SMEs Credit Risk Modelling for Internal Rating Based Approach in Banking Implementation of Basel II Requirement

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Declaration

This thesis is composed by me and that the work is my own. No part of it has been submitted to any other institution for another qualification.

Signature:

Date:

<u>Abstract of Thesis</u>

This thesis explores the modelling for Internal Rating Based (IRB) of Credit Risk for Small and Medium Enterprises (SMEs) as required for implementation of Basel II Accord. There has been limited previous research for this important sector of the economy. There are two major approaches: Accounting Based and Merton Type, and these are compared.

To make the comparison initially a small sample is considered and simulation is used to explore the use of the two approaches. The study indicates some of the limitation of analysis for both Accounting Based and Merton Type approaches, for example the issue of colinearity for the Accounting Based approach and lack of trading of SMEs' equity affecting the Merton Type approach. A large sample is then investigated using standard Credit Scoring approaches for the Accounting Based modelling. Different definitions of default and distress are considered to overcome the problem of low number of defaults. These approaches are found to be viable.

Merton Type model is then compared to benchmark models from the Accounting Based approach. The predictions are compared over differing time horizons. It is found that Merton Type models perform well within a limited period compared to the Accounting Base approach.

Overall, credit scoring models demonstrated better performance when the sample group included a considerable number of 'Bad' firms or cutoff point was selected so that an acceptance rate was relatively low, otherwise model's predictive accuracy would decline. Merton model presented better predictive accuracy with higher acceptance rates. Credit scoring models was able to give early signs of default year. In addition, one may take into consideration that if the company is going to decline credit quality or raise default probability this year, Merton type models can be helpful in adjusting credit rating. When considering a loan to a company, a bank wants to know the likelihood default for duration of loan. In this sense Merton models is only useful for a relatively short loan terms.

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Table of Contents

List of Tables and Figures

Tables

Figures

CHAPTER ONE

Introduction

1.1 Introduction

Over the last two decades, many large banks have developed advanced quantitative credit risk models for allocating economic capital, portfolio credit exposures evaluation, measuring risk-adjusted returns of the financial instruments and at individual credit level, and improving overall risk management.

Credit exposures of banks are typically spread across geographical locations and product lines. The use of credit risk models offers banks a framework for examining these risks in a timely manner, aggregating data on global exposures and analysing marginal and absolute contributions to risk. These properties of models contribute to an improvement in a bank's overall ability to measure and manage risk.

Credit risk models provide estimates of credit risk such as default probability which reflects credit grade of obligor and unexpected loss which reflects individual portfolio composition; hence, credit risk models provide a better reflection of concentration of risk and credit risk of portfolios. Consequently, modelling methodology presents the possibility of providing a more responsive and informative tool for risk management. In addition, models offer more accurate risk and performance based pricing, which contribute to a more transparent decision-making and consistent basis for economic capital allocation.

The advent of these new models and their incorporation into bank credit risk management were an important impetus for the effort to reform the Basel Committee's standards for regulatory capital Basel II BCBS (2006) and, in turn, the new Basel II Accord is encouraging banks to upgrade their credit risk management approaches. Under the Basel II Accord, banks with sufficiently sophisticated risk measurement and management systems can use their own internal rating-based (IRB) approach to estimate key risk parameters that determine regulatory capital minimums. Basel II framework was built on the basis of primarily industry practices developed for corporates, retail, large commercial credits and Small and Medium Sized Enterprises (SMEs). Credit risk assessment for financial institutions provided an appropriate incentive for improvements to risk management, supervision and disclosure.

A number of studies have focused on corporate credit risk models and the special characteristics of retail lending and the importance of relationship banking for solving information asymmetries. However, SMEs sectors remain more problematic area of credit risk modelling because this type of business falls between the stool of corporate and retail characteristics. SMEs firms are more informationally opaque because of the following problems: the lack of external or well-trusted ratings, the less of financial and operational transparency as well as the absence of reliable audited financial statements, the shortage of a credit or relationship history, and the lack of market values for collateral among others. In addition, SMEs attracted more attention from researchers, practitioners and regulators due to New Basel II (2006) special treatment of SMEs exposures as corporates or retail exposures for the purpose of capital requirement.

