhanced reporting requirements for lenders increased their accountability for monitoring loans and may have facilitated more timely declaration of loan defaults.

Further, business failure has dramatically increased since late 1990 (Altman & Hotchkiss, 2006). The higher incidence of failure may increase the sample size, thus facilitating the use of a holdout sample for testing the prediction model.

One of the objectives of this study is to investigate the association between economic indicators and loan default. Accordingly, it is necessary to have a sample drawn from a sufficiently long period to capture variation in economic conditions. The loan default sample is selected using the following four steps.

Step 1 Collection of the List of Loan Default Firms

A list of 379 US loan default events from 1998 to 2013 was obtained from an international credit rating agency. However, the list identifies only the name of borrowers and the date of default for each defaulted loan. The CUSIP of each firm is individually identified by matching it in Compustat, to obtain the financial information of each firm required for subsequent steps.

Step 2 Identification of a Potential Sample

The second step of the sample selection procedure was to identify a potential sample from the initial list. Concurrent loan default events were combined. Thus, when a firm defaulted on more than one loan on the same date, the concurrent defaults by the same firm were treated as one loan default. The initial list of the 379 loan default events included 122 concurrent default events. However, when a firm defaulted on loans in different years, each default was treated as a separate event. Only two firms defaulted twice during the sample period. In each case, their default events occurred over four years apart.[8]

Two loan default events from the finance and banking industry were deleted because financial institutions have business structures that differ from those of firms in other industries (Ohlson, 1980; Jones & Hensher, 2004). As presented in Table 4.1, the potential sample consists of 255 loan default events after exclusion of concurrent loan default events and default events from the banking and finance industry.

Step 3 Determination of the Availability of Financial Data

The third step of the sample selection procedures was to determine the data availability of the potential sample. Following Ohlson (1980) and Jones and Hensher (2004), the availability of data one year before the loan default event was made a criterion for inclusion in the sample. The date that financial statements were released was identified to determine whether the firm defaulted on the loan before or after the financial statements for that fiscal year were released. This is necessary to avoid the backcasting problem[9]. Provided financial data for a firm were available at least one year before loan default, the firm was not deleted from the sample. As

[8] As explained below, the total sample is divided into a test sample that is used to identify variables and develop a prediction model, and two holdout samples that are used to evaluate the accuracy of the prediction model. In the two instances that firms had two loan default events, the two events are not included in the same sample. In both cases, one default event is included in the test sample and the other, in a holdout sample.

[9] The backcasting problem occurs when a firm defaults on a loan or files for bankruptcy after the fiscal year date, but before releasing the financial statements to the public (Hosmer & Lemeshow, 2000).

presented in Table 4.1, 93 loan default events were deleted because of unavailability of financial data one year before default, resulting in a final sample of 162 loan defaults.

Step 4 Subdivision of the Sample

Three sub-samples are used in the research design, namely the test sample (the Test) and two holdout samples, Holdout 1 and Holdout 2, for external validation (Joy & Tollefson, 1975; Jones & Hensher, 2004). The fourth step of the sample selection procedure was to assign each loan default event to the Test, Holdout 1 or Holdout 2. The Test includes 70 default firms drawn from the period 1998 to 2009. This sample is used in the selection of the predictor variables by applying the Elastic Net [10] to derive loan default prediction models [11] using multiple discriminant analysis and logistic regression.

The holdout samples, Holdout 1 and 2, are used to test the predictive ability of the variables extracted from the Test by the application of the Elastic Net. Holdout 1 includes 69 default firms drawn from the same period as the Test (1998 – 2009), whereas Holdout 2 contains 23 default firms drawn from the period from 2010 to 2013. Having two holdout samples was designed to enable evaluation of the effectiveness of prediction models developed in this study with a different sample from the same sample period as well as a sample from a different period. Not many

[10] The Elastic Net, the variable selection model, is explained in Section 3.3.
[11] The statistical techniques employed in this study to develop loan default prediction models are described in Section 4.5.

prior studies tested the prediction accuracy on both within and out-of- period samples for the validation of their prediction models (Refer to Appendix C for the details of the size of test and holdout samples of previous studies).

The procedures for the selection of the loan default sample are summarised in Table 4.1.

Table 4.1 Summary of Sample Selection Procedures

Step	***Procedure***	***Number of Loan Default Events***
1	Initial list of loan default events from 1998 to 2013	379
2	Identification of potential sample	
	• Loan default events combined with a concurrent loan default event	(122)
	• Loan default events from the finance and banking industry	(2)
	Potential sample	255
3	Loan default events for which the firm's financial statements are not available one year before default	(93)
	Final full sample	162
4	Sub-division of full sample	
	Test sample	70
	Holdout 1 – within the same period as the test sample	69
	Holdout 2 – different period from the test sample	23
		162

4.2.3 Selection of the Non-default Sample

Many prior studies have employed a matched pair design for the selection of the non-default sample. A limitation of matched pairs is that the inherent 50 per cent default rate, which is much higher than that faced in real world conditions, causes over-sampling of the default firms (Hopwood, McKeown & Mutchler, 1988). Over-sampling of the default firms causes bias in the prediction accuracy of loan default because Type I accuracy increases with the proportion of default firms sampled but Type II accuracy decreases (Hillegeist, Keating, Cram & Lundstedt, 2004; Duffie, Saita & Wang, 2007; Wu, Gaunt & Gray, 2010).

To avoid over sampling problems and error rate biases associated with a matched pair design (Casey & Bartczak, 1985; Gentry, Newbold & Whitford, 1985; Jones, 1987), this study follows Zmijewski (1984) and Jones and Hensher (2004) in using prior probabilities based on the population. The use of the actual default rate is expected to minimise the misclassification rate of a prediction model (Dietrich & Kaplan, 1982; Reichert, Cho & Wagner, 1983; Ioannidis, Pasiouras & Zopounidis, 2010).

Some studies such as Pinches et al. (1973), Dambolena and Khoury (1980) and Betts and Belhoul (1987) use the average bankruptcy rate of the sample period.

However, as shown in Table 4.2, the loan default rates differ between years and their distribution is highly skewed.[12]

Table 4.2 **Historical Bond Default Rates** (sourced from Altman & Kuehne (2013))

Year	*Par Value Outstanding ($000)*	*Par Value Defaults ($000)*	*Default Rates (%)*
2013	1,392,212	14,539	1.044
2012	1,212,362	19,647	1.621
2011	1,354,649	17,963	1.326
2010	1,221,569	13,809	1.130
2009	1,152,952	123,878	10.744
2008	1,091,000	50,763	4.653
2007	1,075,400	5,473	0.509
2006	993,600	7,559	0.761
2005	1,073,000	36,209	3.375
2004	933,100	11,657	1.249
2003	825,000	38,451	4.661
2002	757,000	96,855	12.795
2001	649,000	63,609	9.801
2000	597,200	30,295	5.073
1999	567,400	23,532	4.147
1998	465,500	7,464	1.603
Mean	960,059	35,106.437	4.031
Median	1,033,300	21,589.5	2.498
Std.Dev	287,915.956	33,941.904	3.870
Skewness	-0.763	1.195	1.188

[12] Pearson's coefficient of skewness was used to determine how each year's default rates are distributed. As the mode of the default rates is indeterminable, the median was used.

Accordingly, the use of the average default rate would not represent each year's default rate. Thus, the actual bond default rate of each year is employed as a proxy of each year's loan default rate. Historical bond defaults rates are used to determine the appropriate proportion of default firms. The use of different default rates for each year minimises the misclassification error rate when the model is applied to the true population of potential borrowers (Altman & Eisenbeis, 1978; Reichert, Cho & Wagner, 1983). The size of the non-default sample is determined such that the ratio of defaulting firms to total firms (default and non-default samples) corresponds to the bond default rate for each year in which a loan default event occurred.

Non-default firms are drawn from the same population as the default firms in terms of industry and size. The four-digit SIC code is used to match industry groups. The asset size of the non-default firms is matched to that of the default firms. The asset size of the default firm ranges from $3,771,200 to $999,538 with average of $1,749,957.

The following procedures were used to select the non-default firms: (1) within each industry group, the firms whose asset size is closest to the asset size of the loan-default firms in that industry group are tentatively selected; and (2) firms are excluded if they defaulted on loans but did not issue financial statements within the sample period. Information about whether the firm defaulted on its loan is obtained from the Wall Street Journal Index and Bloomberg. Five firms, namely Waste Management, Tyco, Healthsouth, Freddie Mac and Saytam, which have been the subject of major financial reporting scandals or fraud, were deleted from the list of non-default firms.[13] The exclusion of firms engaged in financial reporting fraud or scandals is critical because this study seeks to enhance our understanding of the characteristics of loan default firms and to identify the predictor variables relevant to the loan default. The inclusion of misleading or fraudulent accounting and financial information could bias the results of the test.

Following these procedures, an initial sample of non-defaulting firms is identified, comprising 22,484 non-default firms with 229,050 firm-year observations. For the variable extraction and the prediction accuracy tests, non-default firms are randomly selected from the initial sample by applying the historical bond default rate per each year. Random selection from the initial sample is done without replacement to ensure that there is no instance of a non-defaulting firm being included in more than one of the sub-samples; the Test, Holdout 1 or Holdout 2.

As the loan default has not occurred before the issuance of the financial statements used in this study, loan default firms are henceforth labelled as 'defaulting'. Firms in the non-default samples are labelled as 'non-defaulting'.

4.3 CHARACTERISTICS OF THE LOAN DEFAULT SAMPLE

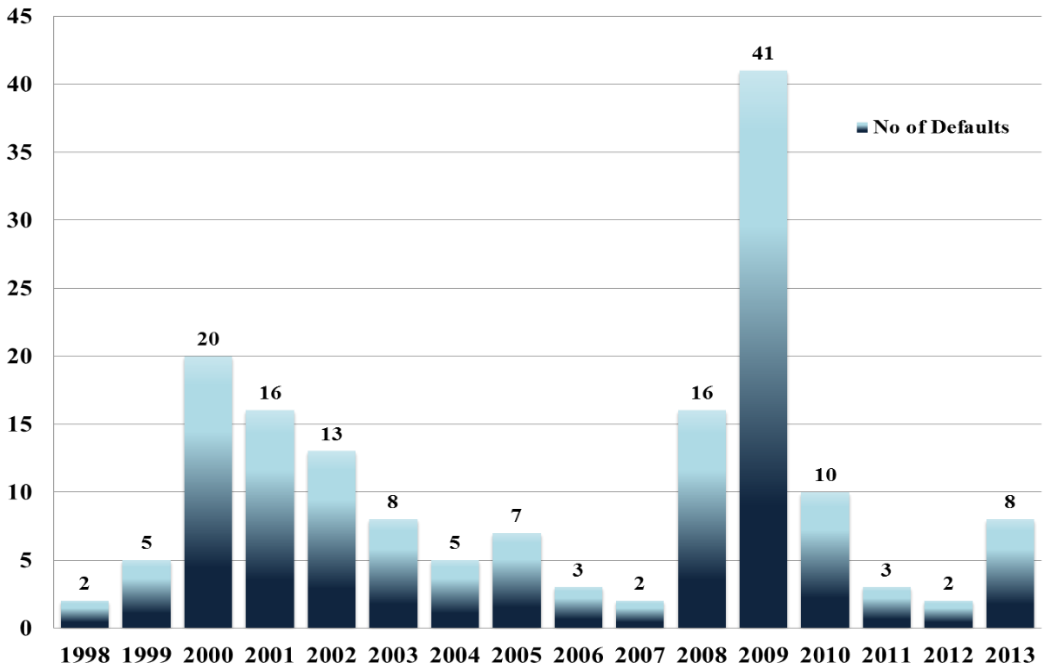
The full loan default sample contains 162 default events. In aggregate, the sample period ranges from 1998 to 2013. Three major financial crises occurred during this

[13] Enron, Lehman Brothers, WorldCom, Bernie Madoff and American Insurance Group, which have also been involved in financial scandals, were not included in the non-default sample because the size of their assets does not fall within the range of assets of loan default firms.

period: the 1998 Asian financial crisis; the 2000-2001 dot-com bubble; and the 2007-2008 global financial crisis (GFC). Figure 4.2 presents the distribution of loan default events of the full sample during the sample period. Unsurprisingly, the number of loan defaults by year clusters around the dot-com bubble and the GFC.

Fluctuation in the default rate under different economic conditions is evident from Figure 4.2. For example, the default rate increased in the aftermath of the 'Asian financial crisis' in the late 1990s, followed by clustering during and following the 'dot-com' bubble. Likewise, the GFC is associated with an increased number of loan default events. Thus, the annual default rates partly reflect the economic conditions.

Figure 4.2 Distribution of Loan Defaults by Year



The figure provides the historical distribution of loan defaults in the full loan default sample comprising the Test, Holdout 1 and Holdout 2.

Several empirical studies have verified time variation in default rates and confirmed that the time variation may to some extent be explained by economic variables (Das, Hanouna & Sarin, 2009; Lando & Nielsen, 2010; Koopman, Lucas & Schwaab, 2011; Azizpour, Giesecke & Schwenkler, 2015). Firms may be exposed to common or correlated risk factors that may be correlated with conditional default probabilities (Das, Duffie, Kapadia & Saita, 2007). A default by one firm may be contagious such that a loan default by one firm tends to precipitate defaults by other firms, as discussed in Section 2.2.5. The characteristics of the external economic environments, which may affect the financial condition of firms, vary over time. This may result in instability in the predictor variables over different periods that are characterised by different economic conditions.

The implications of the association between economic conditions and loan default are twofold. First, they provide further rationale for the consideration of economic variables as potential predictor variables[14]. Secondly, they imply that a setting with different economic conditions offers a more rigorous test of predictive accuracy of a loan default prediction model. Accordingly, the Holdout 2, the out-of-period holdout sample, comprises loan default events between 2010 and 2013 when there were no financial crises. In contrast, the sample used to develop the loan default prediction model comprises loan default events from 1998 to 2009, a period characterised by three financial crises.

[14] The selection of the potential economic variables is further discussed in Section 4.4.2.

All firms in the full loan default sample are classified into 10 different industry groups based on four-digit SIC codes, following industry classification of Chava and Jarrow (2004). The distribution of loan defaults across industries are summarised in Table 4.3.

Loan defaults in the manufacturing industry comprise the majority of the sample (54.32%), followed by transportation, communication and utilities (17.90%), the service (16.67%) and retail trade industries (4.32%). Four loan defaults are from the construction industry and three loan defaults are from the wholesale trade industry. Both the mineral and real estate industries have two loan defaults. As explained in Section 4.2.2, banking and finance industries are excluded from the industry group coded 8. There were no loan defaults by firms from agriculture, forestry and fisheries or public administration industries. Some industry groups may be more prone to loan default than others because of differences in industry specific conditions and structures (Gupta & Huefner, 1972; Chava & Jarrow, 2004; Acharya, Bharath & Srinivasan, 2007).

Table 4.3 Distribution of Loan Defaults across Industries

IND CODE	*SIC CODE*	*INDUSTRY NAME*	*NO (%) OF LOAN DEFAULT_ TOTAL*	*NO (%) OF LOAN DEFAULT_ TEST*	*NO (%) OF LOAN DEFAULT_ HOLDOUT 1*	*NO (%) OF LOAN DEFAULT_ HOLDOUT 2*
1	<1000	Agriculture, Forestry and Fisheries	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
2	1000 to less than 1500	Mineral Industry	2 (1.23%)	1 (1.43%)	1 (1.45%)	0 (0.00%)
3	1500 to less than 1800	Construction Industry	4 (2.47%)	2 (2.86%)	2 (2.90%)	0 (0.00%)
4	1800 to less than 4000	Manufacturing Industry	88 (54.32%)	36 (51.43%)	35 (50.72%)	17 (73.91%)
5	4000 to less than 5000	Transport, Communications and Utilities Industries	29 (17.90%)	14 (20.00%)	13 (18.84%)	2 (8.70%)
6	5000 to less than 5200	Wholesale Trade Industry	3 (1.85%)	1 (1.43%)	1 (1.45%)	1 (4.35%)
7	5200 to less than 6000	Retail Trade Industry	7 (4.32%)	4 (5.71%)	2 (2.90%)	1 (4.35%)
8	6000 to less than 6800	Real Estate Industries	2 (1.23%)	1 (1.43%)	1 (1.45%)	0 (0.00%)
9	6800 to less than 8900	Service Industry	27 (16.67%)	11 (15.71%)	14 (20.29%)	2 (8.70%)
10	8900 to less than 10000	Public Administration Industry	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
Total No (%) of Loan Defaults			162 (100%)	70 (100%)	69 (100%)	23 (100%)

Although ranking is slightly different in each sample, observations were allocated between the Test and Holdout 1 to achieve comparable industry representation. For example, loan default events from manufacturing industry comprise 51.43% and 50.72% of the Test and Holdout 1, respectively. Similarly, loan defaults from the transport, communication and utilities industries comprise 20.00% and 18.84% of the Test and Holdout 1, respectively. Although no loan defaults in Holdout 2 are from the mineral, construction and real estate industries, most loan defaults in the sample are from manufacturing industries (73.91%), transport, communications and utilities industries (8.70%) and service industries (8.70%), which is similar to the Test and Holdout 1.

Figure 4.3 Visualisation of Distribution of Loan Default across Industries

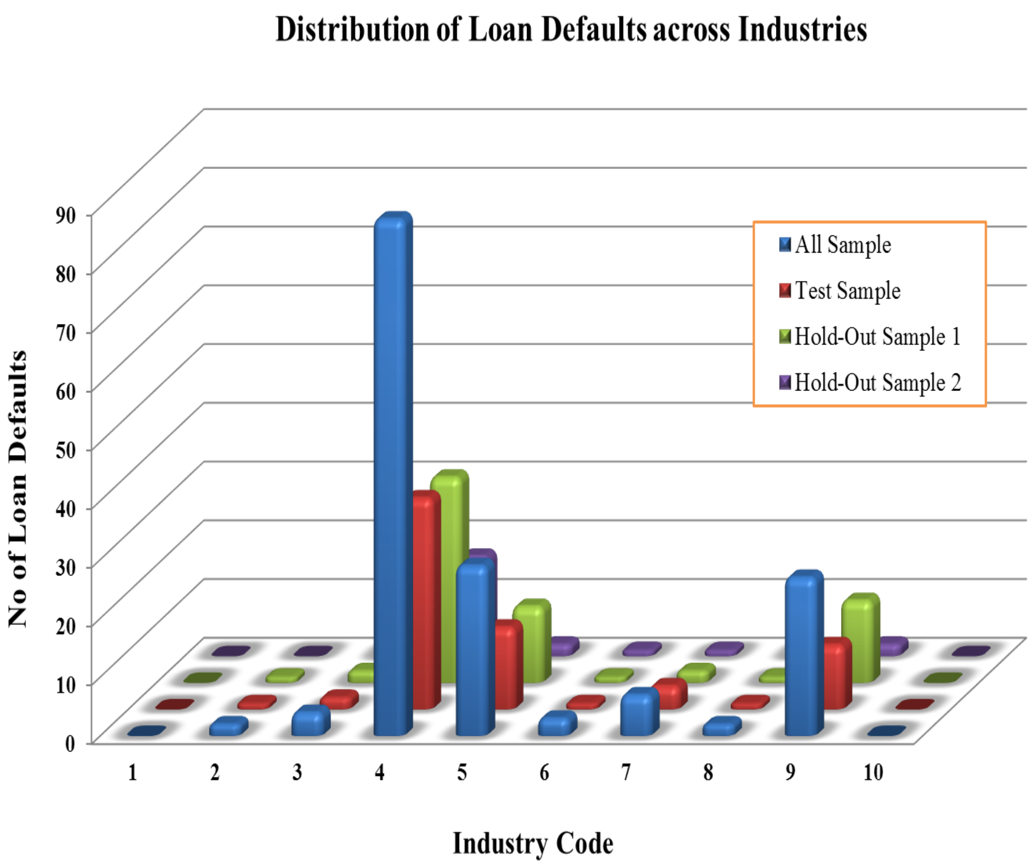


Figure 4.3 shows the similarity in the distribution pattern of loan defaults by industry in each sample – the Test, Holdout 1, which is drawn from the same period as the Test, and Holdout 2, which is drawn from a subsequent period. The red histogram represents the distribution of loan defaults in the Test across industries. The distribution of loan defaults in Holdout 1 and 2 are represented by the green and violet histograms, respectively. Arguably the prediction model constructed on the Test sample can be applied to the holdout samples without constructional differences in the sample affecting the accuracy of loan default prediction.

There is considerable variation in the age of defaulting firms. The firm's age ranges from 1.6 to 163.4 years with an average age of 39.60 years since incorporation. For 14.29% of the sample, the default occurred within 5 years of the firm being incorporated. The default occurred between 5 and 10 years after incorporation for 13.04% of the sample; 18.63% of firms defaulted on a loan 10.1 to 20 years after incorporation and 21.12% of firms aged from 20.1 to 40 years defaulted on their loans. For the firms in the age groups '40 to 80', '80.1 to 100' and '100.1 and over', the distribution is 12.42%, 9.94% and 10.56%, respectively. Thus, a particular trend or relationship between loan default and firm age was difficult to determine.

The majority (94.4%) of defaulting firms in the sample filed for Chapter 11 bankruptcy and sought restructure or reorganisation. Of the firms that filed for Chapter 11 bankruptcy, 82.7% emerged with a successful reorganisation. However, 13.1% of Chapter 11 bankrupt firms experienced 'Chapter 22'[15] within three years

[15] Coined by Altman (1984), Chapter 22 refers to the case where a bankruptcy reorganisation under the Chapter 11 system is unsuccessful and the emerged firm needs to file for Chapter 11 again, or in

of emergence from Chapter 11, with only 25 % surviving; 15.03% of Chapter 11 bankrupt firms were eventaully liquidated (Chapter 7 bankruptcy) and 2.61% of firms were merged.

4.4 COLLECTION OF FINANCIAL AND ECONOMIC DATA

4.4.1 COLLECTION OF FINANCIAL DATA

Financial data up to five year before loan default may contain significant information (Altman, 1968; Ohlson, 1980; Hillegeist, Keating, Cram & Lundstedt, 2004; Jones & Hensher, 2004; Altman & Hotchkiss, 2006; Ebert, Gilbert & Wilson, 2009; Charitou, Dionysiou, Lambertides & Trigeorgis, 2013; Foster & Zurada, 2013). Accordingly, the selection of variable and the development of prediction models utiltise data for up to five years before loan default[16].

Financial data for the samples of defaulting and non-defaulting firms were obtained from the Compustat database. Nine-character alphanumeric CUSIP codes were used to identify the firms in the database. CUSIP was employed, because it is used by the American Bankers Association. Each defaulting firm was identified in the database to obtain the matching CUSIP code. When similar names with different identifying codes were found, each firm was investigated further in the Wall Street

some other way becomes seriously financially distressed within a short period of emerging from Chapter 11 bankruptcy.

[16] The availability of data for each of the preceding five years was not a criterion for inclusion in the sample.

Journal Index, Bloomberg and US States Courts archive to find out which firm filed for Chapter 11.

Subject to availability, financial statement data are collected for each of the five years before the default date for each defaulting firm. Five years' financial statements for the same fiscal years are also collected for the selected non-defaulting firms.

Following Ohlson (1980) and Jones and Hensher (2004), financial statement data are included only if it had been made public before the loan default. The most recent reporting period for which an annual financial report was issued before the loan default was identified for each firm. The financial statement issue date, rather than its fiscal year, is used to determine the age of the financial data. The first year before loan default is defined as the year of issue of the latest financial statements before the default event, that is, the public declaration of loan default. For example, if a firm issues financial statements in September 2007 and defaults on its loan in December 2007, the financial statement issued in September 2007 is chosen for financial data one year before loan default (Year 1) If that firm had defaulted in August 2007, one month before the issue of the financial statement, the previous year's financial statement issued in September 2006 would be chosen for financial data one year before loan default.

The second year before default (Year 2) is the year immediately preceding the first year before default (Year 1). For example, when Year 1 for a firm is 2007, then

Year 2 for that firm is 2006, the second year before loan default. The third, fourth and fifth years are similarly defined[17].

The lead time for each firm between the issue of the most recent financial statement and the loan default date is measured in months. Table 4.4 shows the frequency distribution of lead times for the sample of defaulting and non-defaulting firms. The mean lead time between loan default and the issue of last set of financial statements prior to loan default is 7 months with a minimum of 3 months and a maximum of 14 months. As the thesis follows the criteria of Ohlson (1980) and Jones and Hensher (2004) including financial data, the lead times between the loan default and issue of financial statements is a similar range to those studies. The average lead time in Ohlson's (1980) study between the bankruptcy and the issue of financial statement is 13 months with a minimum of 3 months and a maximum of 33.5 months. The average lead time in Jones and Hensher's (2004) study between the bankruptcy and the issue of financial statement is 6.24 months with a minimum 2 months and a and maximum of >20 months.

[17] For a firm that defaulted in 1998, the data collection period is typically 1993 to 1997.

Table 4.4 The Lead Time between the Issue of Financial Statements and Loan Default

Months	3	3.1 ~ 3.5	3.6 ~ 4.0	4.1 ~ 4.5	4.5 ~ 5.0	5.1 ~ 5.5	5.6 ~ 6.0	6.1 ~ 6.5	6.6 ~ 7.0	7.1 ~ 7.5	7.6 ~ 8.0	8.1 ~ 8.5	8.6 ~ 9.0	9.1 ~ 9.5	9.6 ~ 10.0	10.1 ~ 10.5	10.6 ~ 11.0	11.1 ~ 11.5	11.6 ~ 12.0	12.1 ~ 12.5	12.6 ~ 13.0	13.1 ~ 13.5	13.6 ~ 14.0
Number of Reports	6	8	9	13	15	6	17	10	4	5	6	6	9	9	4	4	4	9	8	3	1	4	1

* Mean 7 months; Mode 4 months: Median 6 months

No financial data less than three months before default are collected. Annual financial statements are available by the end of the third month after firm's fiscal year end because the SEC requires firms to report 10-K within three months of the fiscal year end. For each loan defaulting firm, financial statements must be available at least three months before loan default to be considered the most recent available. If a default occurs within three months from the release of financial statements, the previous year's financial statements are treated as the last available observation (Begley, Ming & Watts, 1996; Shumway, 2001; Vassalou & Xing, 2004).

A criterion for inclusion in the sample is the availability of financial data for Year 1[18]. Thus the number of observations is maximised in Year 1. However, financial statement data are not always available for all of Years 2 to 5. The number of observations decreases as the period before default increases, and is smallest in the fifth year because of data constraints.

No arbitrary limit is placed on the number of potential variables that could be used. For each year for which financial statement are available, 238 ratios and 30 other financial items are computed in an endeavour to consider multi-dimensional characteristics of defaulting and non-defaulting firms. A ratio was excluded if it was merely a transformation of another ratio in the pool. The list of potential financial ratios and other financial information is presented in Appendix D. Following Beaver (1966) and Pinches et al. (1973), the ratios are presented in six

[18] Inclusion criteria of financial data are detailed in Section 4.2.2.

categories, namely profitability, capital intensives, short term liquidity, financial leverage, cash flow and turnover.

4.4.2 COLLECTION OF ECONOMIC DATA

A secondary objective of the thesis is to investigate whether economic indicators are relevant to the prediction of loan default. The economic data used to measure the potential economic variables are from the Federal Reserve of Economic Data (FRED). Following Figlewski, Frydman and Liang (2012) and Koopman, Lucas and Schwaab (2012) the potential economic variables are classified into three categories: 1) general economic conditions, 2) direction of the economy and 3) financial market conditions.

First, the variables in the general economic conditions are those related to the overall health of the economy. This study examines three key indicators of general economic conditions, the unemployment level, inflation and the recession indicator.

Unemployment rate The unemployment level is one of the most visible measures of the overall health of the economy (Lawrence, 1995; Louzis, Vouldis & Metaxas, 2012). High unemployment rates are expected to increase the likelihood of loan default. The yearly unemployment rate is included as a potential predictor of loan default.

Inflation Inflation is widely understood to have an adverse impact on general economic conditions (Figlewski, Frydman & Liang, 2012), thus increasing default risk. However, from the perspective of a firm whose outstanding debt is in nominal dollar amount, inflation reduces the real value of its required financial obligation, which may make it less likely to default. Thus, while the seasonally adjusted Consumer Price Index is included as a potential predictor variable, the nature of its impact on the likelihood of loan default is uncertain.

Recession indicator Though a recession is declared to be in progress if real GDP falls for two consecutive quarters, the formal declaration is made by the National Bureau of Economic Research after taking a number of other factors into consideration. The declaration of a recession is expected to increase the likelihood of loan default. The GDP based recession indicator is included as a potential predictor variable.

Secondly, the 'direction of the economy' category includes indicators that measure whether economic conditions are improving or worsening. This study includes the following four key indicators of economic conditions: Gross National Product (GNP); real Gross Domestic Product (GDP); industrial production; and the leading index.

GNP and Real GDP Both GNP and real GDP presents the current economic indicators (Koopman, Lucas & Schwaab, 2011). Changes in GNP and real GDP are expected to have a negative impact on loan default. Like many macro-level indicators, real GDP and GNP are available quarterly. Accordingly, the yearly average changes of real GDP and GNP were calculated for consistency with other economic and financial variables in the study.

Industrial production and the leading index Industrial production and the leading index are current economic indicators and show a strong negative relationship with the corporate default risk (Koopman, Lucas & Schwaab, 2011). Accordingly, the growth in production and the leading index are included as a potential predictor variables.

Thirdly, the variables included in the financial market conditions category are broadly related to current conditions in financial markets. This study includes the following three key indicators of financial market conditions: interest rates; credit spread; and public debt to GDP.

Interest rate It is expected that high interest rates would correspond to general tightness in the economy and increased difficulty in raising funds (Cortavarria, Dziobek, Kanaya & Song, 2000; Koopman, Lucas & Schwaab, 2011; Figlewski, Frydman & Liang, 2012; Louzis, Vouldis & Metaxas, 2012). Thus interest rates are expected to have a positive effect on the likelihood of loan default. Interest rates are included as a potential predictors variable, measured as the yearly 10-year US Treasury interest rate.

Credit spread The corporate credit spread is expected to be positively related to the likelihood of loan default (Koopman, Lucas & Schwaab, 2011). The corporate credit spread on high-yield bonds is used a potential economic variable.

Public debt to GDP Given the parallels between public and private debt, and the contagion effects (as discussed in Section 2.5), the level of public debt in proportion to the GDP is expected to be positively associated with the likelihood of loan default.

The 10 economic indicators discussed above are included with the 268 financial variables in the pool of 278 potential predictor variables.

4.5 VARIABLE EVALUATION APPROACHES

Using the Test samples of defaulting and non-defaulting firms, the pool of potential variables is regularised with the application of Elastic Net to extract the relevant predictor variables. The prediction-usefulness of identified predictor variables will be tested in conventional prediction models, multivariate discriminant analysis and logistic regression, as well area under receiver operating characteristic curve analysis. These evaluation approaches are discussed below.

4.5.1 MULTIVARIATE DISCRIMINANT ANALYSIS

Multivariate discriminant analysis (hereafter, MDA) aims to model a quantitative dependent variable as a linear combination of other predictor variables. The basic purpose of discriminant analysis is to estimate the relationship between a single categorical dependent variable and a set of quantitative independent variables (Hair et al., 1998). Discriminant analysis derives an equation as a linear combination of the independent variables that discriminates best between the groups in the dependent variable.

The linear combination, known as the multivariate discriminant function, takes the following form.

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (4.1)$$

where, Z is the dependent variable formed by the linear combination of the independent variables X_n, with ε of error term and $\beta_0, \beta_1, \beta_2, \ldots \beta_n$ of discriminant coefficients. The discriminant coefficients assigned to each independent variable are corrected for the interrelationships among the variables (Altman, 1968; Taffler, 1983). The result is a single value representing a combination of the entire set of independent variables that best achieves the objective of the specific multivariate analysis. In multiple regression, the variate is determined in a manner that maximises the correlation between the multiple independent variables and the single dependent variable (Hair et al., 1998). The variate is formed to create scores for each observation that maximally differentiate between the groups of observation.

MDA is useful to test if the classification of the groups in the dependent variable depends on at least one of the independent variables. MDA is widely used for feature selection (Fraley & Raftery, 2002). It is useful to determine which variable discriminates among dependent variables or groups (Hair et al., 1998) and to derive a classification model for predicting the group membership of new observations (Fraley & Raftery, 2002; McLachlan, 2004; Guo, Hastie & Tibshirani, 2006). Thus, the test of Elastic Net predictor variables using MDA is an appropriate way to evaluate the interrelations among Elastic Net predictor variables and the relative contribution of each variable to the classification result. Although the use of MDA is under some restrictive assumptions, such as a normal distribution of the independent variables and equal dispersion of the tested groups, it has several strengths.

Firstly, MDA offers the least expected misclassification cost and is widely applied in situations where the primary objective is the identification and classification of a group, such as defaulting or non-defaulting (Grice & Ingram, 2001; Agarwal & Taffler, 2007; Wu, Gaunt & Gray, 2010).

Secondly, the results of MDA are easy to interpret and apply (Koh & Killough, 1990; McLachlan, 2004; Guo, Hastie & Tibshirani, 2006).

Thirdly, MDA is particularly useful to determine whether statistically significant differences exist between the average score profiles on a set of predictor variables for two categorical groups, i.e., the defaulting and the non-defaulting firms in this thesis. The determination of statistical significance of each predictor variable identified via the application of the Elastic Net is applied to identify which variable accounts for more of the differences in the average score profiles of the defaulting and the non-defaulting firms.

4.5.2 Logistic Regression Analysis

Logistic regression analysis (hereafter, Logit) is used to analyse the relationship between predictor variables and an outcome that is dichotomous, such as default and non-default. It is used to describe data and to explain the relationship between one dependent binary variable and one or more independent variables. Specifically, Logit is used to find the best fitting model to describe the relationship between the dichotomous characteristics of a dependent variable and a set of independent predictor variables. Logit is based on a cumulative logistic function that gives the probability of a firm belonging to one of the predetermined groups, i.e., defaulting and non-defaulting. The Logit model is specified as follows:

$$P = \log\frac{P(x)}{1-P(x)} = \frac{exp^{\beta_0+x_i\cdot\beta}}{1+ exp^{\beta_0+x_i\cdot\beta}} = \frac{1}{1+ exp^{-(\beta_0+x_i\cdot\beta)}} \tag{4.2}$$

Like MDA, Logit is widely used (Hosmer & Lemeshow, 2000) but has fewer restrictive assumptions. Logit does not assume that the independent variables are normally distributed and equally dispersed. Also, it does not assume a linear relationship between the independent variables and the dependent variables. Thus, Logit can accommodate non-linear relationships occurring in the data and unevenly distributed groups (Friedman, Hastie & Tibshirani, 2000). This is pertinent to the current study because the distribution of failing and non-failing firms is based on the yearly bond default rate (as a proxy for population loan default rate) rather than the matched pairs required for evenly distributed groups.

The main strength of logistic regression is its high practicality. The probability of logistic regression is very intuitive and easy to interpret (Hosmer & Lemeshow, 2000). For example, in logistic regression analysis of loan default, if the probability for a firm is given as 0.85, it means there is an 85% probability that the firm will default on its loan.

To determine the statistical significance of the relationship between the predictor variables and outcome, Logit uses a maximum likelihood method, which discovers the precise forms of the equation that maximises the chances of predicting the outcome based on the given predictor variables (Chang, Lipsitz & Waternaux, 2000; Hosmer & Lemeshow, 2000). The results of the likelihood of observing the outcomes is often a small number and to, enhance its usability, twice the natural logarithm of this number is used, thus producing the 2 log likelihood, 2LL, value. This value is the basis for the test of significance. As probabilities are always less than one, the logs of these values are always negative. Thus, using a negative measure, –2LL, generates a positive value. The test is then to compare the difference between the –2LL for the logistic regression and the –2LL for the no predictor model, which is done using chi-square. A perfect fit between the model and the data would give a –2LL value of 0. As deviation from the perfected fit increases, the –2LL value increases. The lower –2LL, the better fit the predictor variables to the prediction model. Thus, the comparison of the –2LL values of predictor models indicates how well the predictor variables explain the outcome.

4.5.3 AREA UNDER ROC CURVE

Further analysis is conducted to evaluate whether the identified variables are useful for identifying a threshold to distinguish between safe and risky borrowers. The area under receiver operating characteristic curves analysis (hereafter, AUC) is the accumulated area under the receiver operating characteristics (hereafter, ROC) curves. ROC curve analysis is a technique for visualising, organising and selecting classifiers based on their performance. AUC[19] is extensively used for evaluating most diagnostic systems in the medical literature (Fawcett, 2006). AUC has been extended for use in visualising and analysing the behaviour of diagnostic systems (Swets, 1986). It is also used in the validation of bankruptcy prediction models (Sobehart & Keenan, 2001; Agarwal & Taffler, 2008; Foster & Zurada, 2013; Jones, Johnstone & Wilson, 2015). AUC has properties that make it especially useful for domains with a skewed class distribution and unequal classification error costs (Swets, 1986; Fawcett, 2006; Hand, 2009). This is pertinent in the application to the validation of models for the prediction of loan default where the costs of misclassifying defaulting and non-defaulting firms differ.

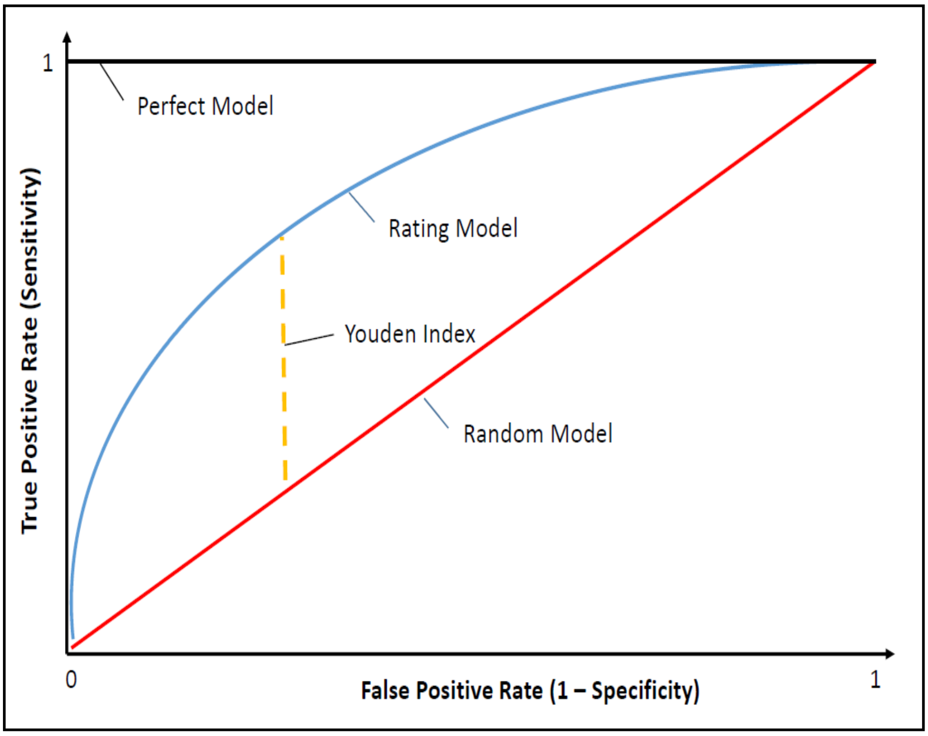
The application of ROC curve is based on the classification of outcomes being positive or negative and true or false. Given a classifier and an instance, there are four possible outcomes. If the instance is positive and it is classified as positive, it is counted as a *true positive*; if it is classified as negative, it is counted as a *false*

[19] Cumulative Accuracy Profile (CAP) analysis also generates a measure of the ability of credit ratings to distinguish between defaulting and non-defaulting borrowers. However, AUC is used in this study because AUC is applied for the diagnostic likelihood threshold to maximise the true positive value and minimise the false positive rate (Engelmann, Hayden & Tasche, 2003).

negative. If the instance is negative and it is classified as negative, it is counted as a *true negative*; if it is classified as positive, it is counted as a *false positive*. A true positive rate, or Type I classification, is the hit rate that correctly classifies a defaulting loan as 'defaulting' and a false positive rate, or Type II classification, is a false alarm rate that incorrectly classifies the non-defaulting loan as 'defaulting'.

The ROC curve is a plot of a true positive rate, or sensitivity, against a false positive rate (1 – specificity) as illustrated in Figure 4.4. The ROC curves are two-dimensional graphs in which the true positive rate is plotted on the *Y* axis and the false positive rate is plotted on the *X* axis. A ROC graph depicts relative tradeoffs between benefits (true positive rates) and costs (false positive rates).

Figure 4.4 Receiver Operating Characteristics Curve (Adopted from Engelmann, Hayden and Tasche (2003))



To construct ROC curves, all firms in the Test sample are ranked by their default probabilities from the highest to lowest. Following Agarwal and Taffler (2008), the percentage of defaulting firms is calculated by dividing the number of defaulting firms by the total number of firms in the sample. The ROC curve is the plot of percentage of the default probability against the percentage of correctly classified defaulting firms. The ROC curve is constructed by varying the cut-off probability. Thus, for every cut-off probability, the ROC curve defines the percentage of defaulting firms that the model correctly classified as defaulting (true positive rate) on the Y-axis and the corresponding percentage of non-defaulting firms that are mistakenly classified as defaulting (false positive rate) on the X-axis.

A prediction model's performance is better, the steeper the ROC curve is at the left end, and the closer the ROC curve's position is to the point. Similarly, a larger area under the ROC curve indicates better performance of the model. The area for a perfect model is 1 and the area for a random model is 0.5. If a rating model is between 0.5 and 1, the model contributes to classification or prediction. The ROC area measure can be interpreted as an unbiased percentage of correct classification. If the area under the ROC curve is 0.85, then the prediction model can be said to have an unbiased accuracy of 85%. Thus, it is useful and readily understood. An optimal cut off point is where the Youden Index reaches its maximum, so that rating model can have largest area under the curve. The Youden Index is maximised at the point for which the combination of sensitivity and specificity is largest. In other words, the optimal cut-off point is the value for which the point on the ROC curve has the minimum distance to the upper left corner, where sensitivity is '1' and specificity is '1'.

Following Engelmann, Hayden and Tasche (2003) and Baur and Agarwal (2014), the cumulative accuracy ratio is calculated by putting the ROC curves into context. The accuracy ratio of a model obtained with the AUC is defined as

$$\text{Accuracy Ratio (AR)} = 2 * (\text{AUC} - 0.5) \tag{4.3}$$

The accuracy ratio is a linear transformation of the AUC. A model with perfect performance has an accuracy ratio of one. All defaulting firms are assigned a larger probability of default than any non-defaulting firms, whereas a model with constant or random prediction has an accuracy ratio of 0. In general, models with higher accuracy ratios exhibit better performance on default prediction.

4.6 SUMMARY

This chapter presents an overview of the research design adopted in this study. The sample selection procedures for the defaulting sample are explained. A sample of non-defaulting firms is formed using population bond default rates. The description of characteristics of defaulting sample provides useful insights into the pattern of default during the sample period, 1998 to 2013. In total 268 financial ratios and other financial statement items and 10 economic variables are calculated or obtained for up to five years for the samples of defaulting and non-defaulting firms.

The chapter also explains the approaches, namely MDA, Logit and AUC analysis, used to evaluate the variables selected using the Elastic Net.

Chapter 5 presents the results of the application of the Elastic Net in regularisation of the pool of 278 variables for the test sample.

CHAPTER 5

IDENTIFICATION OF THE VARIABLES FOR PREDICTION OF LOAN DEFAULT USING THE ELASTIC NET MODEL

5.1 INTRODUCTION

This thesis aims to address the subjective selection of variables in the development of models for the prediction of loan default, as explained in Chapter 2, by extracting relevant predictors of loan default from a large pool of potential variables through the application of Elastic Net (Zou & Hastie, 2005). The methodological superiority of the Elastic Net over other penalised regression approaches and factor analysis, are discussed in Chapter 3.

The Elastic Net is used to identify relevant variables for the prediction of loan default by regularising a set of 278 potential variables including financial ratios, other firm-specific financial information and economic variables. This chapter identifies and analyses the 10 variables identified by the Elastic Net (hereafter, EN variables), including nine financial variables and one economic variable, the interest rate.

Section 5.2 provides comparative descriptive statistics of the EN financial variables for the defaulting firms and non-defaulting firms one year before default. The variables are also compared for defaulting and non-defaulting firms over the five years before the loan default. Section 5.2 also presents an analysis of the interest rates and loan default rates over the sample period. Using MDA and Logit, the significance of each EN variable in the prediction of loan default is analysed in Section 5.3. Section 5.4 summarises and concludes the chapter.

5.2 EN PREDICTOR VARIABLES

5.2.1 DESCRIPTIVE STATISTICS OF EN VARIABLES

The 10 variables extracted by the regularisation of 278 financial and economic potential predictors with the application of the Elastic Net comprise nine financial variables and one economic predictor variable. The Glmnet package, written by Trevor Hastie, Jerome Friedman, Noah Simon and Rob Tibshirani, was employed in R for fitting the Elastic Net model. This package fits and regularises the Elastic Net model paths for logistic and multinominal regression using coordinate descent. When coding in R, Lambda was set to minimum. Thus, the Elastic Net model selects the combination of variables which yields the highest contribution, with the smallest number of variables, to the model. The hyper-parameter, Alpha, was set at 0.5 for the Elastic Net model. Thus, it was not as lenient as the Ridge (Alpha = 0) nor as strict as the LASSO (Alpha = 1).

The 10 EN variables are

- Tangible assets to total assets (A_{TAN}/TA)
- Change in cash flow from financing activities between $year_N$ and $year_{N+1}$ measured in $000 (CH_CFF)
- Sales to tangible equity (S/E_{TAN})
- Net profit to tangible equity (NP/E_{TAN})
- Unadjusted retained earnings to total assets (RE_{UnAdj}/TA)
- Interest expenses to working capital (INTEx/WC)

- Interest expenses to cash flow from operating activities (INTEx/CFO)
- Non-current liabilities to cash flow from operating activities (NCL/CFO)
- Total debts to total assets (TD/TA)
- Yearly 10-year US Treasury interest rate (INT).

Table 5.1 presents the comparative descriptive statistics for the nine financial variables one year before default for the Test sample. The means and medians of defaulting and non-defaulting firms are compared for each variable in the paired test sample[20]. Paired *t-tests* and Wilcoxon signed rank tests are conducted to test for differences in means and medians, respectively

[20] The use of paired samples is to test for differences between means and medians. In all other analyses, the proportion of defaulting firms is based on the population default rate, estimated as the default rate on bonds.

Table 5.1 The Descriptive Statistics of the 10 EN Variables

EN Variables	*Firm sample*	*N*	*Mean*	*Mean diff*	*Median*	*Median diff*	*t-test*	*Wilcoxon Z*
A_{TAN} /TA	Default	70	0.505	-0.333	0.620	-0.231	-16.124***	-7.271***
	Non-default	70	0.839		0.851			
CH_CFF	Default	70	27.795	84.433	-54.279	-51.202	0.421	-1.010
	Non-default	70	-56.638		-3.007			
S/E_{TAN}	Default	70	-18.538	-21.647	-2.882	-5.632	-3.146***	-5.820***
	Non-default	70	3.109		2.750			
$NP/\ E_{TAN}$	Default	70	-0.109	-0.328	-0.007	-0.199	-6.351***	-6.645***
	Non-default	70	0.219		0.193			
RE_{UnAdj}/TA	Default	70	0.455	-0.178	0.458	-0.206	-5.963***	-4.796***
	Non-default	70	0.633		0.664			
INTEx/WC	Default	70	4.926	4.867	1.365	1.326	2.714**	-7.166***
	Non-default	70	0.059		0.038			
INTEx/CFO	Default	70	0.221	0.214	0.061	0.054	3.988***	-7.207***
	Non-default	70	0.007		0.007			
NCL/CFO	Default	70	18.744	18.003	8.311	7.531	2.503**	-5.007***
	Non-default	70	0.741		0.780			
TD/TA	Default	70	0.218	-0.048	0.209	-0.016	-1.714*	-1.466*
	Non-default	70	0.265		0.225			
INT	Default	70	3.450	-0.860	3.543	-1.380	-3.179***	-2.455**
	Non-default	70	4.310		4.923			

Definitions for all variables are as follows: A_{TAN} /TA = Tangible assets to total assets; CH_CFF = Change (in $000) in net cash flow in between $year_N$ and $year_{N+1}$; S/E_{TAN} = Sales to tangible equity; NP/E_{TAN} = Net profit to tangible equity; RE_{UnAdj}/TA = Unadjusted retained earnings to total assets; INTEx/WC = Interest expenses to working capital; INTEx/CFO = Interest expenses to cash flow from operating activities; NCL/CFO = Non-current liabilities to cash flow from operating activities; TD/TA = Total debts to total assets; INT = Yearly 10-year US Treasury interest rates. *N* is the number of firm-year observations in the paired test sample. For the defaulting sample, *t+1* is the number of observations one year before the loan default. The non-default sample is randomly selected from the pool of the non-default sample. Except for CH_CFF, all mean and median differences between default and non-default sample are statistically significant based on Paired *t-test* and Wilcoxon signed rank tests at the following levels. ***significant at the 0.001 level (two-tailed); **significant at the 0.01 level (two-tailed); *significant at the 0.05 level (two-tailed)

There are significant differences between the EN variables for defaulting and non-defaulting firms. Except for CH_CFF, all paired t-tests for differences in means and Wilcoxon tests for differences in medians are statistically significant. The following discussion of the comparison between defaulting and non-defaulting firms is based on the paired t-tests for differences in means. However, substantively similar results are observed for the Wilcoxon tests for differences in medians, as shown in Table 5.1.

The review of the financial figures indicates that the defaulting firms have a lower A_{TAN}/TA than non-defaulting firms. The mean value of A_{TAN}/TA is 0.505 for defaulting firms, compared with 0.839 for non-defaulting firms ($p = 0.001$). The median values of A_{TAN}/TA for defaulting and non-defaulting firms are 0.620 and 0.851, respectively and the difference in the median value is also significant at 0.001 level. That is, defaulting firms have a smaller proportion of tangible assets compared with non-defaulting firms.

As expected, defaulting firms have lower profitability, evidenced by statistically significant lower mean and median values for S/E_{TAN} and NP/E_{TAN} than non-defaulting firms ($p = 0.001$). Tangible equity is the equity calculated by deducting the total liabilities from only the tangible assets. The median and the mean values of these ratios for defaulting firms are negative; mean and median values of S/E_{TAN} for defaulting firms are -18.538 and -2.882, respectively. Also, mean and median values of NP/E_{TAN} for defaulting firms are -0.109 and -0.007, respectively. This reflects a high incidence of negative tangible equity attributed to a lower proportion of tangible assets in the balance sheets of defaulting firms.

The cumulative profitability measure, RE_{UnAdj}/TA, shows statistically significant difference ($p = 0.001$) in both mean and median. The mean for RE_{UnAdj}/TA of defaulting firms is 0.455 compared with 0.633 for non-defaulting firms ($p = 0.001$). The median for RE_{UnAdj}/TA of defaulting firms is 0.458, compared with 0.664 for non-defaulting firms ($p = 0.001$).

The mean value of INTEx/WC for defaulting firms is significantly higher (4.926) than the 0.059 for non-defaulting firms ($p = 0.01$). The median values of INTEx/WC for defaulting and non-defaulting firms are 1.365 and 0.038, respectively and the difference in the median value is also significant at 0.001 level. This attributed to relatively higher interest expense incurred and lower levels of working capital maintained by defaulting firms.

Similarly, defaulting firms have a significantly higher INTEx/CFO mean than non-defaulting firms. The mean value of INTEx/CFO is 0.221 for defaulting firms and 0.007 for non-defaulting firms ($p = 0.001$). The median value of INTEx/CFO is 0.061 for defaulting firms and 0.007 for non-defaulting firms ($p = 0.001$).

The higher financial obligations of defaulting firms as seen in INTEx/WC, INTEx/CFO and the mean NCL/CFO. Defaulting firms have significantly higher NCL/CFO than non-defaulting firms. The mean value of NCL/CFO is 18.744 for defaulting firms, compared with 0.741 for non-defaulting firms ($p = 0.01$). The median values of NCL/CFO are 8.311 for defaulting firms and 0.780 for non-defaulting firms ($p = 0.001$).

Defaulting firms have lower leverage, measured as TD/TA, than non-defaulting firms. The mean value of TD/TA is 0.218 for defaulting firms, compared with 0.265 for non-defaulting firms (p = 0.05). The median value of TD/TA is 0.209 for defaulting firms, compared with 0.225 for non-defaulting firms (p = 0.05).

The mean and median values for the change in financing cash flows, CH_CFF, for defaulting firms are 27.795 and -54.279, respectively. The mean and median values of CH_CFF for non-defaulting firms are -56.638 and -3.007, respectively. The differences between the defaulting and non-defaulting firms for this variable are not statistically significant, as shown in Table 5.1.

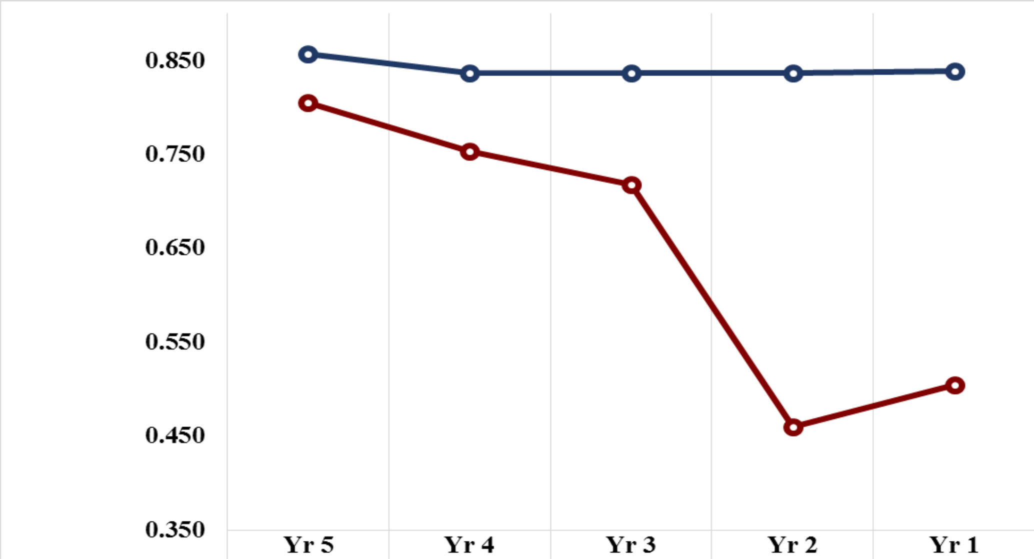
5.2.2 TRENDS IN EN PREDICTOR VARIABLES

Figure 5.1 compares the mean values of the defaulting and non-defaulting firms for each financial EN variable over the five-year period preceding default. The graphs are based on the financial data of the 70 defaulting and 70 non-defaulting firms in the test. The mean values for the defaulting firms are represented by the red line in each graph; the corresponding values for the non-defaulting firms are shown by the blue line.

This presentation provides a preliminary visual indication of the patterns in the variables over the five years before default.

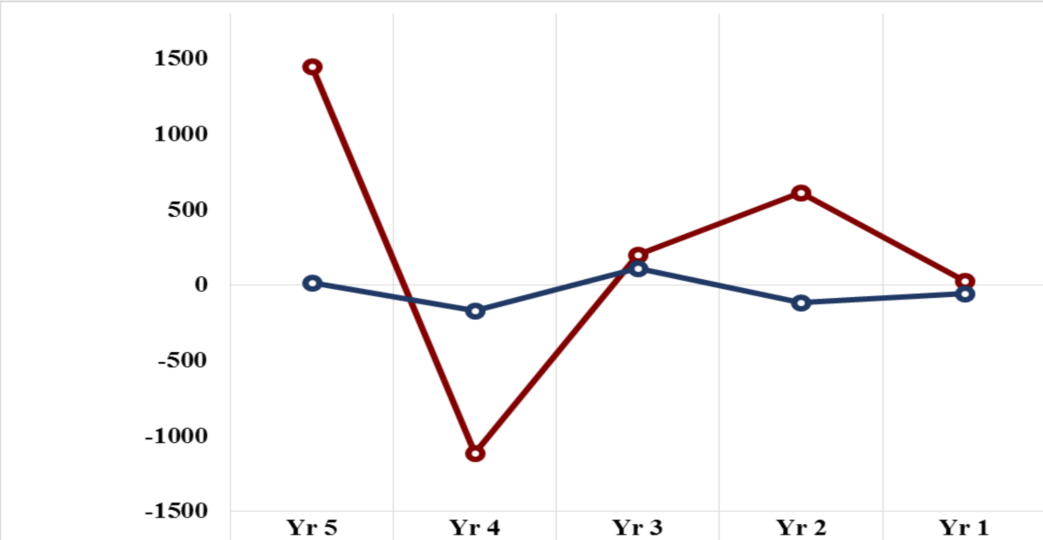
Figure 5.1 The Trends of EN Variables over Five Years before Loan Default

Tangible assets to total assets (A_{TAN}/TA)



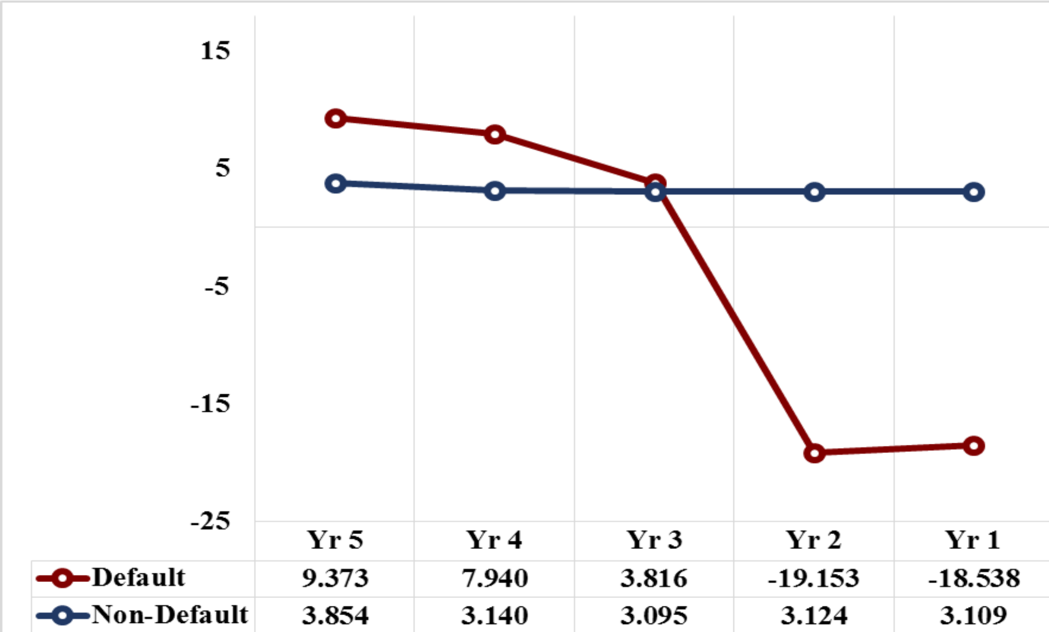
	Yr 5	Yr 4	Yr 3	Yr 2	Yr 1
Default	0.806	0.754	0.718	0.460	0.505
Non-Default	0.857	0.837	0.837	0.837	0.839

Changes in cash flow from financial activities (CH_CFF)

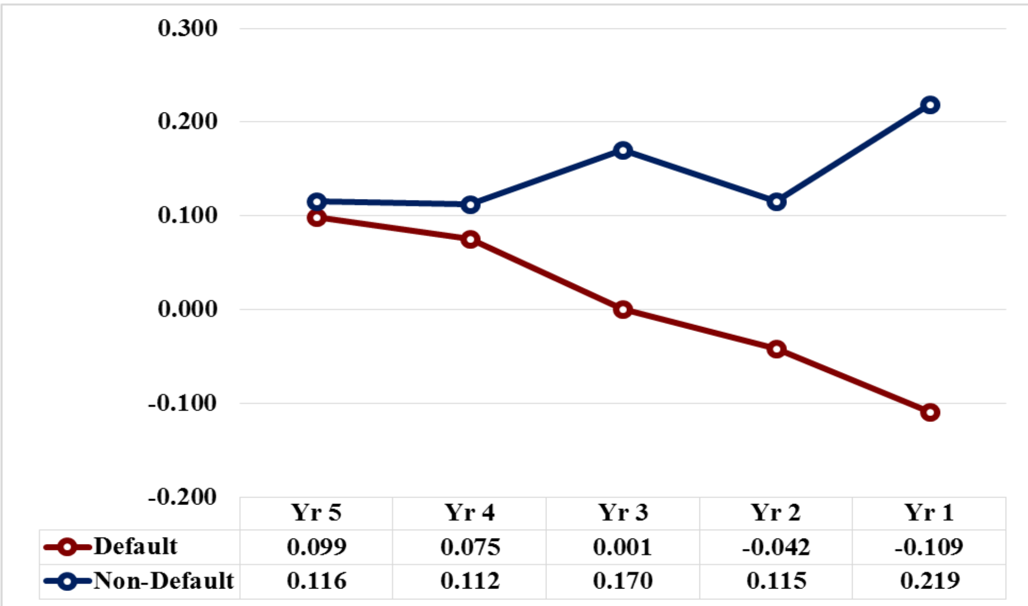


	Yr 5	Yr 4	Yr 3	Yr 2	Yr 1
Default	1450.469	-1109.229	205.107	616.303	27.795
Non-Default	16.981	-168.022	114.262	-114.432	-56.638