The dual nature of SMEs lending makes it possible to assess the credit risk using the approaches from both corporate and retail lending sectors. The corporate world relies mainly on structural market-based models for credit risk measurement, whilst retail lenders use empirical predictive models (credit scoring). To explore SMEs as retail or corporates credit exposures is justified depending on the ability of banks' internal risk rating systems to adequately capture the differences between characteristics of loans and various types of assets, and the methods used to calculate the relevant risk measure. Therefore banks will develop credit risk models to provide banking institutions with an ability to manage effectively their exposure to default risks.

1.2 Research Topic

Since their importance within Basel II there is a need to explore the appropriate credit risk models for SMEs. The main objective of this research is: SMEs Credit Risk Modelling for Internal Rating Based (IRB) Approach in Banking Implementation of Basel II Requirement.

The overall objective can be divided into three main research sections as:

1. Reviewing the framework of Basel Accord in relation to credit risk in banking and SMEs.
2. Developing possible approaches for SMEs credit risk modelling.
3. Validating models predictive accuracy.

1.3 Motive and Goal

The aim of the research is to produce practical recommendations for credit rating of SMEs. Under the New Basel II Accord SMEs may be included in corporates or retail exposures and this will have effects on the bank credit risk management. The research will be of interest to two groups: academics and practitioners. Academics will be interested in whether the Accord achieves its objective for implementing the global accord on risk assessment and bank capital standards. Practitioners will be concerned about the implementation and what models and data they require, but also they will be looking for commercial advantages.

The academic audience will require the approach taken to the research to be systematic, acknowledging previous work in the area and building on it. They will expect the work to be reflective in assessing the issues that arise in carrying out the research and the limitations of the conclusions achieved.

The practitioners will be looking more for the details of implementation, the models to be used, how they ought to be used and what benefits might accrue from their use.

For the research to be valid it is required to be based on sound mathematical models which are consistent with the data available for testing. Hence it is important to test and review carefully the assumptions that are made by the models and to explore them in the context of the empirical evidence. Considerable importance is attached therefore to the data that is used in the study. The data should confirm to a set of predetermined criteria. It should be timely and relevant, covering a sufficient time period and as far as possible lack any element of bias. For practitioners the results need to provide information in relation to SMEs IRB model on actions and strategies so they can apply to regulatory implementation.

1.4 Research Objectives and Questions

New Basel Accord treatment of SMEs credit exposures is viewed as especially important in countries where small and medium-size firms comprise a significant component of the industrial sector. SME borrowers are defined as those with less than €50 million in annual sales (OECD SMEs Outlook 2002; BCBS 2005; BCBS 2006; Beresford and Saunders 2005) . Such exposures are allowed to have up to 20% lower capital requirements than exposures to larger firms. Clearly it is possible to use standard corporate models such as those developed following Merton (1974), but there exists a number of issues relating to the adequacy of the data on which to build the models.

Credit scoring methods has been widely used in financial institutions for the internal processes of portfolio risk measurement and management. It indicates the probability of default of an applicant requesting credit or a borrower already in the portfolio. Credit scoring is also commonly used in UK consumer credit, including mortgage lending, personal loans, bank loans, debt to retailers, credit card debts.

Many different modelling techniques exist to determine credit risk, however, only a few attempts have been devoted to credit risk assessment of small business, although SMEs exposures are important for US, UK and European banks.

Berger and Frame (2005), for example, state that almost half of the U.S. private-sector employment and non-farm domestic product is accounted for by small businesses. Akhavein, Frame and White (2001) find that credit scoring has only recently been applied to small business lending in the U.S. by large banks. More on different lending strategies in relation to SMEs is given in Berger and Udell (2002).

The research focuses on SMEs credit risk modelling in UK industries as well as banking measures of credit risk in relation to Basel II. The research has two objectives:

1. To explore corporate models based on Merton approach and Accounting based credit scoring methods for assessment of SMEs credit risk. To examine which type of model is more appropriate for SMEs credit in banking.

2. To develop a possible modelling approach for SMEs and evaluate model predictive accuracy.

These objectives will be explored through a series of research questions:

1. If a bank holds large SMEs position which may be in part based on micro and small business lending what are the most appropriate credit models for bank to use under the New Basel II Accord?