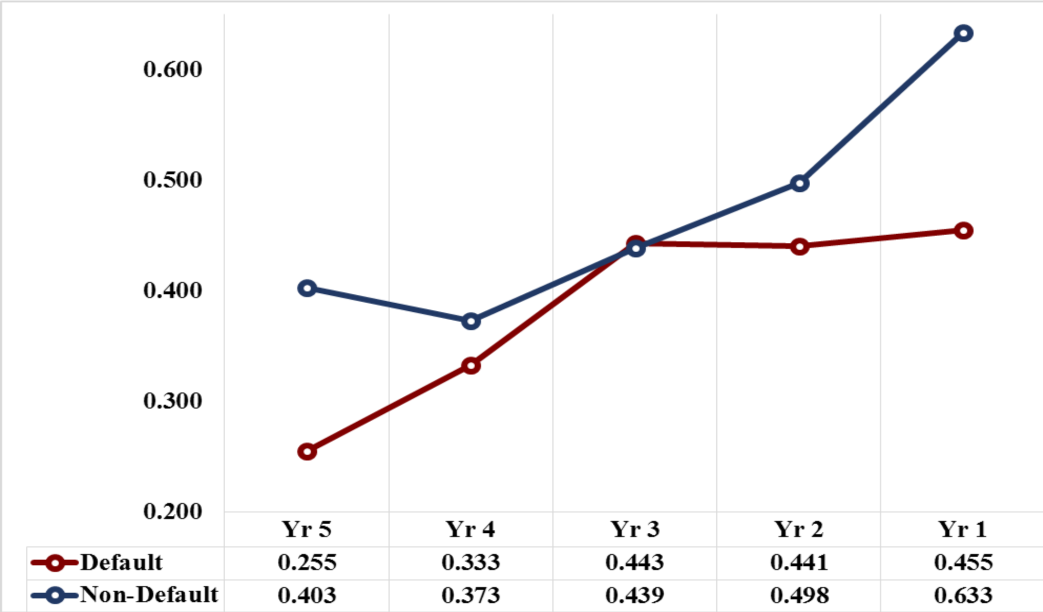
Sales to tangible equity (S/E_{TAN})



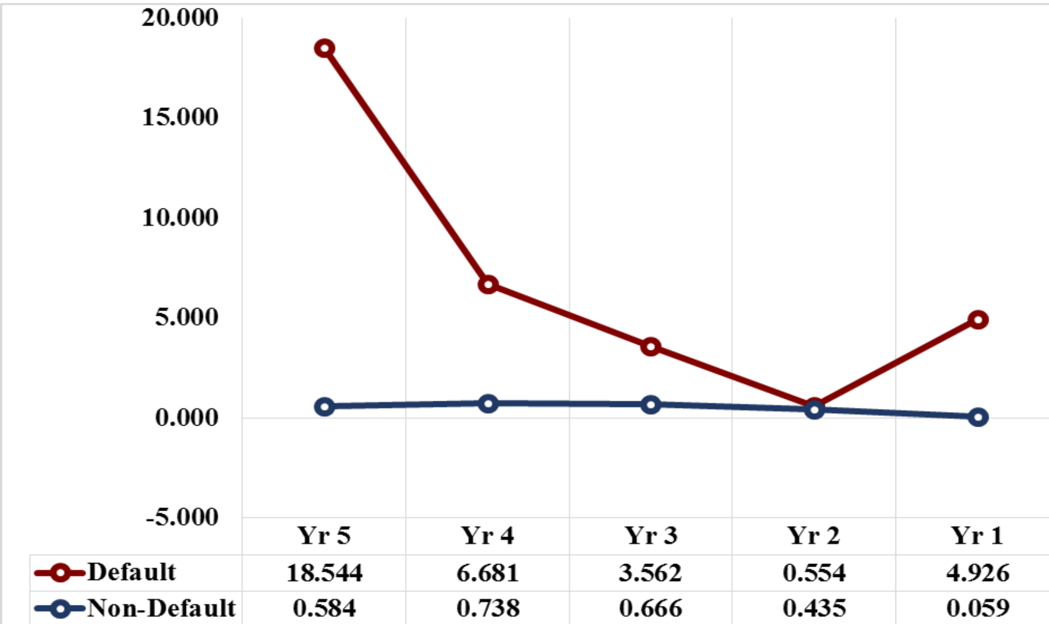
Net profit to tangible equity (NP/E_{TAN})



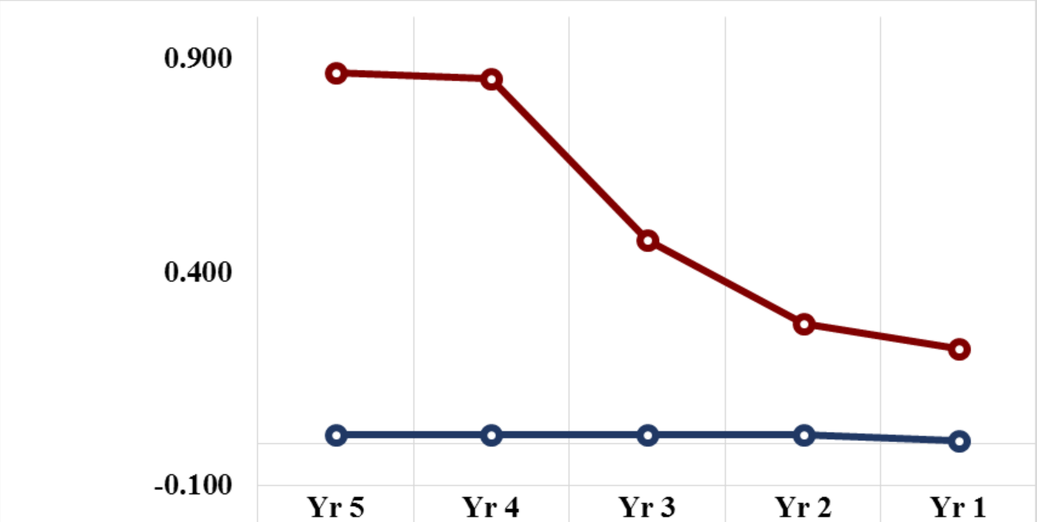
Unadjusted retained earnings to total assets (RE_{UnAdj}/TA)



Interest expenses to working capital (INTEx/WC)

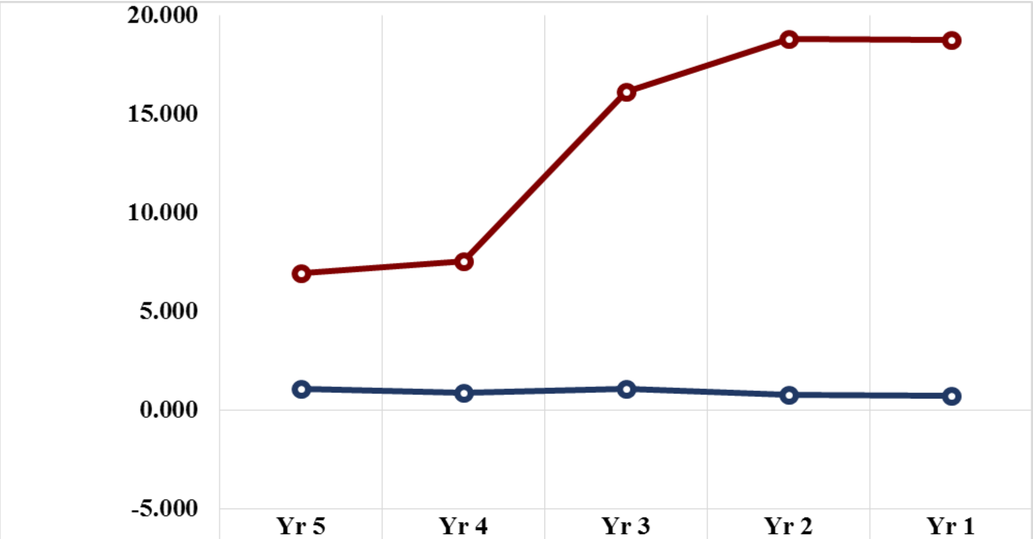


Interest expenses to cash flow from operating activities (INTEx/CFO)



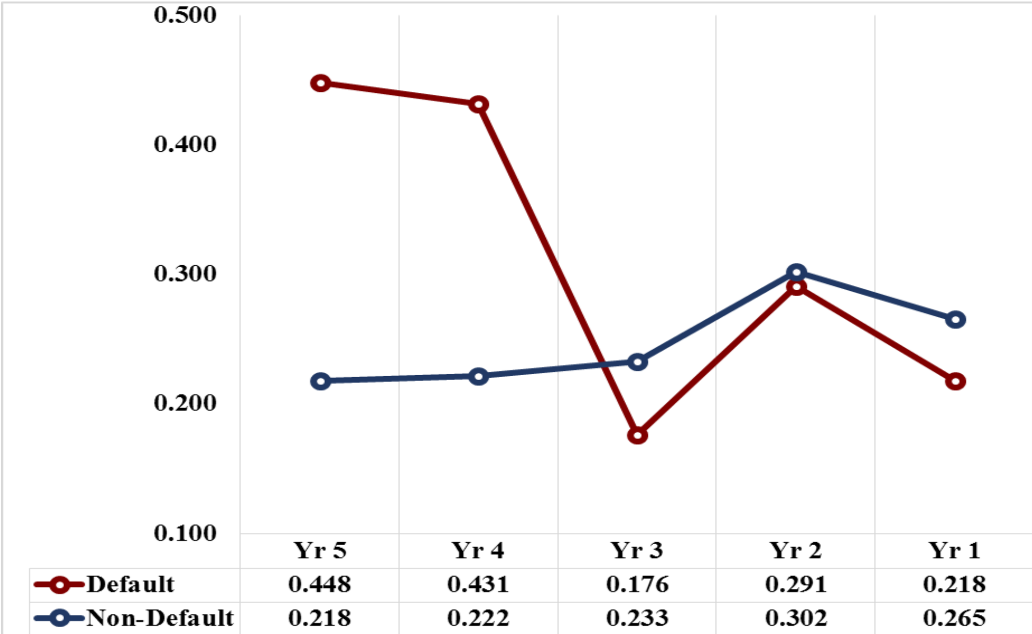
	Yr 5	Yr 4	Yr 3	Yr 2	Yr 1
Default	0.868	0.853	0.478	0.280	0.221
Non-Default	0.020	0.021	0.021	0.021	0.007

Non-current liabilities to cash flow from operating activities (NCL/CFO)



	Yr 5	Yr 4	Yr 3	Yr 2	Yr 1
Default	6.954	7.539	16.121	18.822	18.744
Non-Default	1.068	0.862	1.091	0.791	0.741

Total debts to total assets (TD/TA)



The patterns of some of the financial EN predictor variables show progressive deterioration during the five years before loan default, namely A_{TAN} /TA; S/E_{TAN}; NP/E_{TAN}; INTEx/CFO and NCL/CFO. In particular, there is a noticeable decline in A_{TAN} /TA; S/E_{TAN}; and INTEx/CFO during the three years before loan default. From Year 3 to Year 2, the mean value of A_{TAN} /TA decreased by 0.258 and the mean value of S/E_{TAN} decreased by 22.969.

When compared with the non-defaulting firms, the poor profitability and cash flow of the defaulting firms are evident. The average S/E_{TAN} of defaulting firms was higher than non-defaulting firms until Year 3. However, in Year 2, the mean S/E_{TAN} value of defaulting firms decreased from 3.816 to -19.153. In contrast, the mean values of S/E_{TAN} over the five years for non-defaulting firms are similar. The NP/E_{TAN} of defaulting firms consistently decreased over the five years before the loan default. During all five years, the NP/E_{TAN} means of defaulting firms were lower than for non-defaulting firms, with a continuously wider gap.

Compared with non-defaulting firms, the INTEx/CFO and NCL/CFO means for defaulting firms worsened over the five years before loan default. Though the gap between defaulting and non-defaulting firms for INTEx/CFO became narrower, the mean for INTEx/CFO of defaulting firms is still higher than for non-defaulting firms. NCL/CFO also shows wider gaps between defaulting and non-defaulting firms over five years before loan default.

As Figure 5.1 indicates, the trend for defaulting firms is distinctive from that of non-defaulting firms as the year of loan default approaches. In particular, there is considerable divergence between the mean values for defaulting and non-defaulting firms for A_{TAN} /T; RE_{UnAdj}/TA; S/E_{TAN}; NP/E_{TAN}; and NCL/CFO.

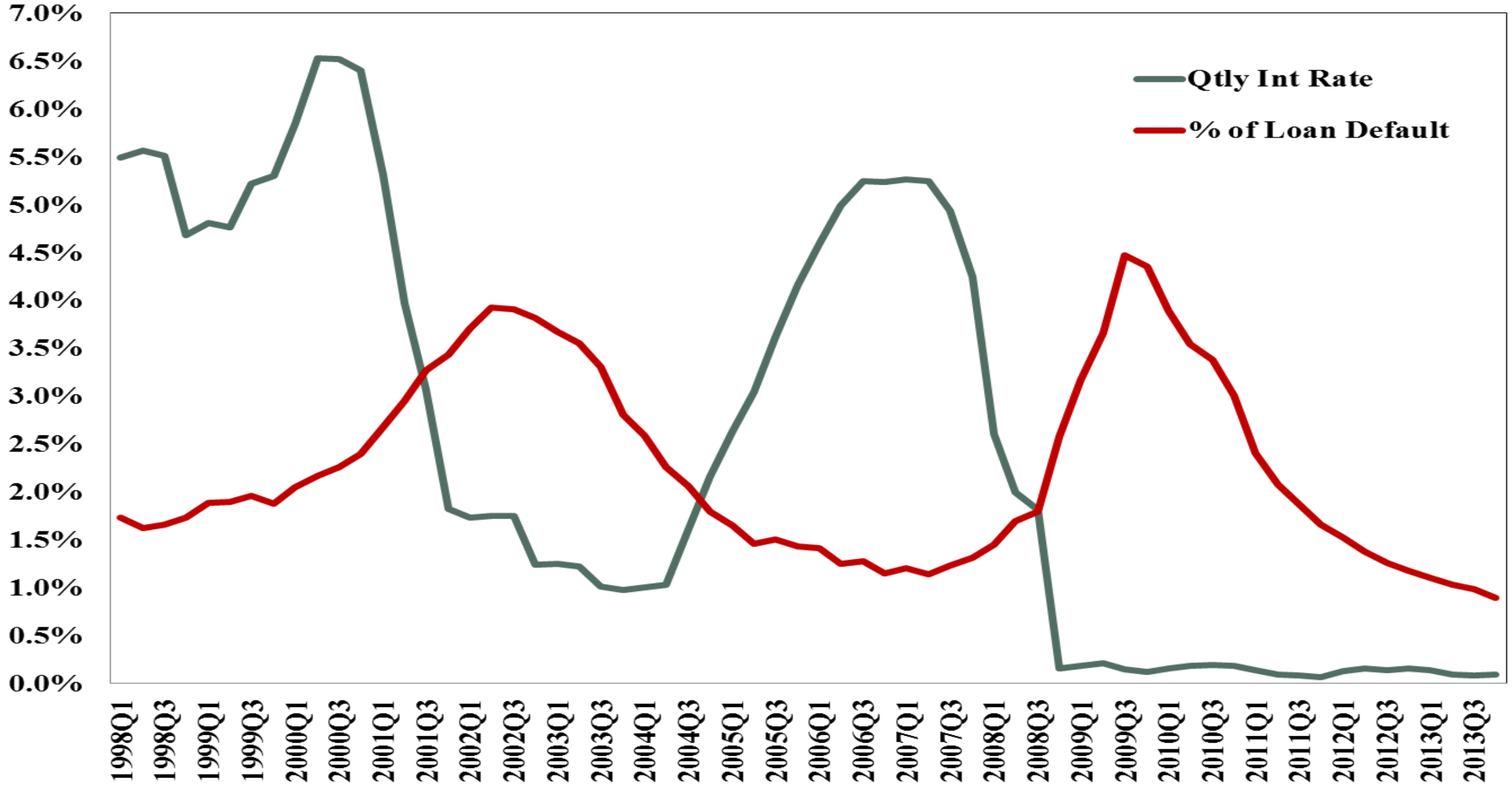
The movements of the mean for TD/TA are greater for defaulting firms than non-defaulting firms at Years 5 and 4, but then converge around Year 3. The mean values of TD/TA of defaulting firms for Year 2 and 1 are slightly lower than non-defaulting firms. Similarly, there is a convergence for the means for CH_CFF. Whereas the CH_CFF of non-defaulting firms show slight changes over five years, the mean for CH_CFF for defaulting firms shows a large change each year over the five years before loan default.

5.2.3 ECONOMIC PREDICTOR VARIABLE

Among the 10 potential economic variables, only the interest rate, measured as the 10-year US Treasury rate, is identified by Elastic Net as relevant to loan default. Consistent evidence is provided by Berge and Boye (2007) in their analysis of the Nordic banking system over the period 1993-2005. They find that problem loans are highly sensitive to changes in interest rates. Higher interest rates are associated with higher costs of servicing debt, which may put a strain on highly leveraged firms, increasing the risk of default. An increase in interest rates may weaken borrowers' capacity to service debt.

Figure 5.2 shows the quarterly 10-year US Treasury interest rate and the proportion of loan defaults in the full sample from 1997 to 2013, inclusive. The proportion of loan defaults follows the quarterly interest rates change, albeit with some lag. The peak quarterly interest rate occurred in 2000 Q1, followed by the peak in the proportion of loan defaults in 2002 Q3. Similarly, another peak in quarterly interest rate between 2006 Q1 and 2007 Q3, is followed by another peak in the proportion of loan defaults in 2009 Q3 to 2010 Q1. Thus, the interest rate is forward-looking, indicating it is useful for predicting loan default.

Figure 5.2 Changes in Quarterly Interest rates and Proportion of Loan Defaults from 1997.Q1 to 2013.Q4



5.3 Contribution of EN Variables to the Prediction of Loan Default

5.3.1 Predictive Power of EN Variables

The EN variables are incorporated into prediction models to assess their usefulness for predicting loan default. Two prediction models are constructed employing multiple discriminant analysis (EN MDA) and logit regression (EN Logit). The EN prediction models are compared with the benchmarks, the Z score model (Z-model) and the O-score model (O-model). All prediction models are constructed using the Test sample and one year before the default.

Table 5.2 presents the Spearman correlation coefficients for the EN variables of paired test sample. With the exception of INTEx/CFO and INTEx/WC (0.816, p = 0.01), all correlations are less than 0.8.

Three main observations can be made. First, the profitability variables show significant correlations with most of variables. S/E_{TAN} is significantly correlated (p = 0.01) with all EN predictor variables except CH_CFF. NP/E_{TAN} is significantly correlated (p = 0.01) with all identified variables except CH_CFF and TD/TA. NP/E_{TAN} is negatively correlated with the interest expense variables, INTEx/CFO and INTEx/WC.

Table 5.2 Spearman Correlation Coefficients of the Test Sample

	A_{TAN}/TA	CH_CFF	S/E_{TAN}	RE_{Unadj} /TA	NP/E_{TAN}	INTEx /WC	INTEx /CFO	NCL /CFO	TD/TA	INT
A_{TAN}/TA	1.000									
CH_CFF	0.010	1.000								
S/E_{TAN}	-0.197**	0.002	1.000							
RE_{Unadj}/TA	0.090**	-0.022	0.332**	1.000						
NP/E_{TAN}	-0.113**	-0.013	0.069**	0.354**	1.000					
INTEx/WC	-0.036*	-0.010	0.249**	-0.004	-0.335**	1.000				
INTEx/CFO	-0.024	-0.006	0.267**	0.008	-0.340**	0.816**	1.000			
NCL/CFO	0.017	0.001	0.191**	-0.345**	-0.585**	0.526**	0.528**	1.000		
TD/TA	0.147**	-0.025	0.171**	0.329**	-0.013	0.255**	0.149**	0.123**	1.000	
INT	0.037*	0.018	0.063**	0.123**	0.049**	0.024	0.012	-0.082**	-0.097**	1.000

A_{TAN} /TA = Tangible assets to total assets; CH_CFF = Change (in $000) in net cash flow between $year_N$ and $year_{N+1}$; S/E_{TAN} = Sales to tangible equity; NP/ETAN = Net profit to tangible equity; RE_{UnAdj}/TA = Unadjusted retained earnings to total assets; INTEx/WC = Interest expenses to working capital; INTEx/CFO = Interest expenses to cash flow from operating activities; NCL/CFO = Non-current liabilities to cash flow from operating activities; TD/TA = Total debts to total assets; INT = Yearly 10-year US Treasury interest rates. All observations are for Year 1, the year before default. N = 70 defaulting and non-defaulting firms in matched pairs.

** Correlation is significant at the 0.01 level (two tailed).
* Correlation is significant at the 0.05 level (two tailed).

As expected, the interest expense variables, INTEx/WC and INTEx/CFO, are positively correlated with the leverage ratios, NCL/CFO and TD/TA ($p = 0.01$). Firms with a relatively high level of liabilities are more likely to have high interest expense.

Lastly, both leverage ratios, NCL/CFO and TD/TA, are negatively correlated with interest rate, INT, at the 1% significance level. This is consistent with more (less) borrowing being undertaken or maintained, particularly long-term debt, when the interest rate is lower (higher).

Table 5.3 presents the coefficients and *F* values of each variable employed in the four prediction models: EN MDA, EN Logit, Z-model and O-model. The EN MDA and the EN Logit factor use the 10 EN variables.

The variable profile of the Z-model is established using the original five variables used in Altman (1968): WCTA (working capital to total assets); RETA (retained earnings to total assets); EBITTA (earnings before interest and taxes to total assets); $E_{MV}TD_{BV}$ (market value of equity to book value of total debts; STA (sales to total assets). Equal distribution is applied to the Z-model. Accordingly, matched pairs are used.

Table 5.3 EN and Benchmark Prediction Models for One Year before Default

	EN MDA		*Z-Model (Altman (1968))*		*EN Logit*		*O-Model (Ohlson (1980))*	
	Coefficients	*F*	*Coefficients*	*F*	*Coefficients*	*F*	*Coefficients*	*F*
A_{TAN}/TA	-0.013	23.152***			-0.011	42.44***		
CH_CFF	0.001	0.035			0.000	0.04		
S/E_{TAN}	-0.014	17.248***			-0.085	14.19***		
NP/E_{TAN}	-1.672	17.474***			-7.699	1.24*		
RE_{Unadj}/TA	-0.199	11.835***			-0.150	24.98***		
INTEx/WC	0.700	6.190**			0.014	0.02**		
INTEx/CFO	0.761	14.45***			43.304	41.34***		
NCL/CFO	0.016	4.790**			0.095	39.54***		
TD/TA	1.445	3.558**			2.050	9.14***		
INT	0.141	4.591**			0.385	25.86***		
WCTA			0.256	6.671***			0.306	119.622***
RETA			0.010	3.810**				
EBITTA			2.711	0.270				
$E_{MV}TD_{BV}$			1.752	48.701***				
STA			-1.300	11.835***				
SIZE							2.311	55.558***

TLTA				2.371	400.934***
CLCA				1.300	163.059***
OENEG				-15.194	515.196***
NITA				-0.031	446.006***
FUTL				-0.924	2.504*
INTWO				-23.199	3247.042***
CHIN				-1.168	9.502***
N	70:70	70:70	70:3249	70:3249	

Definitions for all variables are as follows: A_{TAN} /TA = Tangible assets to total assets; CH_CFF = Change (in \$000) in net cash flow between $year_N$ and $year_{N+1}$; S/E_{TAN} = Sales to tangible equity; NP/E_{TAN} = Net profit to tangible equity; RE_{UnAdj}/TA = Unadjusted retained earnings to total assets; INTEx/WC = Interest expenses to working capital; INTEx/CFO = Interest expenses to cash flow from operating activities; NCL/CFO = Non-current liabilities to cash flow from operating activities; TD/TA = Total debts to total assets; INT = Yearly 10-year US Treasury interest rates. The Z-model factors the five variables of Altman (1968): WCTA = Working capital to total assets; RETA = Retained earnings to total assets; EBITTA = Earnings before interest and taxes to total assets; $E_{MV}TD_{BV}$ = Market value of equity to book value of total debts; STA = Sales to total assets. The O-model factors the nine variables of Ohlson (1980): SIZE = Log of total assets/GNP price-level index at base value of 100 for 1968; TLTA = Total liabilities to total assets; WCTA = Working capital to total assets' CLCA = Current liabilities to current assets; OENEG = One if total liabilities exceeds total assets, zero otherwise; NITA = Net income to total assets; FUTL = Funds provided by operations to total liabilities; INTWO = One if net income was negative for the last two years, zero otherwise; CHIN = $(NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$, where NI_t is net income for the most recent period. All prediction models are constructed using the Test sample for one year before default. *N* represents the distribution of defaulting to non-defaulting firms.

*** Significant at 0.001 level (two-tailed); **Significant at 0.01 level (two-tailed); *Significant at 0.1 level (two-tailed)

The O-model is constructed using the nine variables used in Ohlson (1980): SIZE (log of total assets to GNP price-level index at base value of 100 for 1968); TLTA (total liabilities to total assets); WCTA (working capital to total assets); CLCA (current liabilities to current assets); OENE (one if total liabilities exceeds total assets, otherwise zero was given); NITA (net income to total assets); FUTL (cash flow from operating activities to total liabilities); INTWO (one if net income was negative for the last two years, otherwise zero was given); and CHIN (change in net profit as $(NI_t - NI_{t-1}/(|NI_t| + |NI_{t-1}|)$, where NI_t is net income for the most recent period). Unlike MDA, the Logit does not require even distribution between defaulting and non-defaulting firms. Thus, as explained in Section 4.2.3, the historical bond default rates for each year are used as a proxy to determine the ratio of defaulting firms to total firms.

None of the EN variables is used in either the Z-model or the O-model. However, some similar variables, reflecting similar aspects of performance, are included. For example, the EN model uses the ratio of total debt to total assets (TD/TA); the O-model uses a similar leverage variable, the ratio of total liabilities to total assets (TLTA).

As shown in Table 5.3, all EN variables are significant with the exception of CH_CFF in EN MDA. For the EN predictions, A_{TAN} /TA, S/E_{TAN}, NP/E_{TAN}, RE_{UnAdj}/TA, INTEx/CFO are statistically significant at 0.001 level in both EN prediction models. INTEx/WC, NCL/NCOF and INT are significant at 0.001 level in EN Logit, and significant at 0.01 level in EN MDA. TD/TA is significant at 0.01

in EN MDA, but is only mildly significant ($p = 0.1$) in EN Logit. Lastly, CH_CFF is mildly significant in EN Logit.

The analysis provides evidence that the cash flow from operating activities is associated with loan-default. As stated above, the coefficients on both EN ratios using net operating cash flow, NCL/CFO and INTEx/CFO, are significant in both EN predictor models. This is consistent with the findings of Jones and Hensher (2004).

The coefficients of the EN variables have the same sign in both EN prediction models. A_{TAN} /TA, S/E_{TAN}, NP/E_{TAN}, RE_{UnAdj}/TA show a negative relationship to loan default, consistent with expectations. A higher proportion of tangible assets reduces the likelihood of loan default.

Similarly, firms with higher turnover and profitability, reflected in S/E_{TAN} and NP/E_{TAN}, are less likely to default. The ratio of retained earnings to total assets, RE_{UnAdj}/TA, indicates current and prior period profitability. This indicates that firms with a history of low profitability or losses are more likely to default. Other studies using similar profitability variables find an adverse change in profitability increases the probability of default (Chen & Shimerda, 1981; Chan & Chen, 1991; Altman & Saunders, 1998; Campbell, Hilscher & Szilagyi, 2008).

In the EN prediction models, the interest expense-based ratios, INTEx/WC and INTEx/CFO, have a positive association with the probability of loan default. This indicates that firms with higher interest expense relative to working capital are more likely to default, possibly reflecting greater difficulty in servicing debt from operating cash flow or liquid reserves.

Similarly, the leverage ratios such as NCL/CFO and TD/TA are positively related to loan default. This indicates that firms with relatively more debt and more liabilities and/or lower cash flow from operations are more likely to default on their loans. Lastly, INT is positively associated with the likelihood of default, that is, increases in interest rates increase the likelihood of default.

From the preceding discussion it is evident that the signs of coefficients for the EN variables appear logical for the prediction of loan default and in explaining the characteristics of defaulting firms. In contrast, the signs of coefficients for some of the Z-model and O-model are counterintuitive. For example, the coefficient for WCTA is positive in both models, indicating that relatively higher levels of liquid assets and profitability increase the likelihood of default. Similarly, the coefficient on OENEG is negative and significant (p = 0.001) in the O-model. This variable is expected to be positively related to the loan default[21] because takes a value of 1 if the firm has negative equity.

For the Z-model, all the variables are statistically significant with the exception of EBITTA. WCTA, $E_{MV}TD_{BV}$ and STA are significant at 0.001 level and RETA is significant at 0.01 level. Thus, WCTA, $E_{MV}TD_{BV}$, STA and RETA have significant discriminating power and contribute to distinguish defaulting firms from non-

[21] In Ohlson (1980), the sign of INTWO is negative and opposed to the initial expectation. However, he did not offer any explanation in relation to this.

defaulting firms. Contrary to Altman (1968), EBITTA is not statistically significant and thus is not useful in distinguishing between the defaulting and non-defaulting firms. Also, though STA is not significant in Altman (1968), it is significant in the Z-model. The difference in significant predictor variables may reflect differences in the characteristics of loan defaulting firms and bankrupt firms (Payne & Hogg, 1994; Foster, Ward & Woodroof, 1998; Stein, 2005).

The O-model also shows some results that differ from Ohlson (1980). As shown in Table 5.3, all variables are significant at 0.001 level except FUTL, which is mildly significant at the 0.1 level. Thus, all variables contribute to distinguishing the defaulting firms from the non-defaulting firms.

However, there are some differences in the signs of coefficients between the O-model and Ohlson (1980). CHIN has a negative coefficient in the O-model, but a positive relationship to the prediction of loan default in Ohlson (1980).

Similar findings were obtained by Begley, Ming and Watts (1996) and Hillegeist, Keating, Cram and Lundstedt (2004) in their reconstructions of the Z-model (Altman, 1968) and O-model (Ohlson, 1980). They find several coefficients in the Z-model and the O-model have substantially changed from their original values.

5.3.2 STABILITY OF THE COEFFICIENTS

As discussed in Section 5.3, the coefficients of both the Z-model and O-model differ from their value in the original models. This means that the relationship between the financial ratios and the signs of financial distress have changed over time and the role of financial variables in predicting failure is unstable over periods[22] (Deakin, 1972, 1976; Mensah, 1984; Zmijewski, 1984; Zavgren, 1985; Shumway, 2001) as discussed in Section 2.2.4.

As discussed in Chapter 2, the instability of the coefficients of the prediction models may be caused by subjective or a poorly specified selection of variables. Thus, the incorporated variables tend to be sample specific and, thus, may not be the most useful predictors of loan default.

The EN MDA and EN Logit models derived from the Test are compared with corresponding EN prediction models derive from Holdout 1, which is drawn from the same period as Test (1997 – 2009), and Holdout 2, which is drawn from the period, 2010 - 2013. The coefficients and F-statistics for each model are presented in Table 5.4.

[22] The differences may to some extent be attributable to differences between the distinguishing characteristics of defaulting firms and those of bankrupt firms.