2. The Merton based credit risk models are widely used for corporate credit risk where information is readily available. Can this type of model be appropriate in measuring SMEs credit risk where there is less information available?

3. Credit scoring methods are widely used in retail banking based on assessment of individuals. Can these methods be adapted to measure SMEs risk and how effectively?

4. How do these two approaches compare when applied to SMEs credit risk?

1.5 Research Design Strategy

The research will adopt the deductive research strategy as following:

1. The initial phase of the research is a literature review of the topic and related areas. Exploring the relevant literature provides some answers to the questions posed above. These models are currently used in corporate and retail banking credit, however, they could be applied to SMEs credit risk. There is also a need to explore whether they would be appropriate.

2. The focus is on SMEs since this is one of the most problematic areas. The major problems for SMEs is in a proportion of micro and small business, and private firms which may be the lack of publicly information and the lack of financial transparency, see Wagenvoort (2003). Models used traditionally have been corporate models but if these firms are not publicly quoted, applying a shareprice based model may not be feasible (Carling, Jacobson, Lindé and Roszbach 2007; Jarrow and Turnbull 2000). Alternatively one can use Credit Scoring which is appropriate for consumer credit and individual loans and so might be appropriate for SMEs.

3. The next stage is collection of relevant data**.** Adequate information is required on which to build models. This includes market price information such as shareprice, equity volatility, asset value and asset volatility related inputs in market-based models as well as a range of variables for credit scoring approaches.

4. The research uses the data collected to build Merton type models and Credit Scoring models and compares the two approaches. Analysis is performed and judgments are made about:
   (1) Applicability of the models to the context including the assumptions made.
   (2) Assessment of which model most accurately reflect credit behaviour of SMEs.

1.6 Research Design for Data Collection and Analysis

In order to be able to empirically test the research questions, it is necessary to collect appropriate data. This requires the ability to identify the types of organisation to be sampled, the data required from the sample and the period over which it should be sampled. The data is quantitative allowing the statistical / mathematical analysis used for both Merton-type models and credit scoring models.

For credit scoring methods, the data is collected from Datastream, Osiris, Thomson ONE banker that provide financial statements such as balance sheet, income statement, cash flow statement as well as company profile such as number of employees.

A large set of predictor variables is considered for credit scoring model building, and therefore, the most important variables in relation to SMEs performance and risk indicators are included.

For Merton model, it is necessary to collect shareprice of companies as well as capital structure of firms such as assets, outstanding common shares, current liability, and long-term debt for model inputs.

In addition, insolvent terms of firms and financial distress firms have to be included. The definition of default related to legal terms of insolvency such as administration, receivership, and liquidation have to be checked together with their exact date of becoming delisted as well as available financial information. The insolvent data may be identified from the UK Bankruptcy & Insolvency Website[1] and UK-Wire database[2].

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[1] The UK Bankruptcy & Insolvency Service operates under a statutory framework – mainly the Insolvency Acts 1986 and 2000, the Company Directors Disqualifications Act 1986 and the Employment Rights Act 1996. Website: http://www.insolvency.gov.uk/.

[2] UK-Wire provides Real-time UK Company Press Release service providing the latest regulatory announcements such as trading results and other press releases affecting a Company's financial position). http://moneyextra.uk-wire.com/

A common problem of default prediction consists in a small number of bankruptcies or real defaults available for model-building. This thesis adopts different definitions of default and investigates their impact on the choice of predictor variables and predictive accuracy. Given this consideration, the financial distressed firms with different level of distress are defined based on a theoretical base. Then, individual SMEs borrowers' financial ratios data and other characteristics are analysed to determine possible predictors to produce estimates of default probabilities.

1.7 Framework of Research Thesis

The following provides a brief description of the thesis structure:

Chapter One: Background of Thesis. This chapter provides an introduction of the thesis background. This includes: research motivation, research objectives, research questions, research scope, importance of Basel II related to research objectives, research design strategy and contributions of research.

Chapter Two: Framework of Basel Accord in relation to Credit Risk in Banking and SMEs. The theme of Basel Accord is explored in Chapter Two. Basel I Accord BCBS (1988) took a standardised approach to risk which resulted in an insufficiently differentiated risk estimates. The changes within the banking industry and the New Basel II Accord (2006) have created a greater need for credit risk models. Internal rating based approach (IRB) will then be described and the elements that require to be derived for each credit product under the New Accord. The different types of exposure, Corporate, Business including Small and Medium sized Enterprises (SMEs) and retail will be discussed. It will then proceed to explore the literature on approaches to assessing credit worthiness that may affect banking rating systems for capital requirement, in addition to the issues that may arise on SMEs assess to finance.

Chapter Three: Review of the Literature. This chapter reviews previous studies on statistical methods and credit risk portfolio models: The Accounting-based models that use financial information and accounting data by means of discriminant analysis, logistics models, hazard models, hybrid models and neural networks techniques are introduced. Moreover, Market-based models such as structural form and reduced form models are described. The goal is to illustrate the main reason behind the research motivation and questions as well as to introduce the key issues related to possible approaches for SMEs modelling and default prediction.

Chapter Four: SMEs Credit Risk Methodologies. The main feature of Chapter Four is to look at assessment methodology and make some observations on the results obtained from simulations. It explores the use of full and partial simulation methods to compare credit scoring and Merton type models. This allows for comparison of the information base for SMEs and assesses whether the two models are employing equivalent information. It lays down the foundation for further analysis on the extended data in later chapters.

Chapter Five: Extended Data Collection of SMEs. Data Collection addresses SMEs variable predictors selection which was extended from previous results in Chapter Four. The dataset consists of default, financially distressed and non-defaulting SMEs. Different default definitions, such as Insolvency terms in UK, Basel II reference definition of default events and different levels of financial distress are illustrated. Types of predictor variables and sample selection are described.

Chapter Six: Modelling SME Default over Different Definitions of Financial Distress. Possible modelling approaches such as the transformed variables methods i.e. coarse-classification, weight of evidence and dummy coding, which are standard in credit scoring are demonstrated for SMEs models-building. Different definitions of default based on varying levels of financial distress are proposed, and their effect on predictor variables entering the model and effect on model's predictive accuracy is investigated.

Chapter Seven: Evaluation of Merton Type and Credit Scoring Models. The main focus is on the performance assessment of the default prediction model i.e. Merton model and Credit Scoring approach for SMEs credit risk measurements. Cutoff points are used upon different levels of financial distress in analysis and the magnitude of the Type I and Type II error from models performance is evaluated. The predictive power of models is validated by using Receiver Operation Characteristics (ROC) plots and Area Under ROC (AUROC). In addition, models' predictive capability through 3 year horizon to predict default is examined and compared.

Chapter Eight: Conclusions and Discussions. The findings are summarised in Chapter Eight, which also outlines the limitations and suggests possible future directions for research in the SMEs credit risk modelling and default prediction domain. The further development of credit risk measurement explores such fields as internal rating models development, importance of models validation, cutoff ratio with cost-benefit lending and private firms credit risk models.

1.8 Contributions of Research

The contributions of research are**:**

This research focuses on two clearly delineated approaches: Merton type model and Credit Scoring methods. Both are to be applied to assessment of credit risk for small and medium enterprises (SMEs) in the context of Basel II Accord on risk-based capital requirements of banks.

The research provides, in particular for UK, insight into whether an approach for measuring the implicit credit risk for SME credits can be developed adequately for large banking organisations that are likely to adopt the Advanced Internal Ratings-Based (A-IRB) approach under New Basel II Accord. Hence it addresses a real problem for practitioners.

The research provides an overview of the methodologies involved in developing internal credit risk models for SMEs. Its primary objective is to illustrate how well various modelling for credit risk assessment might be adapted and/or constructed to overcome a number of common problems in assessing credit risk for SMEs. It also provides insight into the comparison of potential credit risk models for banks in the SME credit market. The results of the research may provide some guidance for banking organisations who may have concerns about relative comparative advantages in different types of SME loans.