Table 5.4 Coefficients of EN MDA and EN Logit Analyses

	EN MDA						***EN Logit***					
	Test		*Holdout 1*		*Holdout 2*		*Test*		*Holdout 1*		*Holdout 2*	
	Coeff	*F*	*Coeff*	*F*	*Coeff*	*F*	*Coeff*	*F*	*Coeff*	*F*	*Coeff*	*F*
A_{TAN}/TA	-0.013	23.15***	-0.385	40.49***	-0.745	22.2***	-0.011	42.44***	-0.002	27.98***	-0.001	0.03***
CH_CFF	0.001	0.04	0.010	0.84	0.341	1.11*	0.000	0.04	0.000	3.07	0.000	0.01
S/E_{TAN}	-0.014	17.25***	-0.178	16.91***	-0.741	0.38*	-0.085	14.19***	-0.320	2.16***	-0.083	3.13*
RE_{Unadj}/TA	-0.199	11.84***	-0.700	19.12***	-1.112	1.28*	-0.150	1.24*	1.746	2.29*	-1.075	0.83
NP/E_{TAN}	-1.672	17.47***	-0.842	97.13***	-1.285	4.44**	-7.699	24.98***	-3.335	2.04***	-1.807	0.93*
INTEx/WC	0.700	6.19**	0.174	13.70***	0.235	1.07*	0.014	0.02**	1.244	0.38**	0.119	7.60**
INTEx/CFO	0.761	14.45***	0.366	8.60**	0.563	3.46***	43.304	41.34***	48.568	8.04**	32.245	12.84**
NCL/CFO	0.016	4.79**	0.137	13.63***	0.170	0.49*	0.095	39.54***	0.254	27.12***	0.126	2.04***
TD/TA	1.445	3.56**	0.129	1.77*	0.449	3.46***	2.050	9.14***	2.486	8.39**	4.977	0.60**
INT	0.141	4.59**	0.342	39.59***	0.212	0.21*	0.385	25.86***	54.998	19.11***	0.824	4.33*
N	70:70		69:69		23:23		70:3249		69:3249		23:979	

The observations from the total sample from 1997 to 2013 are randomly assigned to three different sets of sample: the Test, Holdout 1 and Holdout 2. The EN variables are derived from the Test. Holdout 1 is the sample within the same period as the Test, which is from 1997 to 2009. Holdout 2 is the sample outside the period of the Test. *N* represents the distribution of defaulting to non-defaulting firms.

*** Significant at 0.001 level (two-tailed); **Significant at 0.01 level (two-tailed); *Significant at 0.1 level (two-tailed)

With the exception of CH_CFF, all EN variables are significantly related to the classification of defaulting and non-defaulting firms in EN MDA derived from Holdout 1. This is consistent with EN MDA derived from the Test, as shown in Table 5.4.

All EN variables are statistically significant at various levels in EN MDA for Holdout 2. In comparison, except for CH_CFF and RE_{Unadj}/TA, eight EN variables are statistically significant. Most EN variables, except for CH_CFF, are statistically significant in both EN prediction models for the Test and Holdout 1. In Table 5.1, CH_CFF does not show a significant difference between defaulting and non-defaulting firms, which may be to some extent reflected in the tests on the prediction of loan default.

Although there exists some differences in significance levels, it is noteworthy that the EN variables derived from the paired Test sample remain significant when tested in the different sample in the same period and the different sample from a different period. Also, the predictors extracted from the paired sample are still significant when employed in the unevenly distributed prediction models. This may imply that Elastic Net is a very effective identifier of the relevant variables.

The sign of all significant coefficients for EN variables is the same in the EN prediction models derived using Test, Holdout 1 and Holdout 2 for both EN MDA and EN Logit models. Differences in the coefficients of the EN MDA and the EN Logit models are observed between the Test, Holdout 1 and Holdout 2. This is expected because financial variables are sample-specific and subject to change over periods (Grice & Ingram, 2001; Shumway, 2001).

5.3.3 RELATIVE CONTRIBUTION OF EN VARIABLES

As not all measurement units of the EN variables are comparable, simple observation of the coefficients can be misleading. Determining the relative contribution of variables and the interaction between them is useful for the identification of the profile of the prediction model (Altman, 1968; Grice & Ingram, 2001; Agarwal & Taffler, 2007). Table 5.5 presents the scaled vector of the discriminant functions

Following Altman (1968), the relative contribution of a variable is computed by multiplying the square root of the appropriate variance-covariance value for each variable by the discriminant coefficient of that variable in a given function. The relative contribution of each variable of the Z-model is in the order $E_{MV}TD_{BV}$, RETA, WCTA, STA and EBITTA. The relative contribution of each variable of the Z-model also differs from Altman (1968), where EBITTA is ranked first, followed by STA, $E_{MV}TD_{BV}$, RETA and WCTA.

In EN MDA, the relative contribution of each variable is indicated by the scaled vector. The scaled vector indicates that NCL/CFO contributes most to the prediction of loan default, followed by S/E_{TAN}, RE_{UnAdj}/TA, NP/ E_{TAN}, INTEX/WC, A_{TAN} /TA, INTEX/CFO, TD/TA, INT and CH_CFF.

Table 5.5 The Relative Contribution of Predictors in EN MDA and Z-model

Variables	***EN MDA Model***		***Z-Model (Altman (1968))***	
	Scaled Vector	*Ranking*	*Scaled Vector*	*Ranking*
A_{TAN}/TA	29.93	6		
CH_CFF	13.83	10		
S/E_{TAN}	62.90	2		
RE_{Unadj}/TA	61.00	3		
NP/E_{TAN}	54.00	4		
INTEX/WC	45.66	5		
INTEX/CFO	25.30	7		
NCL/CFO	69.00	1		
TD/TA	25.00	8		
INT	25.00	8		
WCTA			7.60	3
RETA			8.90	2
EBITTA			3.74	5
$E_{MV}TD_{BV}$			9.71	1
STA			3.99	4

The relative contribution of each variable is ranked based on the scaled vector computed by multiplying the square root of the appropriate variance-covariance figure for each variable by the coefficient of that variable. The EN MDA factors the 10 variables identified via the application of Elastic Net and the Z-model factors the five variables of Altman (1968) All prediction models are constructed using the Test sample and one year before default.

The predictive ability of each variable of the EN Logit and the O-model is compared based on the *Exp(B)* value of each variable. *Exp(B)* is an odds ratio predicted by the model. This odds ratios can be computed by raising the base of the B^{th} power of each variable, where *B* is the slope from the logit equation. The results are presented in Table 5.6.

Table 5.6 The Predictive Ability of Predictors in EN Logit and O-model

	EN Logit		***O-Model (Ohlson (1980))***	
Variables	*Estimate*	*Exp(B)*	*Estimate*	*Exp(B)*
A_{TAN}/TA	– 0.001	1.000		
CH_CFF	0.001	1.000		
S/E_{TAN}	– 0.085	0.918		
RE_{Unadj}/TA	0.150	1.162		
NP/E_{TAN}	– 7.699	0.001		
INTEX/WC	– 4.014	0.986		
INTEX/CFO	4.304	64.103		
NCL/CFO	0.395	1.100		
TD/TA	2.050	7.772		
INT	0.385	0.680		
SIZE			2.311	10.086
TLTA			2.371	10.713
WCTA			0.306	1.359
CLCA			1.300	3.668
OENEG			– 15.194	0.000
NITA			– 0.031	0.970
FUTL			– 0.924	0.397
INTWO			– 23.199	0.000
CHIN			– 1.168	0.311

The EN Logit factors the 10 variables identified via the application of Elastic Net and the O-model factors the nine variables of Ohlson (1980). All prediction models are constructed using the Test sample and one year before the default.

If the *Exp(B)* of a variable is greater than one, the odds of the outcome, i.e., loan default, increase when that variable is factored in the prediction model. For EN Logit, NCL/CFO, RE_{UnAdj}/TA, INTEX/CFO and TD/TA have an *Exp(B)* greater than 1. The *Exp(B)* value of INTEX/CFO is the highest (64.103), followed by TD/TA (7.772), RE_{UnAdj}/TA (1.162) and NCL/CFO (1.100). The odds of determining the outcome is 64.103 times higher if INTEX/CFO is employed and 7.772 times higher if TD/TA is employed. The power of variables based on operating cash flow is consistent with the findings of Jones and Hensher (2004). For the O-model, SIZE and TLTA are the most powerful variables when predicting whether a firm will default on their loan., with *Exp(B)* values of 10.086 and 10.713, respectively.

5.4 SUMMARY OF FINDINGS

This study applies Elastic Net to identify financial and economic variables relevant to the prediction of loan default. Using samples from 1997-2009, Elastic Net was applied to extract relevant predictor variables from a set of 278 potential variables. The 10 EN variables include nine financial variables and one economic variable, namely the interest rate.

The identified EN variables include predictors that have not usually been employed in financial distress studies. This chapter provides evidence of significant differences in the EN predictor variables of defaulting and non-defaulting firms one year before the default event. The observed differences are in expected directions, with defaulting firms exhibiting a weaker financial position, such as lower profitability, before default. Differences in the patterns of most of the EN variables are observable over three or four years before default. Evidence is also provided that movement in the loan default rate generally lags movement in interest rates.

The chapter demonstrates that EN variables capture the characteristics of the loan defaulting firms and the resulting MDA and logit prediction models more logically explain the loan default compared with their benchmarks, the Z-model and O-model. Nine of the 10 EN variables are significant in both the MDA and logit prediction models. Further, the contribution of the variables is generally robust to other samples from within and outside the period from the Test sample from which the variables were selected.

Thus, the EN variables can be useful for forward-looking prediction of loan default. In Chapter 6, the prediction accuracy of the MDA and logit models using EN variables is tested on the Test sample and further validated on the two sets of holdout samples.

CHAPTER 6

PREDICTION USEFULNESS OF

EN PREDICTOR VARIABLES

6.1 INTRODUCTION

With the application of Elastic Net, predictor variables most closely related to loan default are identified from a large pool of financial and economic variables. The Elastic Net (EN) predictor variables are identified and analysed in Chapter 5, including an evaluation of their significance in prediction models developed using multiple discriminant analysis (MDA) and logistic regression (Logit). The objective of this chapter is to evaluate the usefulness of the EN prediction models for the prediction of loan default.

This chapter reports on the accuracy of EN MDA and EN Logit models compared with that of Altman's (1968) Z-score model (Z-model) and Ohlson's (1980) O-score model (O-model), respectively. If the EN models yield higher accuracy, the EN predictor variables better capture the characteristics of loan defaulting firms and are thus more useful for the classification of loans. The usefulness of the EN predictor variables for the prediction of default is demonstrated if the EN models successfully classify the defaulting and non-defaulting firms when applied to periods other than those from which the models were created.

Section 6.2 evaluates the prediction accuracy of the EN models derived from the test sample, compared with Z-model and O-score models using the same sample. Results for the prediction of loan default one year before the default event, and for each year up to five years before actual loan default, are discussed. The results of external validation of the predictive ability of the EN models are reported in Section 6.3. Analysis of the area under ROC curves is presented in Section 6.4. Section 6.5

analyses the contribution of the economic variable to the prediction of loan default. Finally, Section 6.6 concludes and summarises the chapter.

6.1 Prediction Accuracy of EN MDA and EN Logit

The predictor variables extracted via Elastic Net better explain the characteristics of loan defaulting firms as discussed in the descriptive analyses (refer Section 5.25). MDA and Logit are the most widely used techniques (Balcaen & Ooghe, 2006; Jackson & Wood, 2013) and perform better than other more sophisticated models (Jones, Johnstone & Wilson, 2015). The efficacy of MDA is demonstrated by Agarwal and Taffler (2008) and Das, Hanouna and Sarin (2009). Accordingly, MDA and the Logit are used to determine whether the EN variables are useful for the prediction of loan default.

Type I classification accuracy refers to the correct classification of a defaulting firm as defaulting. Type II classification accuracy refers to the correct classification of a non-defaulting firm as non-defaulting. Thus, a Type I error or false positive classification represents the error of considering a failed one as non-failed. This type of error occurs if the test classifies defaulting loans as performing ones, thus allowing the banks to continue to fund the borrowers who will default. A Type II error or false negative represents the error of considering a non-failed one as failed. This type of error occurs if the test classifies a performing loan as one that will default.

The prediction accuracy of the model is compared with that of the prediction model (Z-model) using the variables of Altman (1968). To satisfy the equal distribution requirement of MDA, the test sample is evenly distributed between defaulting and non-defaulting firms. Thus, there are 70 matched pairs for the test sample used in constructing EN MDA. As the predictor variables are derived from this sample, a high degree of classification accuracy is expected. Unlike multiple discriminant analysis, logistic analysis does not require even distribution. The distribution of defaulting to non-defaulting firms in the test sample is 70 to 3,249.

The prediction results of EN MDA are presented in Section 6.2.1 and the prediction results of EN Logit are presented in Section 6.2.2.

6.1.1 PREDICTION ACCURACY OF EN MDA

The results of EN MDA are compared with those of the Z-model adopting the Z-score model of Altman (1968). The results refer to the prediction accuracy of both models one year before loan default.

As the predictor variables are selected from the Test sample, the same observations are used for both forming and assessing the prediction rule or characteristics of each group, which may underestimate the error rate of the EN MDA (Tibshirani & Tibshirani, 2009). To correct for this possible bias, the jack-knife technique is used for cross validation (Efron, 1983, 1992; Tibshirani & Tibshirani, 2009). The jack-knife estimate is obtained by omitting one observation from each group and applying the prediction rule employed in the original test to the remaining sample.

The resulting model is then used to classify the omitted observation. This process is repeated, each time omitting a different observation from each group. For each iteration, the number of errors is counted to measure the predication accuracy without the omitted observation. Thus, as the sample size for each group is 70 in this test, the prediction rule of the original test is applied 70 times to predict the outcome for 70 firms for both groups. The results are presented in Table 6.1.

Table 6.1 The Classification Results of the EN MDA and the Z-model

	EN MDA			***Z-Model (Altman (1968))***		
	Number Correct (Sample size)	% Correct	% Error	Number Correct (Sample size)	% Correct	% Error
Panel A: Classification Results for Test Sample						
Type I	63(70)	90%	10%	60(70)	85.7%	14.3%
Type II	70(70)	100%	0%	67(70)	95.7%	4.3%
Total	133(140)	95%	5%	127(140)	90.7%	9.3%
Panel B: Cross-Validation with Jack-knife Approach						
Type I	60(70)	85.7%	14.3%	58(70)	82.9%	17.1%
Type II	68(70)	97.1%	2.9%	66(70)	94.3%	5.7%
Total	128(140)	91.4%	8.6%	124(140)	88.6%	11.4%

The classification result is presented in the table in which the rows are the observed categories of classification. The columns present the number of correct classifications, or hit rate with the number of observations shown in parentheses. The accuracy and error percentages are also presented. The EN MDA incorporates the 10 EN predictor variables identified with the Elastic Net. The Z-model factors 5 variables, following Altman (1968). Both models applied to the Test sample, one year before default. Cross-validation is conducted with the application of the jack-knife approach.

Table 6.1 summarises the classification results of both the EN MDA and Z-models. Both EN MDA and the Z-model have over 90% overall accuracy in the classification of defaulting and non-defaulting groups. However, EN MDA has fewer Type I and Type II errors and has more accurate overall classification. Overall accuracy of EN MDA is high; it classifies all non-defaulting firms as non-defaulting and 90% of defaulting firms as defaulting. The EN MDA correctly predicts which firms will default or not one year before the actual outcome with 95% accuracy. This result is 4.3% higher than that of the Z-model. The Z-model also performs well. It correctly classifies 95.7% of the non-defaulting firms as non-defaulting and 85.7% of defaulting firms as defaulting. The prediction performance of the Z-model is 90.7% with a 9.3% of error rate.

Although both EN MDA and Z-model predict the outcome with high accuracy, EN MDA is superior to the Z-model in both Type I and Type II classifications. It is noteworthy that EN MDA correctly classifies 70 (100%) non-defaulting firms as non-defaulting and 63 (90%) defaulting firms as defaulting. In contrast, the Z-model classifies 60 (85.7%) defaulting firms as non-defaulting and 67 (95.7%) non-defaulting firms as defaulting. The relatively high error rate of the Z-model leads to high misclassification costs. Both EN MDA and the Z-model predict the outcome of loans with high accuracy; EN MDA has higher overall accuracy and lower error rate.

From Table 6.1, it can be seen that the higher accuracy rate of EN MDA is consistent with the results of the cross-validation test. Two common results can be found from the cross-validation with the jack-knife approach. First, EN MDA outperforms the Z-model in the overall Type I and Type II classification. Second, both EN MDA and Z-model predict the outcome of the non-defaulting firms better than the outcome of the defaulting firms. Although the accuracy rate of both models slightly decreases for Type I and Type II classification, EN MDA shows a higher accuracy rate than the Z-model following Altman (1968). The overall accuracy rate of EN MDA is 91.4%, compared with 89.3% for the Z-model. Though the EN MDA correctly predicts the outcomes of 60 (85.7%) defaulting firms and 68 (97.1%) non-defaulting firms, the Z-model correctly predicts only 58 (82.9%) defaulting firms and 66 (94.3%) non-defaulting firms. With the application of the jack-knife estimation, both the EN MDA and the Z-model correctly distinguish the defaulting and non-defaulting loans with high accuracy when each model is applied to the sample one year before loan default.

6.1.2 PREDICTION ACCURACY OF EN LOGIT

This section discusses the predictive ability of the EN predictor variables in the logistic regression model, compared with the O-score model of Ohlson (1980). Table 6.2 presents the prediction accuracy by group and in aggregate, for the EN Logit and the O-model.

Table 6.2 The Prediction Results of the EN Logit and the O-model

Panel A: Predictive Accuracy and Likelihood Ratio

EN Logit			***O-Model (Ohlson (1980))***		
Correct Prediction	*– 2LL*	*Cox & Snell* R^2	Correct Prediction	*– 2LL*	*Cox & Snell* R^2
99.6%	168.874	0.142	99.2%	263.678	0.118

Panel B: Classification Results of Models

	EN Logit			***O-Model (Ohlson (1980))***		
	Type I Correct	Type II Correct	Total Correct	Type I Correct	Type II Correct	Total Correct
Accuracy %	88.6%	99.9%	99.6%	60.0%	99.8%	99.2%
N	70	3,249	3,319	70	3,249	3,319

The table presents the prediction results of both Logit models applied to the Test sample. Panel A presents the predictive accuracy of the likelihood ratio. Panel B presents the percentage correct for defaulting firms (Type I), non-defaulting firms (Type II) and overall. EN Logit incorporated 10 EN predictor variables identified by the Elastic Net. The O-model followed Ohlson (1980) and incorporated nine variables that were originally used in Ohlson's (1980) study. Test results refer to the prediction accuracy of both models one year before loan default. Type I correct is sensitivity or true positive and Type II correct is specificity or true negative. To make terms consistent in this study, "sensitivity" and "specificity" are not used. The sample size of the defaulting firms and non-defaulting firms are 70 and 3249, respectively.

The Ohlson (1980) study reported a high accuracy rate for the prediction of bankruptcy, with consistently high performance maintained over three years before failure. The percentage of correct prediction is 96.12% for one year before bankrupt, 95.55% for two years before bankrupt and 92.84% for three years before bankrupt. However, Ohlson (1980) did not report how well the model predicted each group of bankrupt or default and survival or non-default

As summarised in Table 6.2, the EN Logit and the O-models have high prediction accuracy. The overall accuracy of EN Logit (99.6%) is a marginally higher than that of the O-model (99.2%). However, the prediction accuracy of each group, especially the defaulting group, is noteworthy. The EN Logit correctly predicts 88.6% of defaulting firms and 99.9% of non-defaulting firms. It is noteworthy that EN Logit is superior to the O-model in the sensitivity or Type I classification. Although the O-model shows an overall high accuracy rate of 99.2%, it has very low sensitivity (60%). The O-model can classify defaulting firms as defaulting with an accuracy 10% better than random chance of 50%. The main driver of the 99.2% overall accuracy of the O-model is its accuracy with the Type II classification. Although the O-model predicts 100% of non-defaulting firms correctly, it misclassifies 40% of defaulting firms as non-defaulting.

The probability of the observed results, given the parameter estimates, is given in the 2 log likelihood, *–2LL* (Menard, 2000). When comparing two different models, the one with the lower *–2LL* value is preferred. The likelihood (*–2LL*) of the O-model is 263.678 and the likelihood of the EN Logit is 168.874. Thus, the EN Logit offers a potentially more useful diagnostic test for the prediction of loan default and shows a probability that a firm has conditions to default on its loans. *Cox & Snell R^2* shows how well two prediction models fit the data (Cox & Snell, 1989). The higher Cox & Snell R^2 of EN Logit indicates that it is a better fit and is unbiased.

The usefulness of the EN predictor variables is tested on the sample one year before default. The EN MDA and EN Logit prediction models perform better than the models of Altman (1968) and Ohlson (1980), respectively. The accuracy rate of the EN prediction models is superior to that of the Z-Model and the O-score model when their Type I or sensitivity classification results are compared. The next section reports on the results of the predictive ability of the EN predictor variables over five years before loan default.

6.1.3 PREDICTION ACCURACY OVER FIVE YEARS

The EN MDA model is used to classify defaulting firms over the five years before loan default in the Test sample. The Test sample is modified to achieve matched pairs of defaulting and non-defaulting firms required for MDA. Table 6.3 presents the number and percentage correctly classified for Type I, Type II for both the EN MDA and the Z-models. The accuracy of each model using the original sample and the jack-knife cross-validation sample are presented in panels A and B, respectively. The chronological accuracy of both the EN MDA and Z-models is also summarised.

Table 6.3 The Five Year Predictive Accuracy of the EN MDA and the Z-model

Year to Default		EN MDA			Z-Model (Altman (1968))		
		Type I Correct	Type II Correct	Total Correct	Type I Correct	Type II Correct	Total Correct
Panel A: Classification Results for Test Sample over 5 year before loan default							
Year 1	Count (%)	63 (90.0%)	70 (100%)	133 (95.0%)	60 (85.7%)	67 (95.7%)	127 (90.7%)
	N	70	70	140	70	70	140
Year 2	Count (%)	65 (92.9%)	67 (95.7%)	132 (94.3%)	45 (64.3%)	60 (85.7%)	105 (75.0%)
	N	70	70	140	70	70	140
Year 3	Count (%)	58 (84.1%)	69 (100%)	127 (92.0%)	52 (75.4%)	64 (92.8%)	116 (84.1%)
	N	69	69	138	69	69	138
Year 4	Count (%)	57 (83.8%)	68 (100%)	125 (91.9%)	49 (72.1%)	66 (97.1%)	115 (84.6%)
	N	68	68	136	68	68	136
Year 5	Count (%)	54 (80.6%)	67 (100%)	121 (90.3%)	53 (79.1%)	52 (77.6%)	105 (78.4%)
	N	67	67	134	67	67	134
Panel B: Cross Validation for Test Sample Using Jack-knife Approach							
Year 1	Count (%)	60 (85.7%)	68 (97.1%)	128 (91.4%)	60 (85.7%)	67 (95.7%)	127 (90.7%)
	N	70	70	140	70	70	140
Year 2	Count (%)	64 (91.4%)	64 (91.4%)	128 (91.4%)	42 (60.0%)	59 (84.3%)	101 (72.1%)
	N	70	70	140	70	70	140

Year 3	Count (%)	56 (81.2%)	69 (100%)	125 (90.6%)	51 (73.9%)	62 (89.9%)	113 (81.9%)
	N	69	69	138	69	69	138
Year 4	Count (%)	56 (82.4%)	68 (100%)	124 (91.2%)	49 (72.1%)	66 (97.1%)	115 (84.6%)
	N	68	68	136	68	68	136
Year 5	Count (%)	54 (80.6%)	67 (100%)	121 (90.3%)	45 (67.2%)	49 (73.1%)	94 (70.1%)
	N	67	67	134	67	67	134

The classification results are presented in the table in which the rows are the observed categories of the dependent and the columns are the predicted categories. The correct hit rate, the accuracy percentage and the size of sample (*N*) are presented. The EN MDA incorporates the 10 EN predictor variables identified with Elastic Net. The Z-model factors five variables following Altman (1968). The sample in the Test is used for this test. The distribution of defaulting and non-defaulting for Year 1 before loan default is 70 to 70, and Year 2, 70 to 70, Year 3, 69 to 69, Year 4, 68 to 68 and Year 5, 67 to 67. Cross-validation is conducted with the application of the jack-knife approach.

Over the five years' prediction results of both models, EN MDA consistently outperforms the Z-model in Type I, Type II and overall classification results. The overall prediction accuracy of the EN MDA is 95.0% in Year 1, 94.3% in Year 2, 92.0% in Year 3, 91.9% in Year 4 and 90.3% in Year 5. In contrast, the overall prediction accuracy of the Z-model is 90.7% in Year 1, 75.0% in Year 2, 84.1% in Year 3, 84.6% in Year 4 and 78.4% in Year 5. Expectedly, the prediction accuracy decreases as the time moves away from the event of loan default. The accuracy rate of EN MDA in Year 4 is higher than that of the Z-model in Year 1, when it is expected to be highest among the prediction results over the five years.

The accuracy of Type I classification of EN MDA is also superior to that of the Z-model over the five years. EN MDA makes 90.0% of correct Type I classifications in Year 1, 92.9% correct in Year 2, 84.1% correct in Year 3, 83.8% correct in Year 4 and 80.6% correct in Year 5. However, except for the Year 1, the accuracy of correct Type I classification by the Z-model is lower than 80.6%, the lowest accuracy rate of EN MDA. The hit rate of the Z-model for Type I classification is the lowest in the second year for both original and cross validation tests. The highest accuracy rate of the Z-model is 85.7% in Year 1 and the lowest is 64.3% in Year 3.

The difference between EN MDA and the Z-model is more obvious in the accuracy rate of Type II classification. Where EN MDA makes 100% correct Type II classification except for Year 2, the accuracy rate of the Z-model is 95.7% in Year 1, 85.7% in Year 2, 92.8% in Year 3, 97.1% in Year 4 and 77.6% in Year 5. Similar results are found in the cross validation using the jack-knife approach. EN MDA correctly classifies non-defaulting firms as non-defaulting with 100% accuracy rate in Years 3, 4, and 5 and 97.1% in Year 1 and 91.4% in Year 2. However, the prediction accuracy of the Z-model is inferior to that of EN MDA. It is 85.7% in Year 1, 60.0% in Year 2, 73.9% in Year 3, 72.1% in Year 4 and 67.2% in Year 5.

There are some differences between the prediction results of EN MDA and the Z-model. Although the prediction accuracy of both the EN MDA and the Z-models decreases over the years, the accuracy of the Z-model fluctuates in a wider range. In addition, the overall accuracy of the Z-model dropped sharply from 90.7% in Year 1 to 75% in Year 2 and is the lowest among the five years' prediction results. The Type I classification accuracy of the Z-model is also lowest in Year 2 for both the original and the jack-knife cross-validation samples; 64.3% for the original sample and 60% for the cross-validation tests.

The prediction accuracy of EN Logit and the O-model is tested on the Test sample over five years before loan default. The likelihood of loan default and the goodness of fit of the prediction models is also tested. The ratio of defaulting and non-defaulting firms for the model is 70 to 3,249 for one year, 70 to 5,476 for two years, 69 to 2,328 for three years, 69 to 2,067 for four years and 67 to 1,981 for five years before default. The results of the tests are presented in Table 6.4.

Table 6.4 The Five Year Predictive Accuracy and Likelihood Results of the EN Logit and the O-Model

Panel A: Predictive Accuracy and Likelihood Ratio

	EN Logit			***O-Model (Ohlson (1980))***		
Years to Default	Prediction Accuracy	*– 2LL*	*Cox & Snell R^2*	Prediction Accuracy	*– 2LL*	*Cox & Snell R^2*
Year 1	99.6%	118.874	0.142	99.2%	263.678	0.118
Year 2	99.6%	51.678	0.213	99.6%	211.291	0.093
Year 3	99.3%	107.607	0.207	98.9%	148.119	0.181
Year 4	99.3%	165.984	0.185	99.2%	147.184	0.192
Year 5	99.2%	149.284	0.194	99.6%	84.138	0.219

Panel B: Classification Results of Models

		EN Logit			***O-Model (Ohlson (1980))***		
		Type I	Type II	Total	Type I	Type II	Total
Year 1	Correct %	88.6%	99.9%	99.6%	60.0%	100%	99.2%
	N	70	3,249	3,319	70	3,249	3,319
Year 2	Correct %	88.4%	100%	99.6%	70.0%	100%	99.6%
	N	70	5,476	5,546	70	5,476	5,546
Year 3	Correct %	83.8%	100%	99.3%	60.9%	100%	98.9%
	N	69	2,328	2,397	69	2,328	2,397

Year 4	Correct %	77.9%	100%	99.3%	75.0%	100%	99.2%
	N	68	2,067	2,135	68	2,067	2,135
Year 5	Correct %	74.6%	100%	99.2%	91.0%	99.9%	99.6%
	N	67	1,981	2,048	67	1,981	2,048

The table presents the prediction results of both EN Logit and O-model applied to the Test sample. Panel A presents the predictive accuracy of the likelihood ratio. Panel B presents the correct prediction as in percentage for defaulting firms, non-defaulting firms and overall. The sample size (*N*) of the defaulting firms and non-defaulting firms are 70 and 3249, respectively. The ratios of defaulting and non-defaulting firms for the model is 70 to 3,249 for Year 1, 70 to 5,476 for Year 2, 69 to 2,328 for Year 3, 69 to 2,067 for Year 4 and 67 to 1,981 for Year 5.EN Logit incorporated 10 EN predictor variables identified with Elastic Net model. The O-model followed Ohlson (1980) and incorporated 9 variables which were originally used in Ohlson (1980)'s study. Test results refer to the prediction accuracy of both models one year before loan default. Type I correct is sensitivity or true positive and Type II correct is specificity or true negative. To make terms consistent in this study, "sensitivity" and "specificity" are not used. The sample size of the defaulting firms and non-defaulting firms are 70 and 3249, respectively.

The prediction accuracy of the EN Logit exceeds that of the O-model from Year 1 to Year 4. From Year 1 to 3, the – *2LL* value of the EN Logit is lower than that of the O-model, indicating that the EN Logit is more likely to result in correct predictions than the O-model. The predictive ability of EN Logit decreases after Year 3, whereas, contrary to the expectation, the predictive ability of the O-model increases in Years 4 and 5. The same trend is found with the *Cox & Snell* R^2. Up to Year 3, EN Logit shows better predictive power than the O-model. Overall, EN Logit outperforms the O-model up to three years before loan default because it better predicts loan default based on the selected predictor variables.

The prediction accuracy of each group is also tested. Panel B, Table 6.4 reports the Type I, Type II and overall prediction accuracy. When only the overall prediction accuracy is considered for the usefulness of the model, both models perform very well and predictor variables factored in both models are useful in the prediction of loan default. Although the overall accuracy rate of the O-model is high, the high Type II classification, or Type II correct prediction, is the main driver for the overall accuracy of the O-model. When the sensitivity is considered, the difference between the two models is apparent, as shown in Table 6.4. The sensitivity or Type I correct classification rate of EN Logit is 88.6% for Year 1, 88.4% for Year 2, 83.8% for Year 3, 77.9% for Year 4 and 74.6% for Year 5. In contrast, the sensitivity of the O-model is 60% for Year 1, 70% for Year 2, 60.9% for Year 3 and 75% for Year 5. This implies that the predictor variables factored in the O-model explain the characteristics of the non-defaulting firms, but they are less useful to loan classification or lending decisions. With the exception of Year 5, the O-model is less useful than EN Logit in the prediction of defaulting firms.

The prediction results of EN MDA exceed those of the Z-model in overall classification over 5 years' prediction results. The same is found in the test of logistic regression analysis. The overall accuracy of the EN prediction models is superior to those of the Z-model and O-model over 5 years before loan default, with the exception of Year 5 of the logistic regression analysis. Both EN MDA and EN Logit classify defaulting firms as defaulting with highly accurate Type I classification.

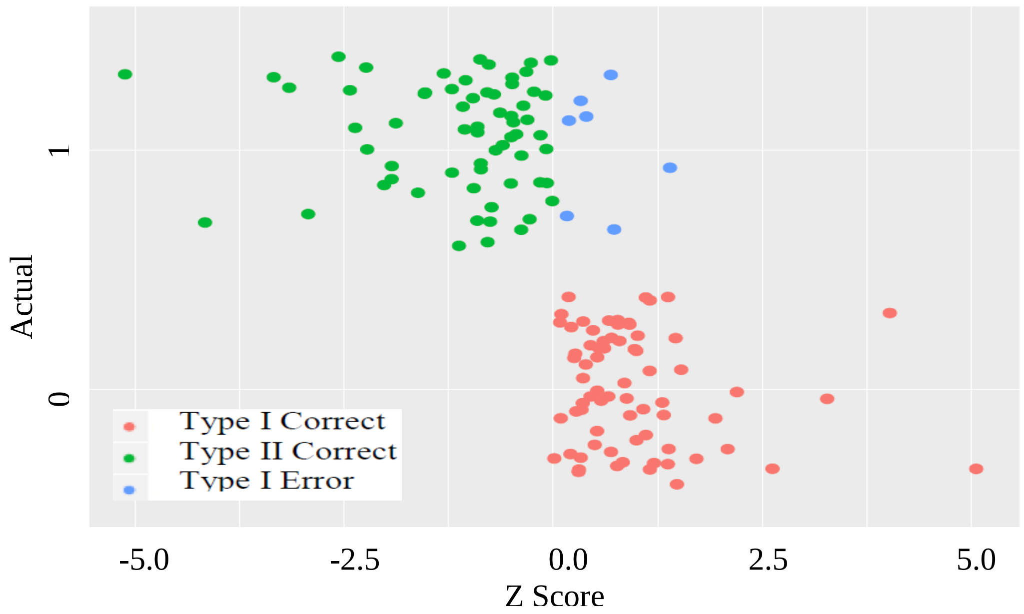
6.1.4 Pictorial Presentation of Prediction Accuracy

Loan default prediction typically involves the classification of firms in a group according to their financial status. Classification is concerned with separating an object from a population into different groups and allocating new observations into one of these groups to derive a classification rule that can be used to optimally assign new observations to each class (Hair, Black, Babin & Anderson, 2009; Cohen, Cohen, West & Aiken, 2013). It should consider the likelihood of an object belonging to each of the classes with prior probability of occurrence (Laitinen & Laitinen, 1998; Sarlija, Bensic & Zekic-Susac, 2009). Thus, the accuracy of the classification can be evaluated by different measures, such as the correct classification rate, Type I error and Type II error. In order to compute these measures, a score is attributed to each firm in the Test sample. By doing so, optimal cut-off points can be determined to discriminate firms according to their status and for classifying firms into groups.

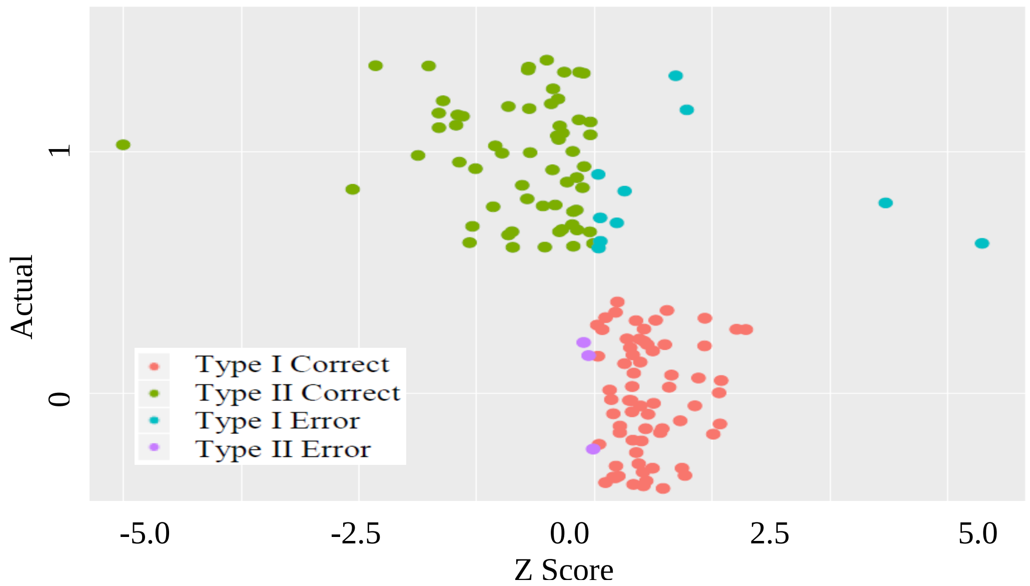
The prediction of potential credit losses is critical for estimating sufficient allocation of regulatory and economic capital (Collins, Shackelford & Wahlen, 1995). In addition, accurate credit decisions will be useful in spreading the cut-off point between lending decision errors, thus allowing improvement of the trade-off between the two types of error, such as an incorrect positive error, Type I, and incorrect negative error, Type II (Barney, Graves & Johnson, 1999). Therefore, although quantification of credit risk in scores, such as the Z-score or O-score, can be useful for the accurate classification, equally critical should be the determination whether a firm with a high score actually does not default on its loan or a firm with low score defaults on its one.

Figure 6.1 A Pictorial Presentation of EN MDA and Z-model Results

a. Classification Results of the EN MDA Model



b. Classification Results of the Z-model



The y-axis in the graphs represents the actual result of the loan. '1' means that the firm defaulted on its loans and '0' means that firm did not default on its loans. The x-axis represent the discriminant scores computed with the multiple discriminant analysis. The dots are colour-coded as follows: green dots represent the correct Type I classification; red dots represent the correct Type II classification; blue dots represent the Type I error; and violet ones the Type II error.

Figure 6.1 visualises potential cut-off points for EN MDA and the Z-model. From Figure 6.1, default firms are clustered around the second quadrant and the non-defaulting firms clustered around the fourth quadrant. As the discriminant score increases, most non-default firms are predicted to be non-defaulting and if it decreases, more default firms are predicted to be defaulting. Although some cases are clustered in the central area, there are areas where all members of that area are predicted to be defaulting and non-defaulting.

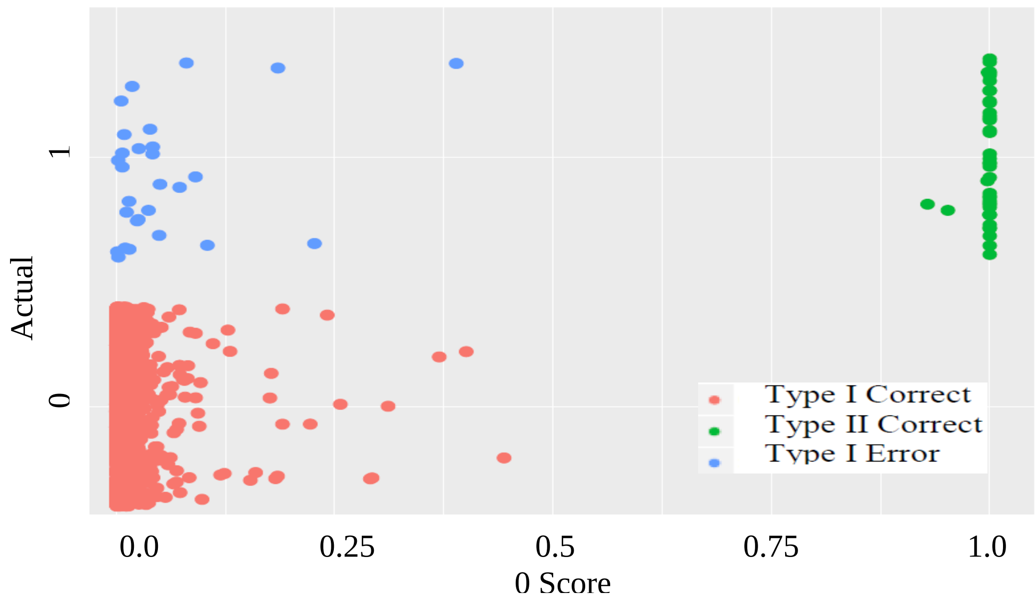
The classification results of the EN MDA and the Z-models provide different cut-off points for Type I and Type II classification. In the case of EN MDA, all firms with discriminant scores equal to and lower than –0.011 are all defaulting with 7 (10%) Type I errors of total 70 defaulting. All firms with a discriminant score greater than 1.397 are predicted to be non-defaulting. Thus there is no Type I error below –0.011 and there is no Type II error above 1.397 (Refer to Appendix E.1). Thus, the likelihood of the group membership of a case can be determined with discriminant scores ranging from -0.011 to 1.397. Seven firms are within this range. As visualised in Figure 6.1, EN MDA shows clearer centroids of each group and an optimal cut-off point can be determined according to the intentions of each preparer (Altman, 1968; Koh, 1992).

In the case of the Z-model, however, Type II error cost cannot be minimised with a discriminant score. All firms are predicted to default if their discriminant score is equal to or lower than –0.137 (Refer to Appendix E.2). However, an area over –0.137 contains the defaulting Type I and Type II errors even though the discriminant score increases to its maximum. The Z-score has no discriminating power when it comes to the classification, especially for non-defaulting. Thus, there can be cases where a loan is classified as non-defaulting when it actually turns out to be defaulting and a bank may suffer unexpected losses. The discriminant score of the Z-model is not effective in discriminating the defaulting from the non-defaulting.

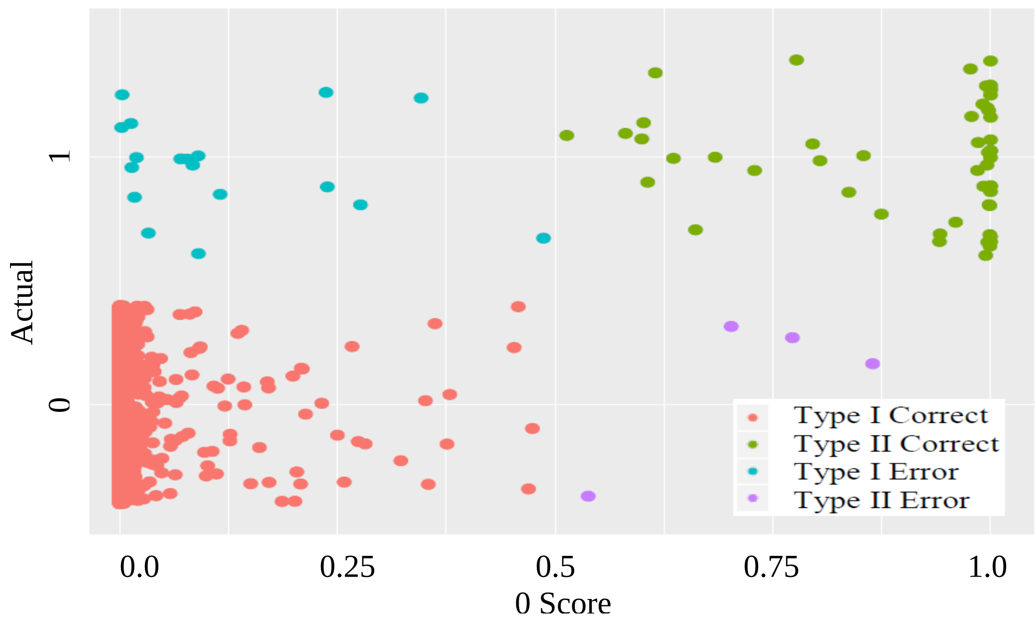
As illustrated in Figures 6.1a and 6.1b, the Z-score is useful for distinguishing defaulting firms from non-defaulting firms, but some firms with high a Z-score default on their loan and some firms with a low Z-score do not default on their loan. Each group is centred on a certain score. As shown in Figure 6.2a, 99.9% of non-defaulting firms scored higher than 0.87 and are correctly predicted to be non-defaulting; they are clustered on the right side of the figure. Further, 88.6% of defaulting firms scored lower than 0.44 and are correctly predicted to be defaulting; they cluster at the left corner of the figure. Only 11.4% of defaulting firms, with scores lower than 0.44, are incorrectly predicted to be non-defaulting when they actually defaulted on their loan one year later. Consistent with the case of Figure 6.1a, there is a discernible difference between the scores of defaulting and non-defaulting firms.

Figure 6.2 A Pictorial Representation of EN Logit and O-model Results

a. Classification Results of the EN Logit



c. Classification Results of the O-model



The y-axis in the graphs represents the actual result of the loan; '1' means that firms defaulted on their loans and '0' means that firms did not default on their loans. The x-axis represents the discriminant scores computed by multiple discriminant analysis. The dots are colour coded: green dots represent the correct Type I classification, red dots represent the correct Type II classification and blue dots represent the Type I error and violet ones the Type II error.

The results of the O-model can be useful to determine defaulting and the non-defaulting firms with reasonable accuracy. However, as illustrated in Figure 6.2b, the defaulting firms form a centroid around scores from zero to 0.48 and non-defaulting firms cluster around scores from 0.52 to 1.0. Between the two centroids exists a broad range (from zero to 0.49) of mixed results that require the practitioner's discretion for determination. If the cut-off point is determined at 0.8, there will no Type II error, but Type I errors will increase by 22.9%. If the cut-off point is determined at a point lower than 0.5, it will decrease Type I errors, but will increase Type II errors.

Compared with the predictor variables of the O-model, the EN predictor variables better capture the differentiating characteristics of defaulting and non-defaulting firms. Thus, the resulting score can be used for an optimal cut-off point for by practitioners.

This section analysed classification accuracy within the Test sample that was used to apply Elastic Net to select the variables. The predictive ability of EN predictor variables is superior to the predictor variables of the Z-score model of Altman (1968), when tested by multiple discriminant analysis. EN MDA outperforms the Z-model in the overall, Type I and Type II prediction accuracy when tested on the Test sample one year before the loan default. The superiority of EN MDA persists in the test results of prediction accuracy over the five years before loan default. Also, the EN predictor variables are useful to distinguish defaulting firms from non-defaulting firms; each group can make centroid so that an optimal cut-off point can be determined.

The next section reports the validation of the EN and MDA models by examining their prediction accuracy when applied to the same and a different period.

6.2 EXTERNAL VALIDATION

Though many previous studies have demonstrated the accuracy of their prediction models, the test of classification accuracy is often conducted on a sample from which it was derived or a contemporaneous sample (see Section 2.2.4 for further discussion). Few examine the usefulness of selected variables when they are applied to a different sample or different period. Also as Baesens, Setiono, Mues and Vanthienen (2003) and Agarwal and Tafffler (2008) point out, the usefulness of variables in prediction models decreases when they are applied in a period from when the variables were not extracted. This may imply that the models were useful for prediction only under the additional assumption that the variables are stationary over time (Eisenbeis, 1977; Mensah, 1984; Castrén, Dées & Zaher, 2010; Shah & Samworth, 2013; Zilberman & Tayler, 2014). As found in Section 5.3.2, the original coefficients of Altman (1968) and Ohlson (1980) are changed when the models are applied to samples from a different period.

The usefulness of EN models is examined with two holdout samples. Holdout 1 is a sample within the same period as the Test, which is 1997 to 2009. Holdout 2 is a sample outside the Test period. The results of the tests on Holdout 1 are presented in Section 6.3.1 and the results of the tests on Holdout 2 are presented in Section 6.3.2.

6.2.1 PREDICTION ACCURACY WITHIN SAMPLE PERIOD

When tested on the Test sample, the EN predictor variables are useful in distinguishing defaulting firms from non-defaulting firms. This is an expected result because the predictor variables are regulated and extracted from the Test. Tests of the EN predictor variables on the data from which they are not derived can provide further evidence on the usefulness of the EN predictor variables. Although the Holdout 1 is from the same sample period, firms in the Holdout 1 may have different financial characteristics. Distribution of defaulting and non-defaulting firms in the holdout sample is almost identical to that of the Test. The classification results of validation tests are presented in Table 6.5.

The overall accuracy of EN MDA increases slightly from 95% to 96.4% in the Test. All non-defaulting firms are classified as non-defaulting, which is the same result as for the Test. The accuracy for Type I classification increases by 2.8% compared with the results of the Test; 64 defaulting firms of 69 in total are correctly predicted to be defaulting and all non-defaulting firms are predicted correctly to be non-defaulting.

In contrast, the results of the Z-model show a 1.6% drop in the overall accuracy of classification. The overall accuracy decreases to 89.1%, compared with 90.7% for the Test. Although the Type I classification show no major difference, the accuracy of Type II classification declines 2.9%; it drops from 95.7% in the Test to 92.8% in the holdout sample within the same period.

Table 6.5 The Classification Results of the Within-Period Holdout Sample

	EN MDA			***Z-Model (Altman (1968))***		
	Number Correct (Sample Size)	% Correct	% Error	Number Correct (Sample Size)	% Correct	% Error
Type I	64(69)	92.8%	7.2%	59(69)	85.5%	14.5%
Type II	69(69)	100%	0%	64(69)	92.8%	7.2%
Total	133(138)	96.4%	3.6%	123(138)	89.1%	10.9%

Test results refer to the prediction accuracy of both models one year before loan default. The correct hit rate (total number of sample) and accuracy percentage are presented. The Z-model employed the same variables of Altman (1968). The EN MDA incorporated the predictor variables identified with the application of the Elastic Net model. The sample period is the same as the Test sample periods, which is from 1997 to 2009.

The predictive ability of EN MDA exceeds the performance of the Z-model when tested with Holdout 1 in the accuracy of the Type I, the Type II and the overall classification. These results are consistent with the results for the Test. When compared with the results of the Test, the accuracy of the overall classification and Type I classification slightly increase but the overall accuracy of the Z-model decreases for Type II classification.

The usefulness of EN Logit is also tested with Holdout 1. The distribution of defaulting and non-defaulting firms in the Holdout 1 is 69 defaulting firms and 3,249 non-defaulting firms. The number of non-defaulting firms is based on the bankruptcy rate for each year. The results of testing the external validity with the two sets of holdout samples are presented in Table 6.6.

EN Logit still outperforms the O-model in tests on Holdout 1. EN Logit has higher *Cox & Snell* R^2 than the O-model. The *–2LL* values of the EN Logit (83.008) are far lower than those of the O-model (198.151), indicating that EN Logit is more likely to make correct predictions than the O-model. When tested on the Holdout 1, the overall accuracy of EN Logit is 99.5%, only marginally lower than the accuracy for the Test sample (99.6%). The accuracies for Type I (sensitivity) and Type II (specificity) are also high: 82.6% of defaulting firms are correctly predicted to be defaulting and 99.8% of non-defaulting firms are correctly predicted to be non-defaulting.

Table 6.6 The Predictive Accuracy of the Within-Period Holdout Sample

Panel A: Predictive Accuracy and Likelihood Ratio

EN Logit			***O-Model (Ohlson (1980))***		
Correct Prediction	*– 2LL*	*Cox & Snell* R^2	Correct Prediction	*– 2LL*	*Cox & Snell* R^2
99.5%	83.008	0.162	99.2%	198.151	0.133

Panel B: Classification Results of Models

	EN Logit			***O-Model (Ohlson (1980))***		
	Type I Correct	Type II Correct	Total Correct	Type I Correct	Type II Correct	Total Correct
	82.6%	99.8%	99.5%	69.6%	99.8%	99.2%
N	69	3,249	3.31,	69	3,249	3.31,

EN Logit incorporated 10 EN predictor variables identified with by Elastic Net. The O-model followed Ohlson (1980) and incorporated the nine variables that were originally used in Ohlson's (1980) study. The data year is one year before the actual loan default. The sample period is the same as the Test sample period, which is 1997 to 2009. The sample is not evenly distributed. Test results refer to the prediction accuracy of both models one year before loan default. Type I correct is sensitivity or true positive and Type II correct is specificity or true negative. To make terms consistent in this study, "sensitivity" and "specificity" are not used. Instead, Type I correct and Type II correct are used.

The performance of the prediction models with the Holdout 1 is similar to that with the Test. This may be a result of the two samples sharing the same economic features that influenced all firms operating in the period. The overall classification accuracy of EN Logit is 99.5%, which is a 0.1% decrease compared with the results of the test on the Test sample. O-model (99.2%) result is the same as that of the Test sample.

The Type I classification by the O-model is 69.6% which is a 9.6% improvement compared with the results of the test on the Test sample. However, it is still inferior to the results of EN Logit, which made 82.6% correct classifications. The high overall classification of O-model resulted from high Type II classification (99.8%), which is identical to the result of tests on the Test sample. Though the Type II classification of the O-model is not changed, the accuracy of the Type II classification of EN Logit is 99.8%, which is 0.1% lower than the Test.

As the O-model gives a weak performance with Type I classification with both the Test and the Holdout 1, the predictor variables incorporated in the O-model may not represent the characteristics of defaulting firms from 1997 to 2009. EN Logit performs better than the O-model because it has higher prediction accuracy when it is applied to not only the Test but also to the Holdout 1 from which the predictor variables are not derived.

The usefulness of the EN predictor variables is validated with the tests on the Holdout 1. Whereas the prediction accuracy of EN MDA improves when tested on the Holdout 1, the prediction accuracy of EN Logit decreases by 0.1%. Both EN prediction models consistently outperform the performance of their benchmarks, the Z-model and the O-model. The EN predictor variables are useful for the prediction of loan defaults for the 1997-2009 period.

6.2.2 PREDICTION ACCURACY OUTSIDE SAMPLE PERIOD

Loan default and bankruptcy prediction models described as having competitively good predictive value typically report somewhat disappointing classification results when tested on samples from the different periods (Grice & Ingram, 2001; Wu, Gaunt & Gray, 2010), as discussed in Section 2.2.2.4. If a model is to be useful for forward-looking or ex-ante prediction, it must have adequate classification accuracy when applied to periods other than those from which the model is derived (Joyce & Libby, 1981; Baesens, Setiono, Mues & Vanthienen, 2003; Jones & Hensher, 2007; Agarwal & Taffler, 2008; Campbell, Hilscher & Szilagyi, 2010; Foster & Zurada, 2013). This section reports the usefulness of the EN predictor variables when tested with the second holdout sample, which is outside the period of the Test sample.

Different firms with different firm-specific characteristics are included in the Holdout 2. Holdout 2 includes loan defaulting firms from 2010 to 2013, when there was no reported financial crisis. Thus the financial characteristics of firms in Holdout 2 may differ from those in the other two samples, and the sample does not share the same economic factors as the other two samples.

To test the usefulness of the *ex ante* prediction, the predictive ability of EN MDA is tested with the holdout sample from outside the initial time period and is compared with the prediction results of the Z-model. The sample is evenly distributed. The data year are one year before the actual loan default. The results of testing the external validity with the holdout sample from outside sample periods are presented in Table 6.7.

Table 6.7 The Classification Results of the Outside-Period Holdout Sample

	EN MDA			***Z-Model (Altman (1968))***		
	Number Correct	% Correct	% Error	Number Correct	% Correct	% Error
Type I	21(23)	91.3%	8.7%	16(23)	69.6%	30.4%
Type II	22(23)	95.7%	4.3%	19(23)	82.6%	17.4%
Total	43(46)	93.5%	6.5%	35(46)	76.1%	23.9%

The Z-model employed the same variables as in Altman (1968). EN MDA incorporates the predictor variables identified with the application of Elastic Net. Holdout 2 includes loan defaulting firms from 2010 to 2013. The data year is one year before the actual loan default. The sample is evenly distributed to meet the operational requirements of MDA.

There is a pronounced difference in the classification results between the EN MDA and the Z-model. Consistent with the two previous tests, EN MDA performs better than the Z-model. Although slightly decreased, the overall accuracy of EN MDA is satisfyingly high (93.5%); 91.3% of defaulting firms and 95.7% of non-defaulting firms are correctly classified. Thus, the predictive ability of the EN predictor variables is not affected by firm specific and macroeconomic differences.

In contrast, the performance accuracy of the Z-model drops significantly in Type I, the Type II and the overall classification. The Z-model classifies 69.6% of defaulting firms as defaulting and 82.6% of non-defaulting firms as non-defaulting. This reflects 17.4% Type II errors, for which banks incur opportunity costs. However, 30.4% of the Type I misclassification would mean 30.4% of the approved loans would subsequently become defaulted and the banks would incur losses. Besides the increased misclassification, the significant drop in the classification accuracy of the Z-model implies that the variables employed in the model do not represent the data and thus are not useful in discriminating between defaulting and non-defaulting firms. When tested with the Test and Holdout 1 samples that are from the same period and share the same economic conditions, the Z-model classifies defaulting and non-defaulting firms with satisfyingly high accuracy, although not as good as EN MDA. However, when the Z-model is tested with the sample from a different period and different economic environment, it does not perform as well as it does with two initial samples. This may imply that the variables incorporated in the Z-model can accurately classify when the variables are stationary over years. Also the variables of the Z-model can discriminate between defaulting and non-defaulting firms when their characteristics are distinctively different.

The predictive ability of EN Logit is also tested with Holdout 2. The results of testing the external validity with the two sets of holdout samples are presented in Table 6.8. The distribution of defaulting and non-defaulting firms in Holdout 2 is 23 defaulting firms and 979 non-defaulting firms, consistent with the bankruptcy rate for each year. The results are presented in Table 6.8

EN Logit still outperforms the O-model in the tests on Holdout 2. When tested with Holdout 2, EN Logit has higher *Cox & Snell* R^2 than the O-model; the – *2LL* value of EN Logit (39.680) is far lower than that of the O-model (106.764), indicating that EN Logit is more likely to make correct predictions than the O-model. As the *Cox & Snell* R^2 of EN Logit (0.164) is higher than that of the O-model (0.106), the EN Logit is a better fitted to the sample period and better captures the characteristics of Holdout 2.

Table 6.8 The Prediction Results of the Outside-Period Holdout Sample

Panel A: Predictive Accuracy and Likelihood Ratio

EN Logit			***O-Model (Ohlson (1980))***		
Correct Prediction	– 2LL	Cox & Snell R^2	Correct Prediction	– 2LL	Cox & Snell R^2
99.6%	39.680	0.164	98.9%	106.764	0.106

Panel B: Classification Results of Models

	EN Logit			***O-Model (Ohlson (1980))***		
	Type I Correct	Type II Correct	Total Correct	Type I Correct	Type II Correct	Total Correct
Accuracy %	82.6%	100%	99.6%	52.2%	100%	98.9%
N	23	979	1,002	23	979	1,002

Holdout 2 includes loan defaulting firms from 2010 to 2013. EN Logit incorporates 10 EN predictor variables identified with Elastic Net. The O-model followed Ohlson (1980) and incorporated nine variables that were originally used in Ohlson's (1980) study. The data year is one year before the actual loan default. The sample is not evenly distributed. Test results refer to the prediction accuracy of both models one year before loan default. Type I correct is sensitivity or true positive and Type II correct is specificity or true negative. To make terms consistent in this study, "sensitivity" and "specificity" are not used. Instead, Type I correct and Type II correct are used.

EN Logit shows a constantly good performance for the prediction of loan default. When tested on Holdout 2, the overall accuracy of EN Logit is 99.6%, slightly higher than the accuracy for the Holdout 1 (99.5%) and identical to the Test sample (99.6%). The accuracy for Type I (sensitivity) and Type II (specificity) is also high: 82.6% of defaulting firms are correctly predicted to be defaulting and 100% of non-defaulting firms are correctly predicted to be non-defaulting. The Type I correct rate is slightly lower than the Test (88.6%) and is identical to Holdout 1 (82.6%). The Type II correct rate marginally increases compared with the Test (99.9%) and Holdout 1 (99.8%).

The overall accuracy of the O-model is 98.9%, which is marginally lower than the accuracy for the Test and Holdout 1 (99.2%). Although the O-model has a very high accuracy (100%) for Type II classification, the decreased accuracy of the overall classification was caused by the poor performance in Type I classification. The O-model performs poorly with Type I classification (52.2%), little different from random classification. The result of Type I accuracy is lower than the Test (60.0%) and Holdout 1 (69.6%). Consistently, the O-model performs poorly with Type I classification. The Type II accuracy slightly increases compared with the Test (99.8%) and Holdout 1 (99.8%). Thus, the main contributor to the overall high prediction accuracy is the correct Type II prediction. Thus, as the misclassification rate of the Type I increased, the predictor variables incorporated in the O-model may not be effective in indicating deteriorating conditions in the defaulting firms from 2010 to 2013.

The EN MDA and EN Logit models outperform the Z-model and O-model, respectively, especially in Type I classification. The validation tests provide evidence that EN MDA and EN Logit are more useful in making an *ex ante* predictions, since they predict the outcome of a loan more accurately when tested with the holdout sample from outside the test period.

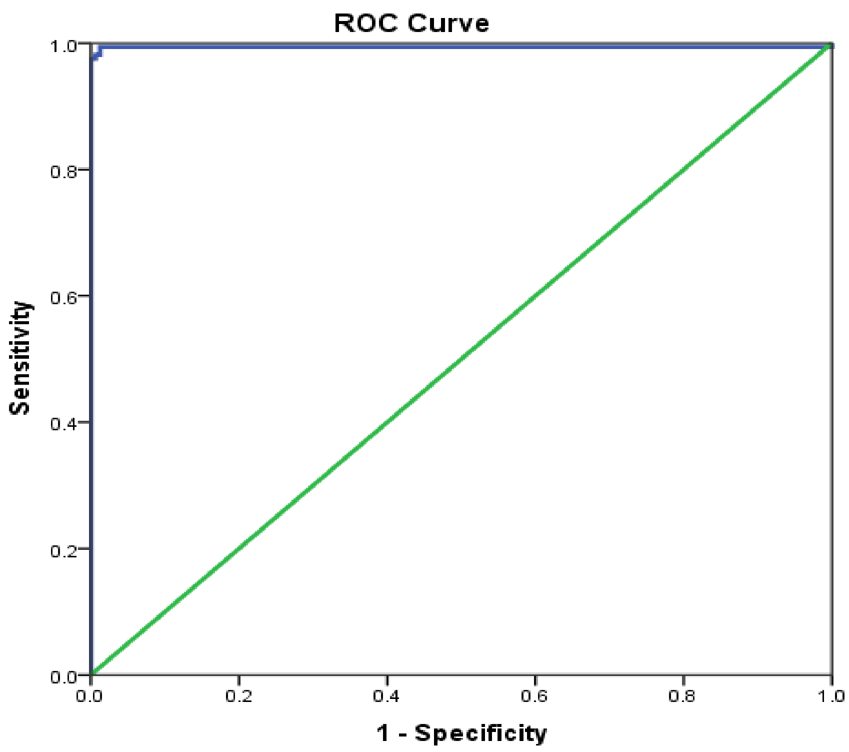
The next section analyses the prediction accuracy of both EN prediction models, the Z-model and the O-model compared with the area under the ROC curve (AUC) and the accuracy ratio.