The developments within the banking industry with the appearance of credit derivatives and the growth in the markets for loan sales and securitisation has required further modelling of credit risk. Along side this regulatory requirement for capital under the New Basel II Accord (BCBS 2006) has meant that there is a need for banks wishing to take full benefit will need to produce their own internal rating-based (IRB) credit risk models based on their trading book exposures**.** The model will also allow the banks to behave in a prudent and conservative fashion.

The New Accord also allows special treatment for retail credit and SMEs loans in recognition of the fact such that exposure derives to a greater extent from idiosyncratic risk and much less from common factor risk. Much of the work done on the differences between the risk properties of retail, SMEs and corporate credit has been based on parameterised model of credit risk.

Driven by Basel II, the research introduces a number of risk-rating models for the U.K. small businesses using an accounting-based approach, which uses a large set of financial ratios to distinguish between defaulting and non-defaulting firms and to predict corporate bankruptcy. It is considered through features typical to retail credit risk modelling to enhance these models performance. This research considers adopting different definitions of default and investigates their impact on the choice of predictor variables and model's predictive accuracy. In addition, the value of predictor variable transformation is examined such as coarse classification, weight of evidence (WOE) and dummy coding for improving models predictive accuracy.

Overall this research demonstrated that an accounting-based approach is a viable way for credit modelling of SMEs. It can be enhanced by certain contribution from modelling retail credit risk, thus leading to more accurate predictions and less capital reserves.

This research investigates the credit scoring approach and Merton type model for predicting the SMEs failure. In the context of SMEs models-building, it is imperative to validate the methodology for assigning credit assessments that is the ability to predict defaults and the accuracy of the default predictive measure. The research applies different cutoff points on the different level of financial distress using this to validate the models and examine the banks' different lending decisions i.e. different levels of acceptance. Furthermore, Merton type model and credit scoring models comparison within different time horizon provides the views on models applicability for early signalling of default.

Overall this research presents an approach used to validate and benchmark quantitative default risk models for SMEs obligors. It discusses performance when applied to different cutoff points of accounting based approach and Merton type models measurement as well as other practical considerations associated with performance evaluation for quantitative credit risk models. This framework specifically addresses issues of data sparseness such as default rate in relation to predictive accuracy of models as well as early signals for company's failure prediction across the time scale of 3 years.

CHAPTER TWO

Framework of Basel Accord in Relation to Credit Risk in Banking and SMEs

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2.1 Introduction

The most relevant change in the financial sector is the New Basel II Capital Accord (BCBS 2006). It signifies recent and impending transforms in the legal and economic framework of bank financing. This Accord is to replace the initial capital measurement system commonly known as the Basel Capital Accord (Basel I), which was introduced by the Basel Committee on Banking Supervision (BCBS).[1] Several different strands in the literature have recently emerged, focusing on the specific parts of the Accord (e.g. internal rating based (IRB) approach adopted for credit risk, operational risk and different Pillars), on the potential impact on banking systems, and on practical implementation issues.

Under Basel II, a small number of large U.S. banking organisations would be required to use the Foundation or Advanced Internal Ratings-Based (F-IRB or A-IRB) approach for credit risk measurement. In addition to these 'mandatory banks', it is expected that a relatively small number of mostly large U.S. banks are likely to adopt Basel II and use the A-IRB. The vast majority of other U.S. banks, however would continue to operate based on standardised approaches under the current Basel capital requirement, see Lang, Mester and Vermilyea (2006). In June 2004, the Basel committee agreed on updated rules of Basel II. Within EU it was decided to apply Basel II to every bank. In July 2004, the Commission set out proposals for a new Capital Requirements Directive (CRD) which would apply Basel II to all banks, credit institutions (CIs) and investment firms and which would allow to choose standardised, Foundation or Advanced IRB for credit risk measurement in the EU.

[1] Bank for International Settlements (BIS): The New Basel Capital Accord: an explanatory note, Basel (January 2001).

In fact, the standardised approach to credit risk in the Basel II (2005, 2006) is conceptually similar to the 1988 agreement (Basel I). It is necessary to address issues of important effect on banking regarding credit risk assessment and capital requirement, and therefore, the framework of first Basel I and New Basel II Accord have to be reviewed for understanding of the key components in measuring credit risk and discussion of relevant policy implications.