6.3 AREA UNDER OPERATING CHARACTERISTIC CURVE (AUC) ANALYSIS

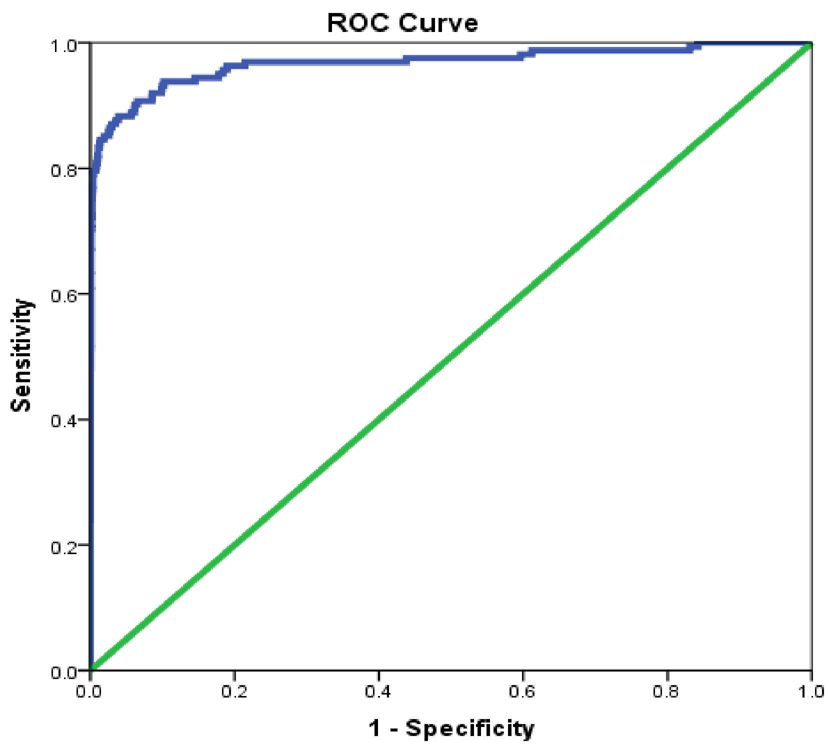
The predictive ability of the EN predictor variables is tested and found to be useful when applied in MDA and logistic analysis. The performance of the EN prediction models is consistently superior to the Z-model and the O-model when tested on the Test, Holdout 1 and Holdout 2. The EN prediction models consistently outperform the Z-model and the O-model especially in Type I classification. To further evaluate the prediction accuracy, the area under receiver operating characteristic curve (AUC) analysis is conducted. AUC is a method to assess the appropriateness of prediction parameters. Sobehart and Keenan (2001) argue that the area under the ROC curve (AUC) is the decisive indicator of a model's predictive ability.

Figure 6.3 ROC Curves for the Predictive Ability of Four Models

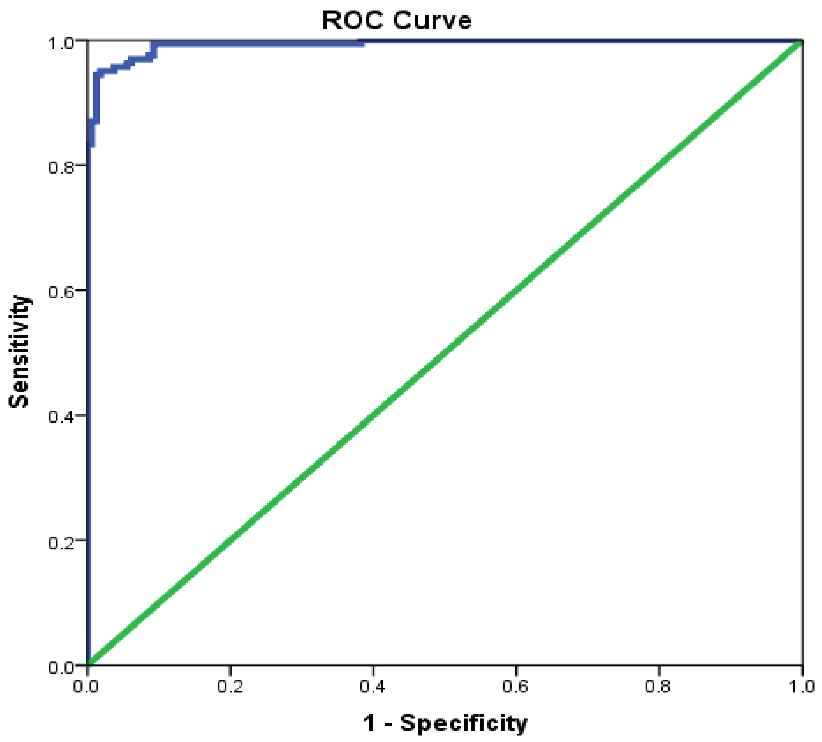
a. ROC curve for the EN MDA



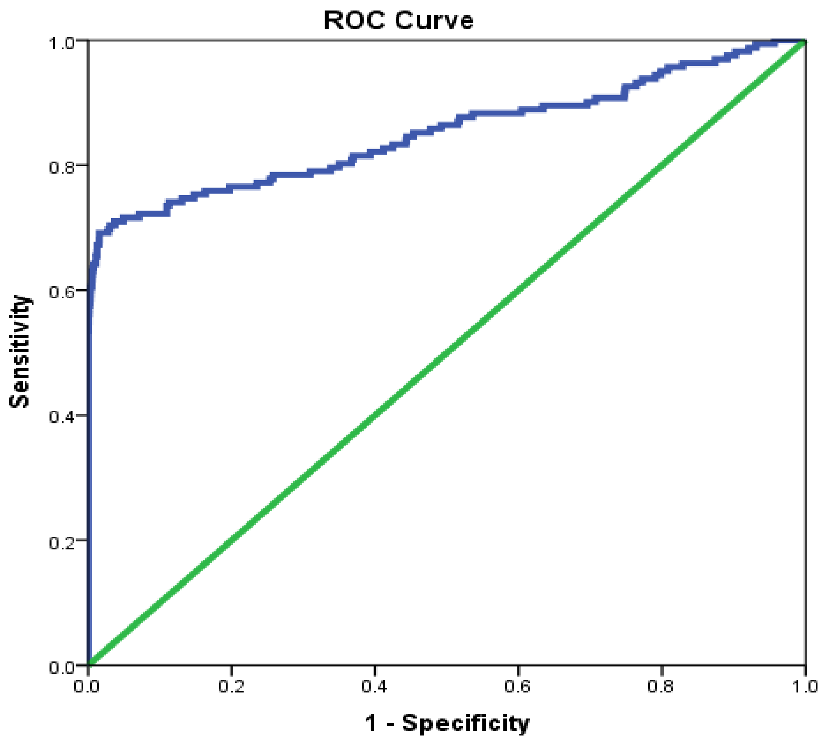
b. ROC curve for the EN Logit



c. ROC curve for the Z Model



d. ROC curve for the O Model



AUCs are based on the Test, which covers 1997 to 2008; the sample is 1 year before loan default. The AUCs of both EN MDA and EN Logit based on the Test, Holdout 1 and 2 samples are presented in Appendix F. The five years' AUC patterns of both EN MDA and EN Logit are also presented in Appendix F.

The AUC has an important statistical property: the AUC of a classifier is equivalent to the probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance (Hanley & McNeil, 1982). As this thesis generates two classifiers, defaulting and non-defaulting, that score each firm by the probability it will default or not, the AUC represents the expected performance of each firm.

As shown in Figure 6.3, the prediction performance of all four models is better than random prediction. However, the prediction performance of some models exceeds that of others. Both EN MDA and the Z-model show outstanding results in the ROC curve. EN MDA, the Z-model and the EN Logit have a steep gradient in the lower range of the x-axis and to the upper right corner, reaching close to 1, Type I classification, or true sensitivity. The green line in the graphs represents the random classification with 50% accuracy. The lowest Type I classification is almost 1 for EN MDA and slightly over 0.8 or 80%. The lowest Type I classification for EN Logit is close to 0.8, which equals a Type I classification of 80%, whereas the O-model's lowest Type I classification is less than 0.6 or 60%.

Figure 6.3 displays the ROC curves of prediction models based on the Test. The figures confirm the EN prediction models better classify defaulting and non-defaulting than their benchmarks, the Z-model and the O-model. The curves plot each model's correctly classified loan defaulting firms divided by the total defaulting firms, or true positive rate, on the Y-axis. On the X-axis, non-defaulting firms incorrectly classified as defaulting divided by the total non-defaulting firms or false positive rate are plotted. The main metric for comparing model performance is the area under ROC curve. The area under the ROC curve (AUC) reflects how good EN Logit is at distinguishing between defaulting and non-defaulting firms. The AUC provides a quantitative performance measure, the higher the classification accuracy, the further the ROC curve pushes upward and to the left. The AUC ranges from 50 percent, for a worthless model, to 100 percent for a perfect classifier. Points closer to the upper-right corner correspond to low cut-off probabilities, whereas points in the lower left correspond to higher cut-off probabilities.

Table 6.9 AUC Summary Statistics for Four Models Predictive Accuracy

	AUC	***SE***	***AR***	***Ranking***
EN MDA	0.994	0.003	0.988	1
EN Logit	0.967	0.010	0.934	3
Altman (1968) (Z-model)	0.993	0.006	0.986	2
Ohlson (1980) (O-model)	0.852	0.021	0.704	4

The prediction accuracy of the four models is tested for all three sets of samples. EN MDA refers to the multiple discriminant model using the 10 EN predictor variables. EN Logit refers to the logistic regression model using 10 EN predictor variables. The Z-model refers to the replicated z-score model following Altman (1968) and the O-model refers to the replicated o-score model following Ohlson (1980). Figures in column 2 are the area under the ROC curve. Column 3 has the standard error of the estimated area and column 4 presents the accuracy ratios (AR = 2 * (AUC – 0.5)).

EN MDA, EN Logit and the Z-model accumulate more area under the ROC curves than the O-model achieving minimum misclassification. Thus, those three models are better prediction models with minimum misclassification. The average overall AUC and the accuracy ratio (AR) score of all models are summarised in Table 6.10. Table 6.9 shows that each model does a better job at predicting loan default than a random model because the AUCs of all models are over 0.5. It also shows that there are no significant differences between the first three models. Both EN prediction models are better than each of their benchmark counterparts. EN MDA is ranked first with an overall average of 0.994, which indicates very strong classification accuracy. This shows that EN MDA is an excellent prediction model that maximises true positives and minimises the false positives (Engelmann, Hayden & Tasche, 2003).

After EN MDA, the Z-model is the second best, with an AUC of 0.993, followed by EN Logit (0.967); the O-model (0.852) is ranked fourth. Although there are a very small difference between EN MDA and the Z-model (0.001), Agarwal and Taffler (2008) and Foster and Zurada (2013) found that a small difference in the AUC for a model can mean a large difference in profit for credit risk model users.

The models ranked in order are EN MDA, followed by the Z-model, EN Logit and the O-model, based on AUC. The AR scores are consistent with the rankings of the AUC. As both MDA models show very high AUC (i.e., close to 1), the efficacy of the multiple discriminant model is confirmed (Agarwal & Taffler, 2008; Das, Hanouna & Sarin, 2009).

6.4 THE PREDICTION USEFULNESS OF AN ECONOMIC VARIABLE

The economic variable, interest rate, is identified as one of the 10 predictors of loan default. As explained in Section 5.2.3, the pattern of the interest rate change is identical to the movement of the loan default rate with a one year lead time between the change of interest rate and loan default rate.

Expansion of loan default prediction models to reflect changed economic conditions will increase the prediction accuracy of a loan default prediction model because it considers present economic conditions under which the users make their decision (Barth, 2006). Thus, the economic sensitivity of the EN prediction models is tested and presented in Table 6.10.

Table 6.10 The Contribution of an Economic Variable to the Prediction of Loan Default

Panel A: EN MDA Model

		EN MDA Model with Economic Variable			***EN MDA Model without Economic Variable***		
Sample	*Distribution (Defaulting:Non-defaulting)*	*Type I*	*Type II*	*Total*	*Type I*	*Type II*	*Total*
Test Sample	70:70	90.0%	100%	95.0%	88.6%	98.8%	93.7%
Holdout 1	69:69	92.8%	100%	96.4%	90.8%	97.3%	94.0%
Holdout 2	23:23	91.3%	95.7%	93.5%	87.0%	92.3%	89.7%

Panel B: EN Logit Model

		EN Logit Model with Economic Variable			***EN Logit Model without Economic Variable***		
Sample	*Distribution (Defaulting:Non-defaulting)*	*Type I*	*Type II*	*Total*	*Type I*	*Type II*	*Total*
Test Sample	70:3,249	88.6%	99.9%	99.6%	65.7%	97.8%	95.1%
Holdout 1	69:3,249	82.6%	99.8%	99.5%	70.3%	98.8%	96.3%
Holdout 2	23:979	82.6%	100%	99.6%	72.3%	94.9%	94.7%

This table presents the prediction results of EN MDA with and without the economic variable interest rate. The prediction accuracy is tested on the Test, Holdout 1 and Holdout 2 one year before loan default. For EN MDA, defaulting and non-defaulting firms are evenly distributed and the sample sizes for the Test, Holdout 1 and Holdout 2 are 70, 69 and 23, respectively. For EN Logit, the ratio of defaulting to non-defaulting firms for the Test is 70 to 3,249; the ratio for the Holdout 1 is 69 to 3,249; the ratio for the Holdout 2 is 23 to 979.

The prediction accuracy of the EN prediction models decreases in all three tests when the economic variable is excluded. The most noticeable difference can be found in the Type I accuracy. EN MDA classifies a loan defaulting firm as defaulting with an accuracy of 90.0% in the Test sample, 92.8% in Holdout 1 and 91.3% in Holdout 2 when all 10 EN predictors are incorporated in the prediction model. The exclusion of the economic variable results in a reduction of prediction accuracy to 88.6% in the Test sample, 90.8% in Holdout 1 and 87.0% in Holdout 2. EN Logit shows a more pronounced reduction in accuracy with exclusion of the economic variable. The accuracy rates of the Test sample, Holdout 1 and Holdout 2 are 88.6%, 82.6% and 82.6% respectively. These accuracy rates are reduced to 65.7% for the Test sample, 70.3% for Holdout 1 and 72.3% for Holdout 2 when the EN Logit is constructed without the economic variable.

Although it is in a subtle way, the overall and the Type II prediction accuracy decrease if the economic variable is excluded from the prediction model. The overall accuracy rates of EN MDA are reduced from 95.0% to 93.7% in the test on the Test sample and from 96.4% and 93.5% to 94.0% and 89.7% in the test on Holdout 1 and Holdout 2, respectively, when the economic variable is excluded from the prediction model. Tests on EN Logit also show a decrease in overall accuracy. The overall accuracy rate is 99.6% for the Test sample, 99.5% for Holdout 1 and 99.6% for Holdout 2 when tested with the economic variable. However, the overall accuracy rate reduces to 95.1% for the Test sample, 96.3% for Holdout 1 and 94.7% for Holdout 2 in tests without the economic variable.

Type II prediction accuracy also shows a slight decrease when the economic variable is not incorporated in the EN prediction models. The Type II accuracy of EN MDA with all 10 predictors is 100% for the Test sample and Holdout 1 and 95.7% for Holdout 2. When tested without the economic variable, it is 98.8% for the Test sample, 97.3% for Holdout 1 and 92.3% for Holdout 2. EN Logit also shows a subtle difference between EN Logit with the economic variable and EN Logit without the economic variable. The accuracy rates are reduced from 99.9% to 97.8% for the Test sample, from 99.8% to 98.8% for Holdout 1 and from 100% to 94.9% for Holdout 2.

Although a slight reduction is noticed when loan default is predicted without utilising the economic variable, it is found that the inclusion of the economic variable increases the accuracy of the overall, Type I and Type II predictions. The inclusion of the economic variable is especially useful and with fewer misclassification errors for the detection of defaulting firms before an actual default event occurs. As discussed in Section 6.3.2, the misclassification costs of the Type II errors may be foregone investment opportunities for banks. However, the misclassification costs for Type II errors can be even more costly with greater reduction in expected revenue. Accurate Type I classification may assist banks to prepare a sufficient amount of capital set aside to absorb losses from loan defaults.

The subtle decrease in the accuracy of the overall prediction and Type II prediction may be explained by the impact of economic changes being incorporated, at least in part, into firm-specific financial data (Fuster, Laibson & Mendel, 2010; Louzis, Vouldis & Metaxas, 2012). This finding implies that the accounting and financial information of the EN predictors is very useful in the prediction of loan default and is not necessarily backward-looking with lack of relevance to prediction (Beaver, McNichols & Rhie, 2005; Agarwal & Taffler, 2008; Baixauli, Alvarez & Módica, 2012). Also, accounting and financial information carries some information which is not captured by the economic information (Hillegeist, Keating, Cram & Lundstedt, 2004; Campbell, Hilscher & Szilagyi, 2008), although the inclusion of economic variable enhances the performance of the prediction model.

6.5 Conclusion and Summary of Findings

A conceptually richer and more accurate classification model to predict loan default is very important to academics, regulators and banks (Shumway, 2001; Jones & Hensher, 2004). This study employed Elastic Net as a regularisation approach to identify predictor variables relevant to loan default prediction. The usefulness of the EN predictor variables was tested by incorporating them in models developed using MDA and Logit. EN MDA classified defaulting and non-defaulting firms more accurately than the Z-model following Altman's (1968) study. Similarly, EN Logit yields higher prediction accuracy than the O-model of Ohlson's (1980) study. EN Logit outperforms the O-model with more accurate prediction, higher likelihood rate and better coefficients of determination. EN Logit is especially superior to the O-model in correct Type I classification. The EN prediction models perform better that the Z-model and the O-model in the tests on the Test, Holdout 1 and Holdout 2 samples. Also, they are superior to the Z-model and O-model over multiple prediction periods.

In conclusion, the EN predictor variables are useful for the prediction of loan default before the actual event, whether they are applied in the models derived from multiple discriminant analysis or logistic analysis. Inclusion of the interest rate improves the performance of EN MDA and EN Logit. Specifically, the inclusion of interest rate improves Type I prediction of EN MDA and EN Logit. This may have potential to provide some guidance to preparers on what accounting and economic variables need to be considered when determining the credit quality of loans and classifying performing and non-performing loans.

CHAPTER 7

CONCLUSION

7.1 SUMMARY OF FINDINGS

The development of empirical models that successfully discriminate between firms that default and firms that do not default on loans is an important accomplishment of the financial distress studies. However, a critical examination of the existing loan default and bankruptcy prediction literature identifies five major limitations. First, the method of selecting predictor variables is underdeveloped. A second and related limitation is the inconsistencies found in predictor variables between models. These limitations, combined with the tendency to focus on increasing prediction accuracy, has contributed to the third limitation, which is the inclusion of predictor variables with illogical or counterintuitive relations with the likelihood of default. Fourth, the accuracy of the models typically declines when they are applied outside the period of time in which they were developed, limiting their usefulness for prediction. Lastly, there has been limited consideration of forward-looking economic variables.

The objectives of this study are to introduce model for the systematic selection of variables that are relevant to the prediction of loan default, and to investigate whether economic indicators form part of the set of relevant predictors.

This study identified the financial and economic predictor variables relevant to the forward-looking prediction of loan default and investigated the predictive ability of the identified predictor variables. The study uses a sample of US loan defaulted firms from the period 1998-2013. The sample of non-defaulting firms is developed, based on yearly bond default rates as an estimate of the population default rate. A pool of 278 potential predictor variables are considered, comprising 268 financial ratios and other financial statement items, and 10 economic indicators.

The regularisation of the set of 278 potential variables using the Elastic Net (Zou & Hastie, 2005) identified ten predictor variables, comprises nine financial variables and one economic predictor variable. The identified variables are: Tangible assets to total assets (A_{TAN}/TA); Changes in cash flow from financing activities (CH_CFF); Sales to tangible Equity (S/E_{TAN}); Unadjusted retained earnings to total assets (RE_{UnAdj}/TA); Net profit to Tangible equity (NP/E_{TAN}); Interest expenses to working capital (INTEX/WC); Interest expenses to cash flow from operating activities (INTEX/CFO); Non-current liabilities to cash flow from operating activities (NCL/CFO); Total debts to total assets (TD/TA); and interest rate (INT).

The usefulness of identified variables was tested using multiple discriminant analysis (MDA) and logistic regression (Logit) and compared with the Z-score model of Altman's (1968) study (Z-model) and O-score model of Ohlson's (1980) study (O-model). The prediction models were tested using the three different samples, namely the Test, Holdout 1 and 2. The Test is the sample used to identify the predictor variables using the Elastic Net. Holdout 1 is from within the same periods as the Test, which is from 1998 to 2009. Holdout 2 comprises loan default events occurring between 2010 and 2013.

The MDA prediction model derived from the variables selected using the Elastic Net (EN MDA) correctly classifies more accurately defaulting and non-defaulting firms than the Z-model. EN MDA outperforms the Z-model when applied to a different sample within the same period (Holdout 1) and to a sample from a different period (Holdout 2).

Similarly, the logistic regression model derived using the variables identified by the Elastic Net (EN Logit) yields higher prediction accuracy than the O-model. In particular, the EN Logit has more accurate Type I classification. Further, the EN Logit model outperforms the O-model when applied to a different sample within the same period and in a different period.

The prediction accuracy of the EN MDA and EN Logit models is consistently superior to the Z-model and the O-model, respectively, over five years prior to loan default. The EN MDA and EN Logit classifies the defaulting firms and non-defaulting firms with considerably lower Type I and Type II error rates.

Further, the inclusion of the interest rate improves the prediction accuracy of the EN MDA and the EN Logit. The inclusion of the interest rate variable reduces both Type I and Type II errors in the Test sample and in both holdout samples in both the EN MDA and EN Logit models.

7.2 POTENTIAL LIMITATIONS OF RESEARCH

Financial statement data is only included in the analysis if the financial statements were already in the public domain on the date that the firm's default was declared. Thus, a criterion for inclusion in the sample is that the financial statement data for a firm is available in the year prior to default. Application of this criterion resulted in 93 firms being excluded from the sample. There is a possibility that the financial characteristics of defaulting firms for which financial data was not available differs from that of defaulting firms for which financial data is available, which could potentially bias the results. Thus, the identified characteristics of defaulting firms might have limited generalisability to firms that fail to lodge financial statements.

Further, 10 economic indicators were considered as potential predictors of loan default. Although this study covers diverse aspects of economic risk factors, there may be other relevant economic predictors that were not considered.

7.3 CONTRIBUTIONS OF THE THESIS

No consistent framework for the selection of predictor variables from data sets has emerged from the literature (Roszbach, 2004), contributing to the lack of consensus on inconsistency in prediction models (Baesens, Setiono, Mues & Vanthienen, 2003; Zou & Hastie, 2005; Yuan & Lin, 2006; Shah & Samworth, 2013), and ensuing lack of consensus on which variables are the best predictors of loan default. To address the underlying problem of variable selection, this thesis introduces and applies the Elastic Net to identify relevant financial and economic variables for the prediction loan default.

The Elastic Net extracts relevant variables and is robust to the size of the set of potential predictor variables exceeding the number of observations. This feature of the Elastic Net is critical to its application to the prediction of loan default, which is characterised by a large pool of potential variables and smaller sample sizes.

This study has identified 10 financial and economic variables that are relevant to the prediction of loan default. The consistency of these variables as relevant to the prediction of loan default is evidenced their robustness to other samples both within and beyond the sampling period from which the models were developed. Thus the findings of this thesis contribute to addressing the inconsistency of the composition of default prediction models in the literature and their limited success when applied to different periods.

Lastly, this study enhances our understanding of the role of economic indicators, in the prediction of loan default. In particular, this thesis provides evidence that the accuracy of loan default prediction models is improve by the inclusion of interest rates.

7.4 IMPLICATIONS OF THE THESIS

The assessment of credit quality of a loan applicant is critical for decision regarding granting credit. The identification of distinguishing characteristics of defaulting firms in this study can inform the internal evaluation of the lending operations of financial institutions and facilitate the development of processes for assessing the credit risk of commercial loan applicants.

The timely or early detection of changes in the credit quality of loans is critical for financial institutions (Cicchetti & Dubin, 1994; Crotty, 2009; Baixauli, Alvarez & Módica, 2012). The findings of this study can inform the assessment by financial institutions of the credit quality of loans. The misclassification of loans and ensuing inaccurate determination of credit risk may cause banks to set aside insufficient reserves to enable them to survive a significant economic shock (Beattie, McInnes & Fearnley, 2004; Handorf & Zhu, 2006; Huizinga & Laeven, 2009).

The importance of the identification of characteristics of defaulting firms has increased with the introduction of an 'expected loss model' for the recognition of impairment of loans, replacing the previous 'incurred loss model' in the preparation of financial statements under International Financial Reporting Standards and US GAAP. Under the expected loss model, banks are required to anticipate the probability of loan default prior to the actual event and proactively classify the loans based on the assessment of changed credit quality using forward-looking financial and economic indicators (e.g., IFRS 9, para. 5.5.3-4, 5.5.9-11). The application of the expected loss model relies on the preparer's ability to identify and gather relevant information to assess credit quality and forecast credit losses. However, concerns have been raised about lack of practical guidance on the selection of information relevant to the determination of loan quality. For example, the survey by Deloitte (2011) highlights the major concerns of banks about the uncertainty regarding which information needs to be incorporated into the assessment of credit impairment.

The identification of a change in credit quality may be influenced by the choice of variables used as indicators or in a loan default prediction model. Similarly, the estimation of credit losses may be influenced by the variables used to estimate the likelihood of loan default. Inconsistencies between financial institutions in the identification of relevant information for the evaluation of credit quality and the prediction of loan default may impede the understandability and transparency of information presented in financial statements (IASB, 2008). This also may increase the burden to auditors. The predictor variables identified in this thesis indicate connections between changes in the economic environment, specifically, interest rates, and the financial performance of the firm, and the likelihood of loan default. Thus, the identification of forward looking financial and economic variables that are relevant to the prediction of loan default may facilitate the identification of indicators of a decline in credit quality, which is critical to the classification of loans in the application of the expected loss model in the preparation of financial statements.

7.5 SUGGESTIONS FOR FURTHER RESEARCH

This thesis introduces the Elastic Net to regularise potential variables and posits that an improved selection method of predictor variables enhances the performance of prediction models and provides a richer and more logical explanation of loan default. The underdevelopment the selection of predictor variables is a common issue identified in the financial distress literature. Thus, further research could examine whether the application of the Elastic Net model for the selection of variables enhances the accuracy of prediction of other financial distress events, such as consumer loan default, bond default, bankruptcy.

While this study has focussed on an event, specifically the declaration of loan default, the Elastic Net model may also be useful in research that seeks to explain human judgments. For example, it could be useful for identifying relevant predictors of event such as a going concern qualification, granting credit, and changes in credit ratings, to name a few.

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APPENDIX A Request for Information by the IASB

The IASB sent out the *Request for Information* to seek information with a regard to making the expected loss method feasible and operational, 88 respondents provided their responses to all or part 6 questions. The responses are summarised in Part 1 and the questions asked in the *Request for Information* and the description of the respondents are presented in Part 2 and 3, respectively. The operational guidance provided is not sufficient for the application of the expected loss model. As for the question of whether the definition of the expected model is explained clearly, 82% of respondents in the *Request for Information* replied that the IASB needed to clarify the expected loss model. The main argument was that there could be possible diversity on how a credit loss should be estimated and which financial and non-financial information an entity should incorporate into the assessment of an expected loss of loans. In addition, respondents unanimously raised concerns regarding the level of estimation and judgement involved in the application of the expected loss model when there are no guidelines provided. The sources of responses are available from the IASB. **(http://www.ifrs.org/IASCFCMS/Templates/Project/LetterList.aspx).**

1. Summary of Responses to Request for Information by the IASB (Emphasis added)

RESPONDENT	*Q 1*	*Q 2*	*Q 3*	*Q 4*	*Q 5*	*Q 6*
1. NEO CFO (India)	*Simpler approach to the application of the expected loss model is needed*					
2. BUSINESS EUROPE (Belgium)	*Need to clarify* about how to determine future cash flows	Operational, depeAnding on the guidance finally laid down	It depends on the final form of guidance	Using EIR on good book and reassessed EIR on bad book	An entity should be allowed to exercise judgement	Necessary to focus on the objective and principles
3. Dept of Finance and Deregulation (AUS)	We are concerned that the project focuses narrowly on implementation of the Expected Cash Flow Approach *without considering some of the more significant conceptual issues*. We believe that the Board should consider the broader conceptual issues as an integral part of this project.					
4. Royal Bank of Scotland	There are a number of issues that *require clarification*.	This is not operational for large corporate lending	Hard to make any reasonable quantification of costs.	Ability to pay is not affected by changes in benchmark rates.	It is unclear whether under the IASB's proposed approach.	Revenue recognition should not incorporate future losses.
5. Nationwide Building Society (AUS)	*Not provide details* on the expected cash flow.	The move would be operationally challenging.	Require a significant amount of consideration.	Support the treatment of 'repayments of principal'	Approach (a) provides the detail required for management	A single methodology for loss estimation

6. The Clearing House Association (USA)	*Not discuss the details* regarding how to apply	Extensive system & operational are required	Difficult to estimate the magnitude of the costs.	We support a recalculation of the effective interest rate.	No reclassification from collective to individual	The approach will result in significant changes in systems
7. Banking Association (South Africa)	*Not been defined sufficiently*	Not operational in the short or long term	Considerable system and procedural changes	More application guidance is needed	Change to an individual is required.	Expanding on current principles and guidance
8. The Union of Co-Operatives	*The need to have guidance* on the operational issues	This approach could lead to significant cost being incurred	Not been able to give us a view on magnitude	We would support the Approach A as in the appendix	The collective approach should continue to be used	Given the nature of this change we can see no simplification
9. Association of Enterprises	We wonder whether the Board is contemplating all financial assets carried at amortised cost. The expected loss model would create major implementation difficulties that are not justified in our view by any significant change and improvement in financial reporting. This model could *call for quite subjective estimates and lessen the confidence* that users would have					
10. Institute of CA (England and Wales)	Would produce *less useful information than now*	It could be only applied with inherent limitation	Potential problem arising from the lack of historical data	Neither of the two approaches to the amortisation	Removing impaired assets from a portfolio	Entities would end up holding large expected future losses
11. German Accounting Standards Board	*Not clear* how an expected loss model should be applied	An expected cash flow approach can be implemented.	We would like to refer to our answer to question 2	Applying the effective interest method to variable rate	Depends on the characteristics of financial assets	The treatment of trade account receivables is not described
12. Dr. Niels Kröner	*Not explain* enough	Resulting dubious quality	See question 2	Market data & adjusted EIR	separate treatment	
13. Ed Trott (EGY)	I do *not believe* the use of an expected loss model for measuring and recognising credit losses for debt instruments held as assets would be *sufficient improvement over the incurred loss model* as commonly used in practice today to justify the cost of creating the systems to implement such a model					
14. Finance Reporting& Auditing Committee (AUS)	From a theoretical point of view, *the approach is clear*.	the Basel II approach needs to be developed and implemented	The costs would be high and would outweigh the benefits	The EIR should not be changed subsequently		
15. Allianz SE (Ger)	*The need for clarity exists* for the timing and amount	Operational if final guidance reduces complexity	Difficult with uncertainties around implementation	In favour of a continuous adjustment of the EIR	Difference should not result in different impacts	Would lead to large amendments

16. MAZAR	The Board should remain with a principle based approach	The approach is not operational *due to complexity*	No information concerning the magnitude of costs	We support approach A	The choice between (a) and (b) should remain with the entity	Short term receivables would simplify the proposal
17. ANZ (AUS)	The methodology *conveys complexity*	Difficult to accurately make assessment at this early stage	Lead time is at least 12 months for design and testing on	The approach is not suitable for floating rate notes	Individual assessment provides the accurate loss assessment	To modify historical loss on the basis of current observable
18. CBA (AUS)	*Not defined clearly* enough to understand	We do not consider the approach to be operational	Very significant costs and time to implement	The complexity is far in excess so as not to be workable	Individual assessment is accurate	Not use expected cash flow model
19. ROCHE (Switzerland)	*We see a danger* that non-financial entities could be subjected to detailed application rules which go far beyond what is necessary to achieve the overall objective in their relatively simple circumstances and which impose substantial additional costs without actually producing any more decision-useful information					
20. Swedish Bankers' Association	Approach is *clearly defined*	The approach is not operational	The cost will be very high for implementing and ongoing	Portfolio basis is much easier to handle		
21. Accounting Standard Council (Singapore)	To facilitate comparison, need to provide *more guidance*	Operational with significant costs	The quality of information remains a question	Alternative B appears to be more practical	Combination of (a) and (b) would produce best estimates	Provision for specific guidance on deriving the probability
22. Volkswagen AG (Ger)	The disclosed approach of spreading credit losses over the life of the receivables is *much too complex and does not support the general goal of the IASB* in reducing the complexity of accounting for financial instruments					
23. Industrial Bank of Korea	We believe that the exclusion of initial expected loss from interest income would *not be appropriate* from the accounting perspective, because revenue would have to be recognised on a gross basis and it is not probable that credit risk premium included in contractual interest would be realisable.					
24. The Institute of CA of Scotland	We are concerned that the proposed expected loss model does not meet the objective of financial reporting and will result in increased complexity and a lack of transparency. We believe that the expected loss model is *very complex* and particularly the requirement for continual reassessment of expected losses and therefore will be costly and time-consuming to implement.					
25. Building Societies Association	While the IASB's request for information and associated papers set out the proposed approach at a reasonably high level, we do *not feel sufficient details has been given* to assess in full the practical implications of implementing the model, which could potentially be significant.					

26. Norwegian Accounting Standards Board	Clearly defined, *but not sufficient guidance*	Can be implemented without undue cost	We do not have a basis for responding on this question	We have not been able to analyse the approach in details	We have not been able to analyse the approach in details	We have not been able to analyse the approach in details
27. Barclays PLC	*Not clearly defined*	Could work with significant cost and time	Could work with significant cost and time	More consistent with Approach B in Appendix	For homogeneous assets, allocate similar PDs & LGDs	Need some simplification and additional clarification
28. KPMG	*need to provide a clearer explanation* of 'expected' cash flows	The practical application challenges are identified	Significant operational and system changes	Objective and general principles should be clarified	The selection should be left with preparers	Simplifications of expected model for receivables
29. CA of Ireland	Define with sufficient clarity, some *clarify required though*	Very challenging both for techniques and resources	Need a significant lead time to implement the proposals	Approach A results in clearer presentation	Should allow for collective provisioning for assets	No comments on simplification at this time
30. French Banking Federation	*Additional guidance* would be helpful	Not operational when applied to short-term loans	Costs may reach tens of millions euros per bank	Approach B is easier to apply	The selection should be based on business specific natures	Adopt 'expected loss through the life of the portfolio
31. European Insurance CFO of Forum	We do not currently have a view on the conceptual attraction of an expected loss model over an incurred loss model or vice versa. We believe that *the current lack of clarity* around how such a model might operate is such that we are unable to fully comment on the feasibility or otherwise of adopting such an approach					
32. European Association of Cooperative Banks (Belgium)	*Lack some important details* at this stage	Implementation is very challenging	Difficult to give a realistic estimate of cost	We support Approach A for both cases	The selection should be based on business specific natures	It is almost impossible to constitute simplifications
33. Investment Banking Association	*Need more clarification and depth of explanation*	It would incur substantial additional costs and resources	The magnitude of costs is likely to be considerable	We do not yet have a consensus view	Either could be used depending on system & data	Constant reassessment of the expected loss
34. Canadian Bankers Association	*Need more clarification and depth of explanation*	could not be made operational without undue costs	Costs to implement would be significant	Unclear how the examples would be impacted	Either approach would depend on technology	Modification of the incurred loss model would be simple

35. HSBC Holdings PLC (Lukka & Kasanen)	There is *limited guidance* to assist implementation	Could be implemented but the cost would be too excessive when weighted against the questionable benefits`		B is theoretically pure, but A is easier to apply	It is conceptually flawed to apply to an individual asset	Reduction in time period of estimates of expected losses
36. Ministry of Finance (USA)	The concept is *clearly defined*	Could not be applied without considerable additional costs	Significant initial and ongoing costs	Assessing each rate reset date as sale and repurchase	The approach (b) is being managed to diversify risk	Defining specific terms for specific types of assets
37. The World Bank	*More clear definition*	Depend on final standard	Depend on final standard	Preference for Approach A	Depend on asset	Need transition guidance
38. Swiss Holdings	*need more clarification*	Depend on final standard	Depend on final standard	Decision depends on the assets	Based on business	Need more clarification
39. Australian Bankers' Association	We have serious concerns about the feasibility of the proposed model and the ability of Australian banks to implement it at a reasonable costs or in a reasonable time frame, because it is *not clearly understandable*					
40. Japanese Bankers' Association	We do *not* believe that details are *defined clearly*	Not operational, because it requires a great burden both in terms of systems and administrative procedures		The selection should be based on business specific natures	Decision should depend on assets	Modification of the incurred loss model would be simple
41. Malaysian Accounting Standards Board	*Additional guidance is needed*	We are doubtful of it being capable to be implemented without significant cost and time		Decision depends on the type of assets	Decision depends on the type of assets	Cannot identify any simplifications
42. Foreningen af Statsautoriserede Revisorer (Denmark)	The new approach is *not defined clearly* and might be less operational. It is decided to proceed with considering this expected loss model, we would suggest that the presentation and disclosure requirements are considered as well					
43. Federation of Insurance Society (France)	*Not clearly defined* in the request for information	Depend on final standard	Significant initial and on-going costs	Examples provided underline additional complexity	Need for additional development on approaches	Simplification to avoid burdensome analysis
44. Zentraler Kreditausschuss (Ger)	*It remains unclear* about application	The approach is not feasible & does not reduce complexity	Additional data collection would require substantial costs	No specific method should be imposed	Not clear about individual assessment	It is almost impossible to constitute simplifications
45. AICPA (USA)	*Need for additional guidance*	Operational challenges of applying the expected model to variable rate loans are particularly great		Develop alternative approach	Decision depends on the type of assets	

46. Austrian Federal Economic Chamber	*Clearly defined*, some additional specification needed	Challenging, but operational	The magnitude would be near to 'tens of millions'	Approach A is preferable	Decision depends on the type of assets	Need more clarification to reduce complexity
47. South African Institute of CA	*Clearly defined* and can be operational					
48. Fujitsu (Japan)	A number of practical issues *needed to be considered for understanding concept* and implementing the model					
49. Korean Accounting Standards Board	The expected loss model may entail 'subjectivity' in estimating future cash flow reliably and accurately. To make a reliable and accurate estimation of future cash flow, *a further in-depth study would be needed*. The initial and ongoing cost for system will be considerable					
50. Life Insurance Association of Japan	We feel that *additional guidance is needed*	Impossible to apply without considerable costs	Not enough information for implementation	Not answered	Not answered	Not answered
51. Japanese Institute of CPA	*Additional guidance is required*	Not answered	Not answered	Both approaches are inconsistent	Decision depends on the type of assets	Not answered
52. Prof. Dr. Konrad Wimmer and Dr. Stefan Kusterer (Ger)	*Need more clarification*	Can be implemented	Not answered	Decision depends on the type of assets	Not answered	Not answered
53. Department of Treasury and Finance (Aus)	*Lack of information* would put more onus on entities to implement this model					
54. British Bankers Association	*Extremely complex*	Very challenging to implement	Cost of implementing this method would be significant	Decision depends on the type of assets	Decision depends on the type of assets	Approach should be based on calculating at a portfolio level
55. UBS (Switzerland)	*Further guidance is needed*	Operational if sufficient lead time is provided	At this age, unable to provide meaningful estimate	Alternative B would be a fair presentation	The selection should be based on business specific natures	Consideration of principles
56. Group of 100 (Aus)	*Similar opinion as with Australian Bankers Association (39)*. Implementing the expected loss approach is likely to have the most significant operational impacts and costs on entities					
57. AASB	*Requires clarification*	Burdensome and significant costs involved	Decision depends on the type of assets	Clarifying existing model		

58. Committee of European Banking Supervisors	Need *a clearer and more sufficient application guide*	Costs and timing can be operational challenge	‘A’ for upfront costs and ‘B’ for variable rate instruments	Portfolio should be maintained throughout the life of it	Simplify the approach if it does not affect quality of information	
59. Institute of International Finance (USA)	It is apparent that additional work is required to develop this model to be fully operational. And this model *needs a clearer explanation*					
60. Telstra Corp Ltd (Aus)	The Board *should provide more details and guidance* in relation to all financial assets					
61. Hong Kong Institute of CPA	The IASB *should clarify this approach*	Conceptually operational	Depends on how far an entity has developed experience	A for amortising upfront costs	The selection should be based on business specific natures	Implementation can be a great burden to businesses
62. Ernst & Young	*Further clarification needed*	Not operational	Significant initial costs	Approach A is correct	Depend on assets	Modify incurred loss model
63. Organismo Italiano di Contabilita (Italy)	*Well defined and described*	A little complex	Implementation issues and costs	In favour of approach A	Prefer a collective basis	Not answered
64. Canadian Accounting Standards Board	*Need more clarification on application*. Implementing the proposal would entail extensive and expensive systems modification that would take some time to implement					
65. European Banking Federation (Belgium)	*Sufficiently clear*, but lack of some operational details	Practical difficulties are expected	Major implementation issues and costs	Not necessary to assign the impairment calculated on a collective basis		Net answered
66. Belgian Financial Sector Federation	*Well defined*, very difficult to apply though	Cannot operate without undue cost	Difficult to comment on the operational issues	Using variable rate would lead to higher processing burden	The selection should be based on business specific natures	Reconciliation between accounting and Basel methods
67. Westpac (Australia)	*Clearly defined*, but Westpac does not favour this method	Difficult to ascertain without more clarity	Depends on the final methodology	Variable rate by updating the interest rate	In favour of A	More definitive guidelines
68. American Bankers Association	Although the use of expected losses may be an appropriate solution, we believe using the expected cash flow methodology leads to operational issues that will cost far more than any benefits the Board perceives will be derived. *It is unclear whether expected prepayments should continue to be included in the estimate*					

69. The Co-Operative Financial Services	*More detail is needed*	Significant time and resource would be required	Take at current rate and refresh it every month	Residential loan portfolios with a similar approach	Align this model with the one of Basel	
70. Basel Committee on Banking Supervision (Switzerland)	*Need more clarification* on approach	Operational with reasonable implementation period	Decision depends on the type of assets	Decision depends on the type of assets		
71. Duff & Phelps (Germany)	*The description is clear*	It will be difficult to implement consistently because it requires a good deal of judgement to determine changes		Simple application to variable rate instruments		
72. The Allstate Corp	This model *needs more development* and operational challenge would exist as most insurance companies do not develop loan loss reserves					
73. Deutsche Bank	*Not clearly defined*	Considerable and manageable effort and costs to implement	Approach A is appropriate	Modified retrospective transition		
74. NAB	*Not clear from document*	Not operational	Significant costs	Decision depends on the assets	Cannot simplify this model	
75. Santander (USA)	*Clearly described*	The proposal is quite complex to implement	Not possible to estimate the effective costs	Use fixed rate and adjust it later	No need to change the entire portfolio	Permit key information to evaluate performance
76. Conseil National de la Comptabilite (France)	*More guidance* would be helpful	May be operational with resources worth tens of millions of euros per bank		The selection should be based on business specific natures	The selection should be based on business specific natures	Recognising expected losses collectively
77. JP Morgan (USA)	JP Morgan does not support further development or application of this model because of *lack of clarity*. It will be extremely complicated to apply in practice					
78. European Financial Reporting Advisory Group	*Lack of details in explanation*	Implementation is operationally challenging	The cost will be significant	EFRAG supports Approach A	Any approach is fine as long as satisfactory assessments are made	Simplification for short-term receivables
79. Accounting Standards Board (France)	*Crucial details are missing*	Initial and on-going implementation costs will be significant		No technical superiority between two approaches	Decision depends on the type of assets	Cannot see any superiority of this model
80. German Insurance Association	From a conceptual point of view, this approach should *contribute to a less arbitrary* and subjective application of impairment rules. Implementation of this model would raise a significant number of implication and operational issues					

81. Groupo Santander (Brazil)	*Clearly defined*	Adoption of this approach is very critical and implementation and on-going basis costs are very high	The selection should be based on business specific natures	Decision depends on the type of assets	Revise this model
82. Institute of CA (India)	*Cleary defined*	Significant cost associated with implementation	Approach A	Collective model	No comments
83. Federation of European Accountants (France)	*Same view as EFRAG*				
84. Pricewaterhouse Coopers	*Neither clearly defined* nor provides a framework	It would be difficult to conclude on the operational viability of the model from a cost/benefit perspective	Support Approach A	The selection should be based on business specific natures	Provision of clear framework
85. International Banking Federation	Explanation of model was *provided clearly*, but we do not consider this approach to be operational and our member banks are unlikely to be able to implement it at a reasonable cost or time.				
86. Dutch Accounting Standards Board	*Support EFRAG's view*				
87. Swedish Financial Reporting Board	*The approach is clearly defined*. But, we do not support the implementation of an expected cash flow approach for impairment as proposed. We fail to see merit in this model.				
88. CFA	*The approach is clearly defined*. But, we understand the costs if this approach would be significant				

2. Questions asked by the IASB in the Discussion Paper

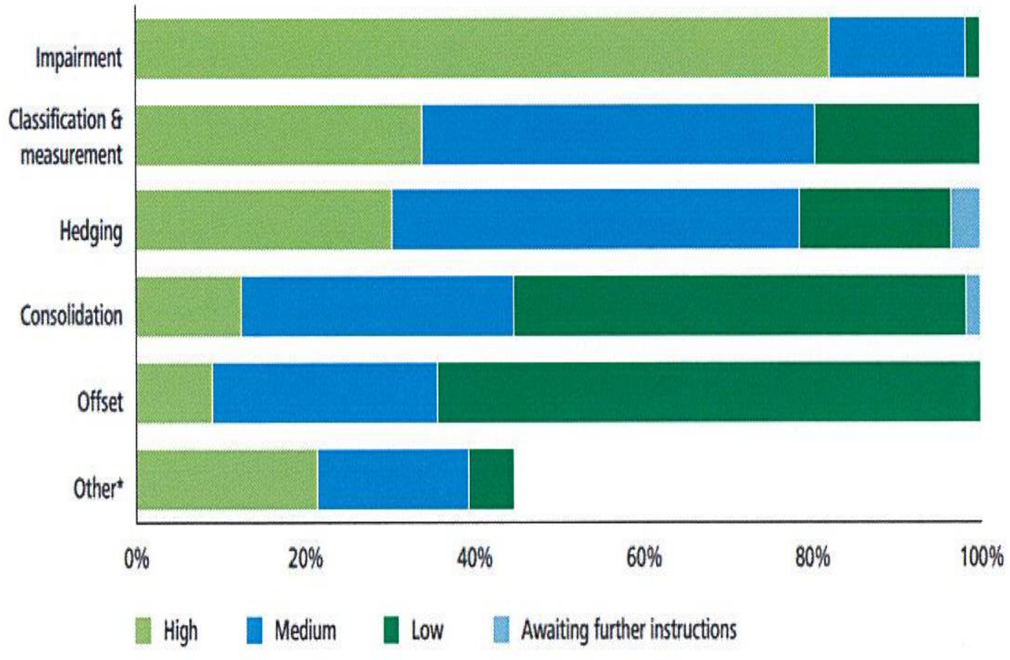
Q 1	Is the approach defined clearly? If not, what additional guidance is needed, and why?
Q 2	Is the approach operational (i.e. capable of being applied without undue cost)? Why or why not? If not, how would you make it operational?
Q 3	What magnitude of costs would you incur to apply this approach, both for initial implementation and on an ongoing basis? What is the likely extent of system and other procedural change that would be required to implement the approach as specified? If proposals are made, what is the required lead time to implement such an approach?
Q 4	How would you apply the approach to variable rate instruments, and why? See the Appendix for a discussion of alternative ways in which an entity might apply the expected cash flow approach to variable rate instrument
Q 5	How would you apply the approach if a portfolio of financial assets was previously assessed for impairment on a collective basis and subsequently a loss is identified on specific assets within that portfolio? In particular, do you believe (a) changing from a collective to an individual assessment should be required? If so, why and how would you effect that change? (b) a collective approach should continue to be used for those assets (for which losses have been identified) (c) ? Why or why not?
Q 6	What simplifications to the approach should be considered to address implementation issues? What issues would your suggested simplifications address, and how would they be consistent with, or approximate to, the expected cash flow model as described?

3. The Description of the Respondents to the 'Request for Information' by the IASB

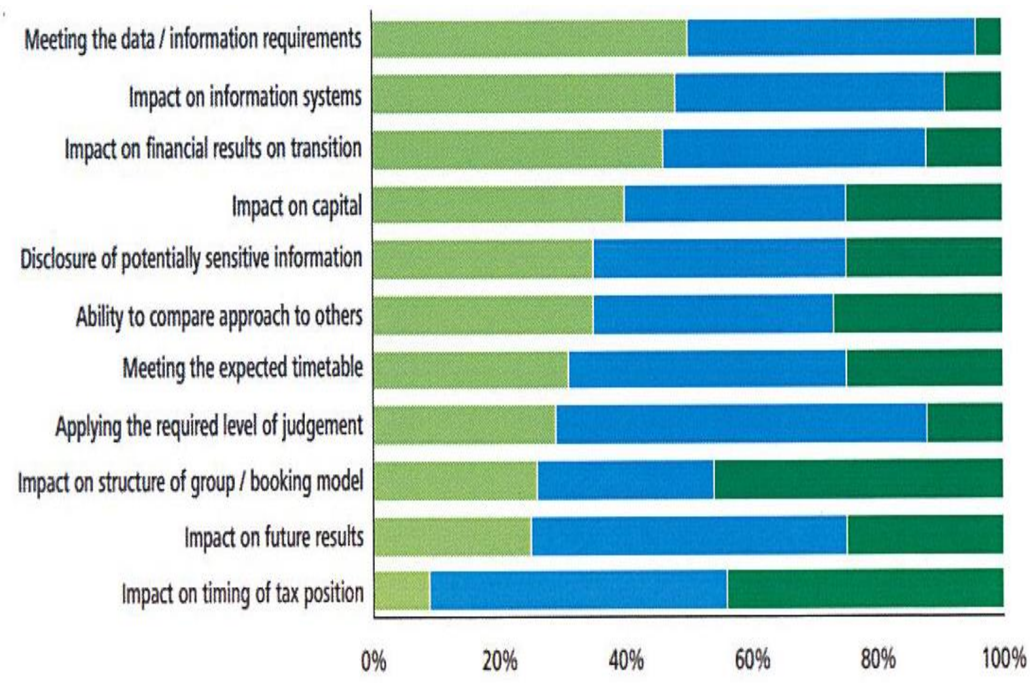
	Accounting Firm/ Financial Service	*Government/ Bank Supervision*	*Financial Institutions*	*Business (Manufacturing/ Construction/ Communication)*	*Accounting Professional Bodies (CPA, CA, CFA)*	*Standards Setters*	*Academic*	*Total*
Count	13	18	26	7	11	10	3	88
%	14.77%	20.45%	29.55%	7.95%	12.50%	11.36%	3.41%	100%

APPENDIX B Sample Questions from Survey by Deloitte (2011)

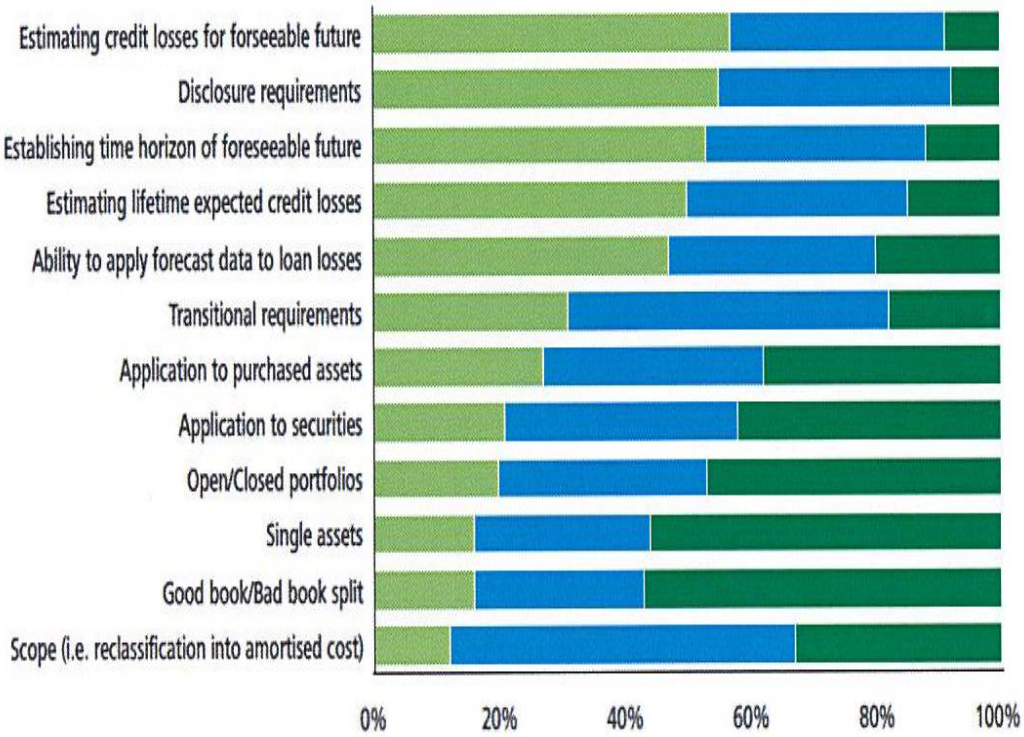
Question 7 In relation to accounting change, which of the following do you believe will have the greatest impact on your business model and/or financial statements?



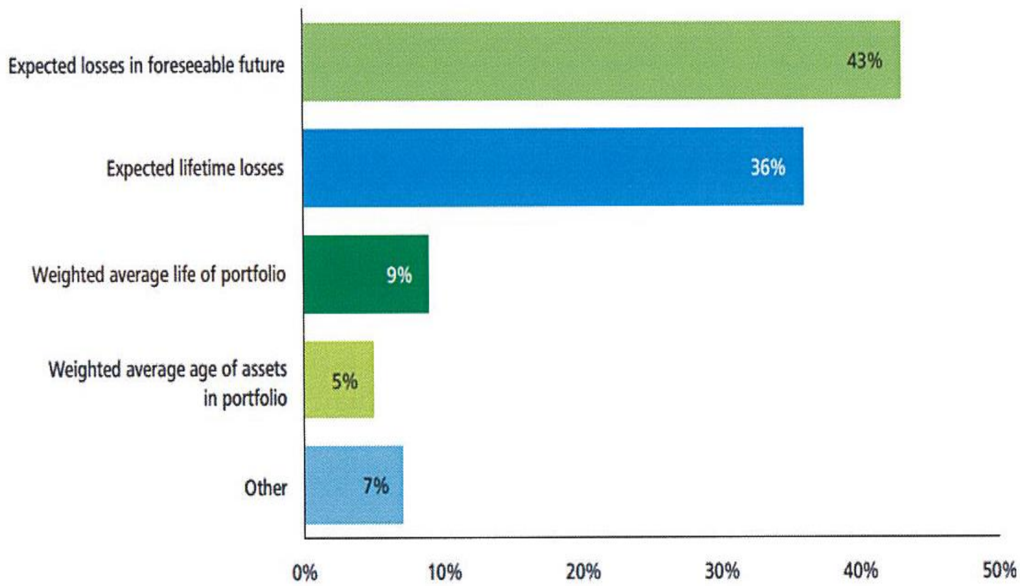
Question 9 Which of the following areas concern you about the proposed requirements of IFRS 9 regarding impairment?



Question 25	Which areas of the technical requirements are you concerned by with respect to practical implementation or operation?



Question 28	Which aspect will be the greatest challenge in terms of gathering necessary data to implement the proposed requirements as they currently stand?



APPENDIX C Sample Sizes of Test Sample and Validation Samples

The figures provided in the table are the number of firms. The figures with * are the number of observations. 'Not Provided^' means the study conducted the validation using samples within test sample period, but number of firms or observations are not provided. 'Rolling windows#' is a series of rolling out-of-sample estimations. For example of Wu, Grant and Gray (2010), the first estimation is based on firm-year observations from 1980 and bankruptcies in 1981. The estimated coefficients are then used to predict bankruptcies in 1982 with data up to 1981. The second set of estimated coefficients is then used to predict bankruptcies in 1983 with data up to 1982. The window continues expanding; the estimated coefficients used to predict bankruptcies in 2006 are based on firm-year observations from 1980 to 2004 and bankrupties from 1981 to 2005.

	Test Sample		***Validation Sample _Within Sample Period***		***Validation Sample _Out of Sample Period***	
	Default /Bankrupt	Non-Default /Survival	Default /Bankrupt	Non-Default /Survival	Default /Bankrupt	Non-Default /Survival
Altman (1968)	33	33	25	66		
D & K[1] (1980)	23	23				
Ohlson (1980)	105	2,058				
Hamer (1983)	31	44				
Izan (1984)	51	48	10			
G, N & W[2] (1985)	33	33				
Zavgren (1985)	45	45				

B & P[3] (1993)	74	Not Provided^				
H, M & M[4] (1994)	118	16	80	80		
Shumway (2001)	229	Not Provided^	Not Provided^			
H, K, C & L[5] (2004)	756	14,303*				Rolling windows#
D, S & W[6] (2007)	2,700	Not Provided^	Not Provided^			
W, G & G[7] (2010)	887	49,724*				Rolling windows#
L & M[8] (2010)	73	138			150*	350*
C, D, L & T[9] (2013)	1,212*	119,395*				
F & Z[10] (2013)	111*	1,017*				
B, G & L[11] (2013)	313	1.871*				
B, A & M[12] (2013)	50	39				

1. Dambolena and Khoury (1980)
2. Gentry, Newbold and Whitbold (1985)
3. Beneish & Press (1993)
4. Hopwood, KcKeown and Mutchler (1994)
5. Hillegeist, Keating, Cram and Lundstedt (2004)
6. Duffie, Saita and Wang (2007)
7. Wu, Grant and Gray (2010)
8. Li and Miu (Li & Miu, 2010)
9. Charitou, Dionysiou, Lambertides and Trigeorgis (2013)
10. Foster and Zurada (2013)
11. Bhimani, Gulamhussen and Lopes (2010)
12. Baixauli, Alvarez and Módica (2012)

APPENDIX D List of Potential Financial Variables

List of Financial Ratios	
GROUP I – Profitability	131 Total Liability to Tangible Equity
1. Sales to Common Equity	132 Total Liability to Sales
2. Sales to Market Value of Equity	133 Total Liability to Gross Profit
3. Sales to Tangible Equity	134 Total Liability to Net Profit
4. Sales to Total Assets	135 Total Liability to Operating Profit
5. Sales to Tangible Assets	136 Total Liability to EBITDA
6. Sales to Non-current Assets	137 Total Liability to EBIT
7. Sales to Capital	138 Total Liability to EBI
8. EBITDA to Sales	139 Total Liability to Net Operating Cash Flow’
9. EBITDA to Common Equity	140 Total Liability to Net Cash Flow
10. EBITDA to Market Value of Equity	141 Non-current Liability to Total Assets
11. EBITDA to Tangible Equity	142 Non-current Liability to Non-current Assets
12. EBITDA to Total Assets	143 Non-current Liability to Tangible Assets
13. EBITDA to Non-current Assets	144 Non-current Liability to Cash
14. EBITDA to Tangible Assets	145 Non-current Liability to Operating Cash Flow
15. EBITDA to Capital	146 Non-current Liability to Net Cash Flow
16. EBIT to Sales	147 Non-current Liability to Tangible Assets
17. EBIT to Common Equity	148 Non-current Liability to Common Equity
18. EBIT to Market Value of Equity	149 Non-current Liability to Market Value of Equity
19. EBIT to Tangible Equity	150 Non-current Liability to Tangible Equity
20. EBIT to Total Assets	151 Non-current Liability to Sales
21. EBIT to Non-current Assets	152 Non-current Liability to Gross Profit
22. EBIT to Tangible Assets	153 Non-current Liability to Net Profit
23. EBIT to Capital	154 Non-current Liability to Operating Profit
24. EBI to Sales	155 Non-current Liability to EBITDA
25. EBI to Common Equity	156 Non-current Liability to EBIT
26. EBI to Market Value of Equity	157 Non-current Liability to EBI
27. EBI to Tangible Equity	158 Non-current Liability to Net Operating Cash Flow
28. EBI to Total Assets	159 Non-current Liability to Net Cash Flow’
29. EBIT to Non-current Assets	160 Total Debts to Total Assets
30. EBI to Tangible Assets	161 Total Debts to Non-current Assets
31. EBI to Capital	162 Total Debts to Tangible Assets
32. Operating Profit to Sales	163 Total Debts to Cash
33. Operating Profit to Common Equity	
34. Operating Profit to Market Value of Equity	
35. Operating Profit to Tangible Equity	
36. Operating Profit to Total Assets	
37. Operating Profit to Tangible Assets	
38. Operating Profit to Non-current Assets	
39. Operating Profit to Current Assets	
40. Operating Profit to Capital	
41. Gross Profit to Sales	
42. Gross Profit to Common Equity	
43. Gross Profit to Market Value of Equity	

44. Gross Profit to Tangible Equity
45. Gross Profit to Total Assets
46. Gross Profit to Non-current Assets
47. Gross Profit to Tangible Assets
48. Gross Profit to Capital
49. Net Profit to Sales
50. Net Profit to Common Equity
51. Net Profit to Market Value of Equity
52. Net Profit to Tangible Equity
53. Net Profit to Total Assets
54. Net Profit to Tangible Assets
55. Net Profit to Non-current Assets
56. Net Profit to Current Assets
57. Net Profit to Capital
58. Dividend Payout

GROUP II – Capital Intensiveness

59. Tangible Assets to Total Assets
60. Working Capital to Total Assets
61. Current Assets to Total Assets
62. Quick Assets to Total Assets
63. Retained Earnings Adjusted to Total Assets
64. Retained Earnings Unadjusted to Total Assets
65. Working Capital to Current Assets
66. Quick Assets to Current Assets
67. Non-current Assets to Total Assets
68. Property, Plant and Equipment to Total Assets
69. Inventory to Total Assets
70. Non-current Assets to Capital
71. Property, Plant and Equipment to Capital
72. Inventory to Capital

GROUP III – Short Term Liquidity

73. Current Liability to Net Cash Flow
74. Current Liability to Cash
75. Current Liability to Operating Cash Flow
76. Current Liability to Current Assets
77. Current Liability to Working Capital
78. Current Liability to Quick Assets
79. Current Liability to Total Assets
80. Current Liability to Common Equity
81. Current Liability to Market Value of Equity

164 Total Debts to Operating Cash Flow
165 Total Debts to Net Cash Flow
166 Total Debts to Common Equity
167 Total Debts to Market Value of Equity
168 Total Debts to Tangible Equity
169 Total Debts to Sales
170 Total Debts to Gross Profit
171 Total Debts to Net Profit
172 Total Debts to Operating Profit
173 Total Debts to EBITDA
174 Total Debts to EBIT
175 Total Debts to EBI
176 Total Debts to Net Operating Cash Flow
177 Total Debts to Net Cash Flow
178 Non-current Debts to Total Assets
179 Non-current Debts to Non-current Assets
180 Non-current Debts to Cash
181 Non-current Debts to Operating Cash Flow
182 Non-current Debts to Net Cash Flow
183 Non-current Debts to Tangible Assets
184 Non-current Debts to Common Equity
185 Non-current Debts to Market Value of Equity
186 Non-current Debts to Tangible Equity
187 Non-current Debts to Sales
188 Non-current Debts to Gross Profit
189 Non-current Debts to Net Profit
190 Non-current Debts to Operating Profit
191 Non-current Debts to EBITDA
192 Non-current Debts to EBIT
193 Non-current Debts to EBI
194 Non-current Debts to Net Operating Cash Flow
195 Non-current Debts to Net Cash Flow

GROUP V – Cash Flow

196 Cash to Total Assets
197 Cash to Current Assets
198 Cash to Working Capital
199 Cash to Common Equity
200 Cash to Market Value of Equity

82. Current Liability to Tangible Equity
83. Current Liability to Sales
84. Current Liability to EBITDA
85. Current Liability to EBIT
86. Current Liability to EBI
87. Current Liability to Operating Profit
88. Current Liability to Gross Profit
89. Current Liability to Net Profit
90. Current Liability to Total Liability
91. Current Debts to Net Cash Flow
92. Current Debts to Cash
93. Current Debts to Operating Cash Flow
94. Current Debts to Current Assets
95. Current Debts to Working Capital
96. Current Debts to Quick Assets
97. Current Debts to Total Assets
98. Current Debts to Common Equity
99. Current Debts to Market Value of Equity
100. Current Debts to Tangible Equity
101. Current Debts to Sales
102. Current Debts to EBITDA
103. Current Debts to EBIT
104. Current Debts to EBI
105. Current Debts to Operating Profit
106. Current Debts to Gross Profit
107. Current Debts to Net Profit
108. Current Debts to Current Liability
109. Current Debts to Total Debts
110. Interest Expenses to Net Cash Flow
111. Interest Expenses to Cash
112. Interest Expenses to Operating Cash Flow
113. Interest Expenses to Current Assets
114. Interest Expenses to Quick Assets
115. Interest Expenses to Working Capital
116. Interest Expenses to Retained Earnings
117. Interest Expenses to Retained Earnings Adjusted
118. Interest Expenses to Common Equity
119. Interest Expenses to Market Value of Equity
120. Interest Expenses to Tangible Equity
121. Interest Expenses to Sales
122. Interest Expenses to EBITDA
123. Interest Expenses to EBIT
124. Interest Expenses to EBI

201 Cash to Tangible Equity
202 Cash to Capital
203 Cash to Sales
204 Cash to Gross Profit
205 Cash to Net Profit
206 Cash to Operating Profit
207 Operating Cash Flow to Total Assets
208 Operating Cash Flow to Current Assets
209 Operating Cash Flow to Common Equity
210 Operating Cash Flow to Market Value of Equity
211 Operating Cash Flow to Tangible Equity
212 Operating Cash Flow to Capital
213 Operating Cash Flow to Sales
214 Operating Cash Flow to Gross Profit
215 Operating Cash Flow to Net Profit
216 Operating Cash Flow to Operating Profit
217 Net Cash Flow to Total Assets
218 Net Cash Flow to Current Assets
219 Net Cash Flow to Common Equity
220 Net Cash Flow to Market Value of Equity
221 Net Cash Flow to Tangible Equity
222 Net Cash Flow to Capital
223 Net Cash Flow to Sales
224 Net Cash Flow to Gross Profit
225 Net Cash Flow to Net Profit
226 Net Cash Flow to Operating Profit
227 Cash Interval

GROUP VI – Turnover

228 Working Capital to Total Assets
229 Current Assets to Sales
230 Quick Assets to Sales
231 Working Capital to Sales
232 Receivable to Sales
233 Cost of Goods Sold to Inventory
234 Inventory to Sales
235 Inventory to Current Assets
236 Inventory to Working Capital
237 Inventory to Quick Assets
238 No Credit Interval

GROUP VII – Raw Financial Information

239 Changes in Sales
240 Changes in Gross Profit

125. Interest Expenses to Operating Profit 126. Interest Expenses to Gross Profit 127. Interest Expenses to Net Profit 128. Interest Coverage ***GROUP IV – Financial Leverage*** 22 Total Liability to Total Assets 23 Total Liability to Non-current Assets 24 Total Liability to Tangible Assets 25 Total Liability to Cash 26 Total Liability to Operating Cash Flow 27 Total Liability to Net Cash Flow 28 Total Liability to Common Equity 29 Total Liability to Market Value of Equity 30 Total Liability to Tangible Equity	241 Changes in Net Profit 242 Changes in Operating Profit 243 Changes in EBITDA 244 Changes in EBIT 245 Changes in EBI 246 Changes in Common Equity 247 Changes in Market Value of Equity 248 Changes in Tangible Equity 249 Changes in Capital 250 Changes in Retained Earnings 251 Changes in Retained Earnings Adjusted 252 Changes in Current Assets 253 Changes in Quick Assets 254 Changes in Working Capital 255 Changes in Current Liability 256 Changes in Current Debts 257 Changes in Total Liability 258 Changes in Non-current Liability 259 Changes in Total Debts 260 Changes in Non-current Debts 261 Changes in Cash 262 Changes in Operating Cash Flow 263 Changes in Investing Cash Flow 264 Changes in Financing Cash Flow 265 Changes in Net Cash Flow 266 Difference between Common Equity and Market Value of Equity 267 Difference between Common Equity and Tangible Equity 268 Difference between Adjusted Retained Earnings and Unadjusted Retained Earnings

APPENDIX E Misclassification Tables of EN MDA and Z-model

Appendix E.1 Misclassification Table of EN MDA Model

Firm ID No	Actual Outcome	Predicted	Discriminant Score	Missed	Misclassification
422091	0	0	5.063	0	Clear Area of Non Defaulted
422124	0	0	4.029	0	
402316	0	0	3.279	0	
410167	0	0	2.625	0	
417209	0	0	2.198	0	
415950	0	0	2.088	0	
422132	0	0	1.941	0	
418536	0	0	1.714	0	
419776	0	0	1.531	0	
900075	0	0	1.481	0	
402336	0	0	1.465	0	
7	1	0	1.397	1*	Grey Area
406461	0	0	1.382	0	
413359	0	0	1.374	0	
905584	0	0	1.372	0	
404397	0	0	1.323	0	
414706	0	0	1.305	0	
419778	0	0	1.206	0	
400361	0	0	1.157	0	
424251	0	0	1.157	0	
414722	0	0	1.154	0	
411852	0	0	1.109	0	
402352	0	0	1.108	0	
400343	0	0	1.078	0	
421094	0	0	1.011	0	
404396	0	0	0.997	0	
402345	0	0	0.995	0	
404427	0	0	0.975	0	
400346	0	0	0.920	0	
404467	0	0	0.913	0	
410200	0	0	0.904	0	
400691	0	0	0.879	0	
900862	0	0	0.853	0	

902574	0	0	0.832	0
416007	0	0	0.793	0
406478	0	0	0.776	0
417398	0	0	0.772	0
414761	0	0	0.765	0
38	1	0	0.729	1*
413471	0	0	0.698	0
416127	0	0	0.692	0
40	1	0	0.690	1*
406553	0	0	0.668	0
418618	0	0	0.659	0
410181	0	0	0.610	0
400412	0	0	0.605	0
417296	0	0	0.574	0
400406	0	0	0.548	0
410210	0	0	0.527	0
413432	0	0	0.527	0
904559	0	0	0.525	0
408413	0	0	0.497	0
417328	0	0	0.477	0
411997	0	0	0.448	0
905619	0	0	0.447	0
9	1	0	0.396	1*
902937	0	0	0.390	0
400411	0	0	0.359	0
406585	0	0	0.357	0
408473	0	0	0.353	0
410265	0	0	0.339	0
406531	0	0	0.329	0
31	1	0	0.329	1*
904096	0	0	0.308	0
904575	0	0	0.303	0
903659	0	0	0.276	0
406520	0	0	0.264	0
406530	0	0	0.251	0
424429	0	0	0.216	0
425458	0	0	0.206	0
96	1	0	0.188	1*
414796	0	0	0.185	0
33	1	0	0.164	1*
425479	0	0	0.098	0
408458	0	0	0.090	0

408492	0	0	0.082	0	
424412	0	0	0.013	0	
95	1	1	-0.011	0	
25	1	1	-0.027	0	
1	1	1	-0.075	0	
116	1	1	-0.083	0	
11	1	1	-0.092	0	
19	1	1	-0.153	0	
55	1	1	-0.156	0	
108	1	1	-0.230	0	
136	1	1	-0.268	0	
82	1	1	-0.283	0	
16	1	1	-0.309	0	
126	1	1	-0.321	0	
68	1	1	-0.357	0	
65	1	1	-0.380	0	
59	1	1	-0.383	0	
92	1	1	-0.442	0	
63	1	1	-0.477	0	
71	1	1	-0.491	0	
4	1	1	-0.491	0	
28	1	1	-0.502	0	**Clear Area of Defaulted**
69	1	1	-0.503	0	
27	1	1	-0.507	0	
12	1	1	-0.604	0	
61	1	1	-0.636	0	
5	1	1	-0.689	0	
134	1	1	-0.710	0	
114	1	1	-0.737	0	
80	1	1	-0.755	0	
129	1	1	-0.771	0	
122	1	1	-0.785	0	
100	1	1	-0.789	0	
133	1	1	-0.865	0	
48	1	1	-0.867	0	
2	1	1	-0.874	0	
104	1	1	-0.906	0	
50	1	1	-0.906	0	
73	1	1	-0.909	0	
103	1	1	-0.951	0	
15	1	1	-0.960	0	

77	1	1	-1.048	0
76	1	1	-1.059	0
138	1	1	-1.081	0
127	1	1	-1.128	0
56	1	1	-1.211	0
110	1	1	-1.212	0
90	1	1	-1.310	0
132	1	1	-1.533	0
79	1	1	-1.539	0
44	1	1	-1.618	0
128	1	1	-1.883	0
120	1	1	-1.932	0
93	1	1	-1.933	0
52	1	1	-2.024	0
125	1	1	-2.227	0
123	1	1	-2.239	0
111	1	1	-2.370	0
106	1	1	-2.433	0
54	1	1	-2.569	0
37	1	1	-2.933	0
10	1	1	-3.160	0
22	1	1	-3.346	0
43	1	1	-4.167	0
45	1	1	-5.125	0

Appendix E.2 Misclassification Table of Z-model

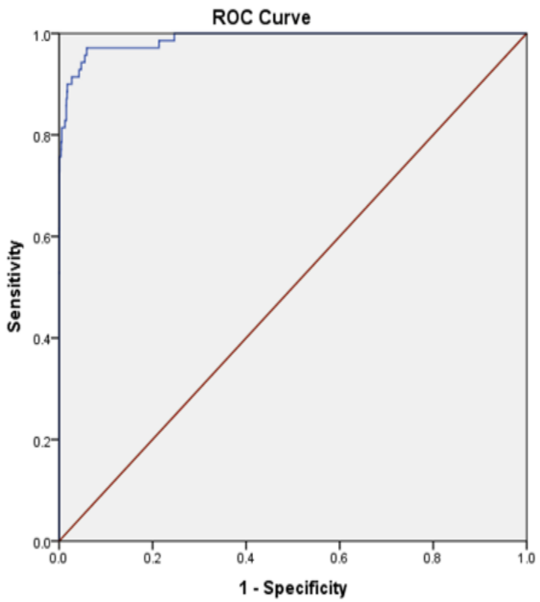
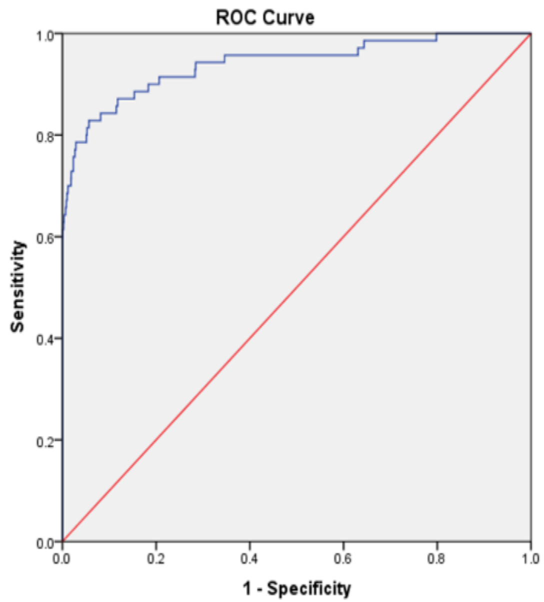
Firm ID No	Actual Outcome	Predicted	Discriminant Score	Missed	Misclassification
95	1	0	4.938	1*	Grey Area
11	1	0	3.709	1*	
400411	0	0	1.929	0	
904559	0	0	1.812	0	
408473	0	0	1.614	0	
424412	0	0	1.599	0	
904096	0	0	1.588	0	
903659	0	0	1.513	0	
404396	0	0	1.407	0	
402345	0	0	1.402	0	
406530	0	0	1.325	0	
411852	0	0	1.279	0	
16	1	0	1.176	1*	
904575	0	0	1.153	0	
413471	0	0	1.115	0	
410181	0	0	1.092	0	
114	1	0	1.036	1*	
406520	0	0	0.981	0	
425479	0	0	0.952	0	
404427	0	0	0.924	0	
410265	0	0	0.896	0	
413432	0	0	0.873	0	
417398	0	0	0.864	0	
406585	0	0	0.838	0	
424429	0	0	0.780	0	
404467	0	0	0.753	0	
417328	0	0	0.743	0	
905619	0	0	0.739	0	
400412	0	0	0.683	0	
406553	0	0	0.671	0	
418618	0	0	0.660	0	
408458	0	0	0.652	0	
406478	0	0	0.631	0	
415950	0	0	0.631	0	
902574	0	0	0.623	0	
902937	0	0	0.619	0	

400691	0	0	0.598	0
424251	0	0	0.587	0
400406	0	0	0.583	0
900862	0	0	0.573	0
410210	0	0	0.564	0
417296	0	0	0.532	0
404397	0	0	0.529	0
422091	0	0	0.501	0
905584	0	0	0.497	0
402352	0	0	0.489	0
417209	0	0	0.489	0
419776	0	0	0.481	0
421094	0	0	0.479	0
413359	0	0	0.468	0
419778	0	0	0.456	0
408413	0	0	0.444	0
402336	0	0	0.414	0
54	1	0	0.384	1*
414722	0	0	0.383	0
408492	0	0	0.324	0
400361	0	0	0.323	0
410200	0	0	0.305	0
414706	0	0	0.293	0
68	1	0	0.285	1*
414796	0	0	0.274	0
900075	0	0	0.269	0
402316	0	0	0.264	0
400346	0	0	0.241	0
416127	0	0	0.239	0
411997	0	0	0.214	0
422124	0	0	0.193	0
410167	0	0	0.142	0
418536	0	0	0.140	0
406461	0	0	0.100	0
116	1	0	0.076	1*
133	1	0	0.073	1*
416007	0	0	0.058	0
37	1	0	0.054	1*
90	1	0	0.048	1*
400343	0	0	0.044	0
406531	0	0	0.036	0

19	1	1	-0.014	0	
422132	0	1	-0.017	1*	
2	1	1	-0.052	0	
44	1	1	-0.053	0	
40	1	1	-0.059	0	
425458	0	1	-0.075	1*	
79	1	1	-0.132	0	
414761	0	1	-0.137	1*	
76	1	1	-0.140	0	
93	1	1	-0.152	0	
28	1	1	-0.192	0	
128	1	1	-0.197	0	
50	1	1	-0.221	0	
73	1	1	-0.224	0	
65	1	1	-0.231	0	
4	1	1	-0.269	0	
43	1	1	-0.269	0	
136	1	1	-0.276	0	
7	1	1	-0.281	0	
111	1	1	-0.349	0	
12	1	1	-0.384	0	
33	1	1	-0.408	0	
48	1	1	-0.414	0	
56	1	1	-0.442	0	
55	1	1	-0.447	0	**Clear Area of Defaulted**
22	1	1	-0.456	0	
132	1	1	-0.464	0	
123	1	1	-0.474	0	
5	1	1	-0.499	0	
61	1	1	-0.528	0	
138	1	1	-0.535	0	
96	1	1	-0.551	0	
38	1	1	-0.607	0	
59	1	1	-0.632	0	
134	1	1	-0.655	0	
82	1	1	-0.820	0	
122	1	1	-0.831	0	
120	1	1	-0.838	0	
69	1	1	-0.845	0	
25	1	1	-0.856	0	
71	1	1	-0.920	0	

129	1	1	-1.040	0
110	1	1	-1.050	0
126	1	1	-1.096	0
108	1	1	-1.097	0
31	1	1	-1.177	0
100	1	1	-1.263	0
1	1	1	-1.290	0
10	1	1	-1.515	0
106	1	1	-1.554	0
15	1	1	-1.591	0
63	1	1	-1.679	0
92	1	1	-1.722	0
103	1	1	-1.742	0
9	1	1	-1.762	0
127	1	1	-1.929	0
125	1	1	-1.981	0
77	1	1	-1.983	0
104	1	1	-2.112	0
80	1	1	-2.247	0
52	1	1	-2.788	0
27	1	1	-3.081	0
45	1	1	-6.004	0

APPENDIX F ROC Curves of EN Logit and O-Model

<table>
<tr><th></th><th>EN LOGIT</th><th>O-MODEL</th></tr>
<tr><td colspan="3">Panel A: Cross Validation on Test Sample, Holdout Sample within Sample Period and Holdout Sample outside Sample Period</td></tr>
<tr><td>Test Sample</td><td>
</td><td>
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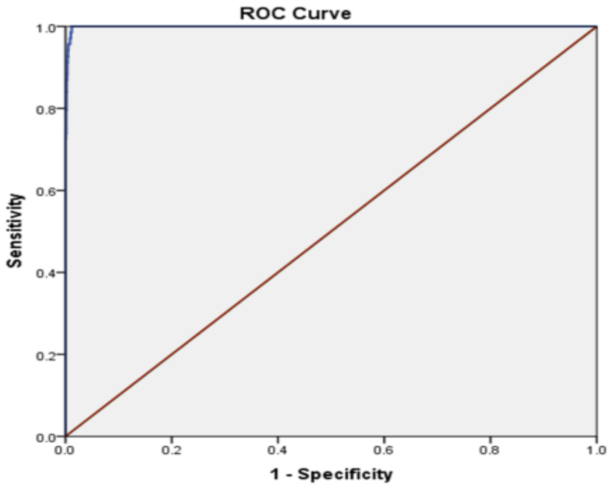
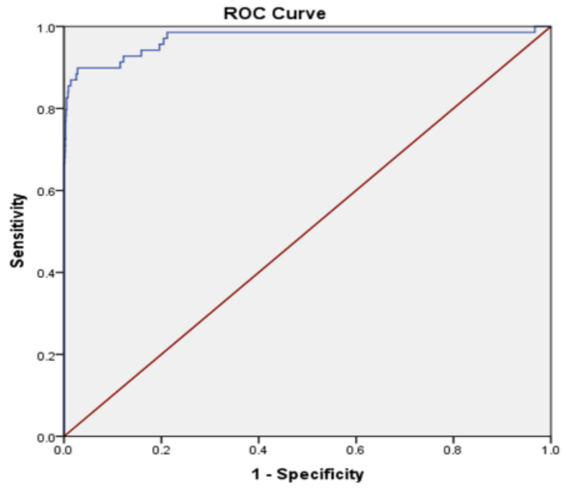
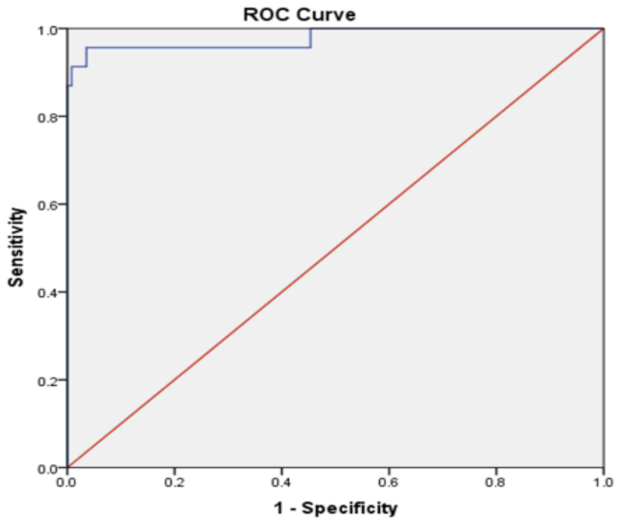
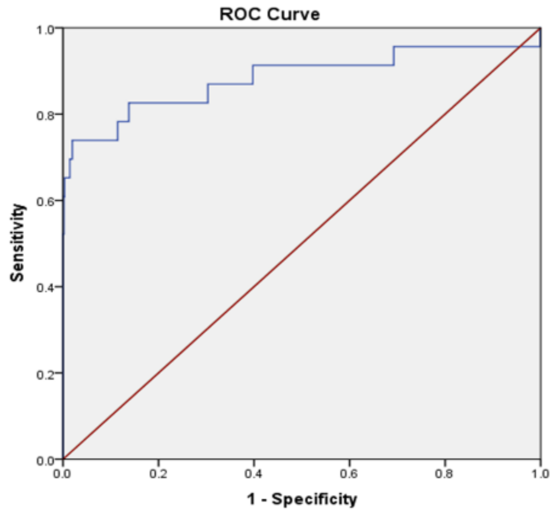
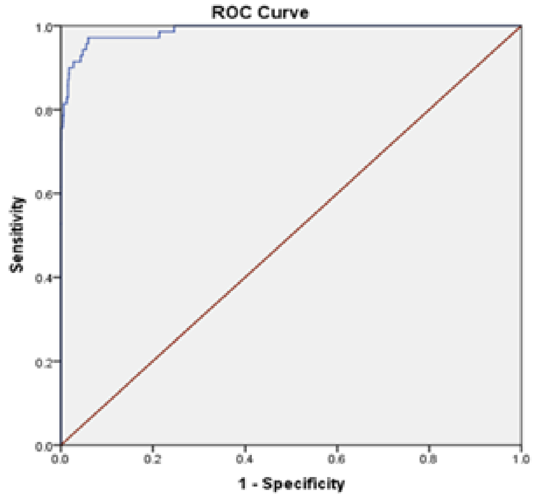
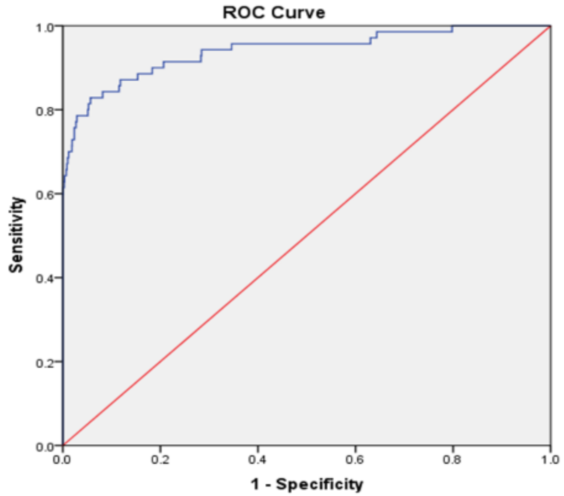
Holdout 1		
Holdout 2		

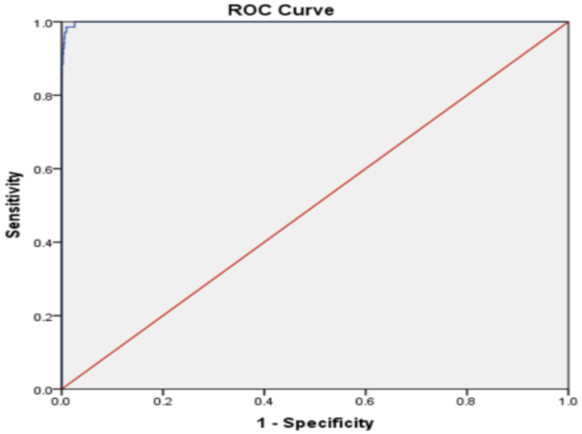
Panel B: Chronological Comparison of ROC Curves over Five Years Prior to Loan Default

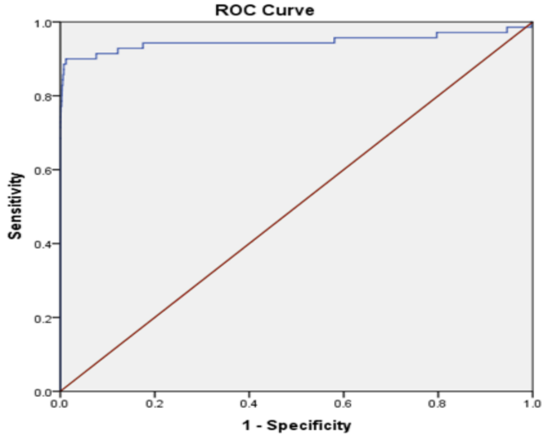
Year 1

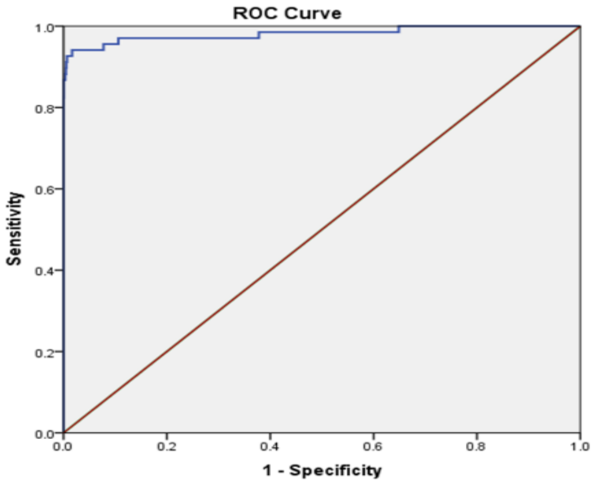
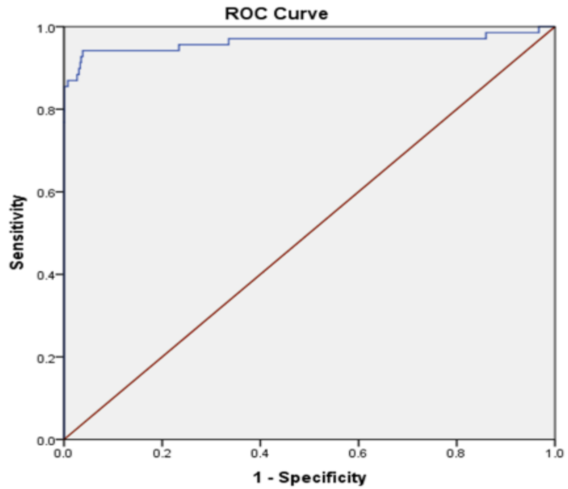
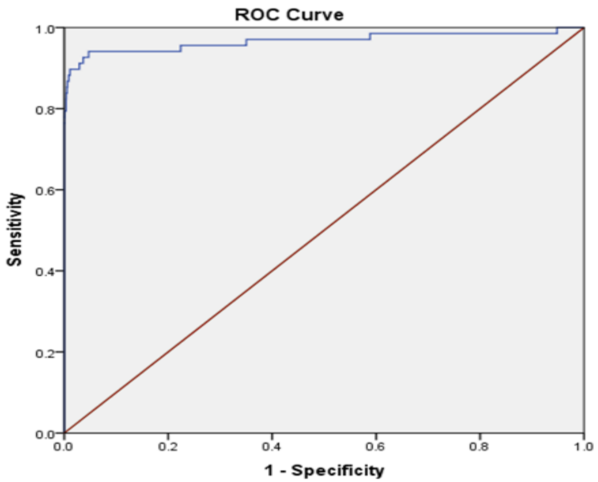
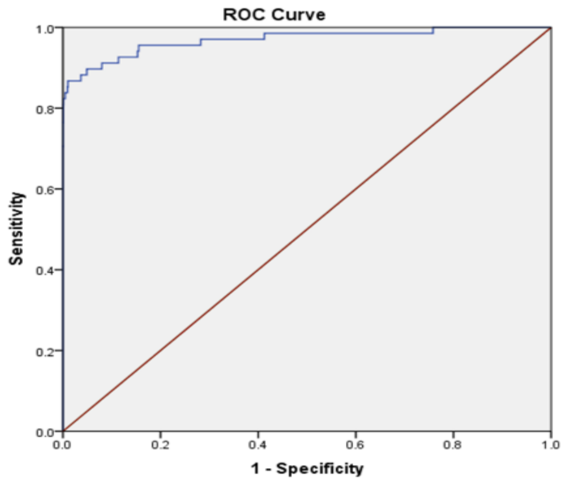




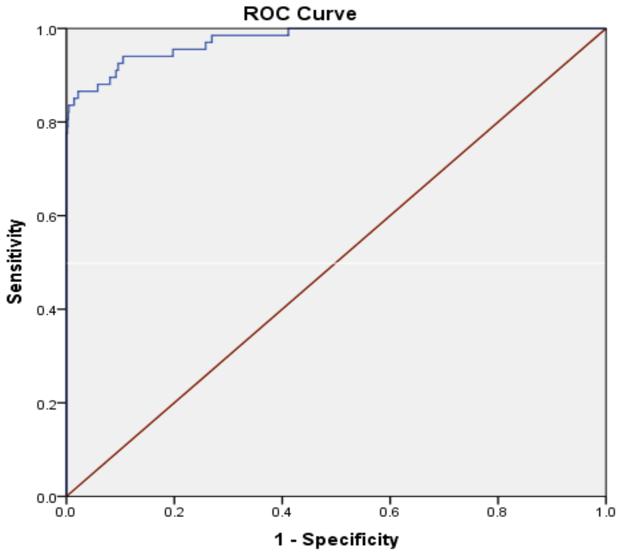
Year 2

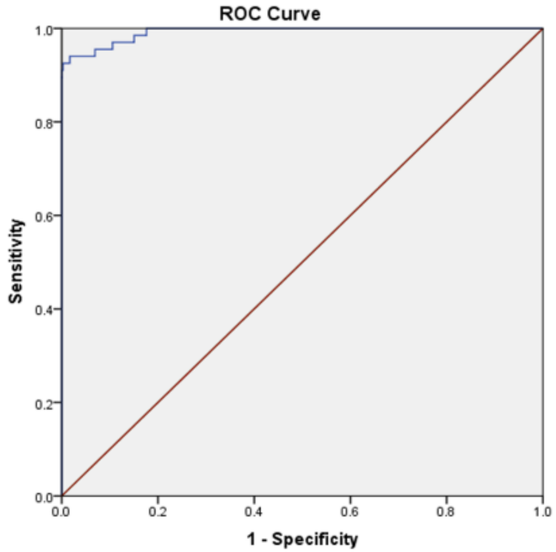




Year 3	ROC Curve
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0	ROC Curve
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0
Year 4	ROC Curve
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0	ROC Curve
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0

Year 5


ROC Curve
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0


ROC Curve
Sensitivity
1 - Specificity
0.0
0.2
0.4
0.6
0.8
1.0