2.2 Background of Basel I

The Basel Committee on Banking Supervision, established in 1974 by the Central Bank Governors of the G-10 central banks and banking supervisory authorities (Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom, and the United States known as G-10, currently comprising 13 countries). The committee, which meets, and has its secretariat, at the Bank for International Settlements (BIS) in Basel, Switzerland, has no formal authority. This committee issued non-binding but authoritative recommendations on prudential supervision of banks. Agreements are developed by consensus, but decisions about which parts of the agreements to implement and how to implement them are left to each nation's regulatory authorities. Recommendations of Committee are usually translated into EU banking legislation, taking into account the specific nature of the EU banking sector (European Commission 2000).

Basel I (1988) was revolutionary in that it sought to develop a single capital requirement for credit risk assessment across the major banking countries of the world. Its main objectives were to promote the soundness and stability of the international banking system and to ensure a level playing field for internationally active banks. "This would be achieved by the imposition of minimum capital requirements for credit (including country transfer) risk, although individual supervisory authorities had discretion to build in other types of risk or apply stricter standard" (Basel I 1988). Even though it was originally intended solely for internationally active banks in G-10 countries, during the 1990s, the Capital Accord became an internationally accepted standard, being applied in most other countries, currently numbering over 100, have also adopted, at least in name, the principles prescribed under Basel I (Stephanou and Mendoza , 2005).

2.3 Capital Requirements in Practice: The 1988 Basel Accord

The key to the 1988 Basel Accord is the requirement for internationally active banks to continually meet two capital adequacy ratios, the so-called Tier 1 and Total capital (Tier 1 capital + Tier 2 capital) ratios. Both ratios have the same denominator, which is a risk-weighted sum of banks' on balance and off-balance sheet activities.

Tier 1 capital consists mainly of stockholder equity capital and disclosed reserves also called 'core capital' such as common stock and perpetual preferred stock. Tier 2 capital includes elements such as undisclosed reserves, preferred stock and subordinated term debt instruments provided that their original fixed term to maturity does exceed five years defined as 'supplementary capital'. The difference between Tier 1 and Tier 2 capital thus reflects the degree to which capital is explicit or permanent. Total capital is equal to Tier 1 plus Tier 2 capital.

A portfolio approach is taken to the measure of risk, with assets classified into four buckets (0%, 20%, 50% and 100%) according to the debtor category. This means that some assets (essentially bank holdings of government assets such as Treasury Bills and bonds) have no capital requirement, while claims on banks have a 20% weight, which translates into a capital charge of 1.6% of the value of the claim. Virtually all claims, however, on the non-bank private sector receive the standard 8% capital requirement.

A simplified formula of the risk-weighted assets (RWA) of a bank is given by:

$$RWA = 0 \times (Bucket1) + 0.2 \times (Bucket2) + 0.5 \times (Bucket3) + 1.0 \times (Bucket4) \qquad (2.3.1)$$

Each bucket reveals different risk weight, where:

Bucket1: consists of assets with zero default (e.g. Cash, OECD Government/ Securities which includes the U.S.)

Bucket2: assets with a low rate of default (e.g. claims on banks incorporated in OECD countries)

Bucket3: medium-risk assets (essentially residential mortgage claims)

Bucket4: remaining assets (in particular loans to non-banks e.g. consumers and corporations).

Thus, the denominator of both capital adequacy ratios represents the accounting value of banks' assets adjusted for their individual risk.

It is notably that formula (2.3.1) is only valid for on-balance sheet assets. There is also a scale of charges for off-balance sheet exposures through guarantees, commitments, forward claims, etc. This is the only complex section of the 1988 Accord and requires a two-step approach whereby banks convert their off-balance sheet positions into a credit equivalent amount through a scale of conversion factors, which then are weighted according to the counterparty's risk weighting. Its detail interpretation is discussed by Dewatripont and Tirole (1994) for the precise regulatory definition of Risk Weight Asset (RWA) under first Basel I (1988).

The 1988 Accord has been supplemented a number of times, with most changes dealing with the treatment of off-balance sheet activities. A significant amendment was enacted in 1996, when the Committee introduced a measure whereby trading positions in bonds, equities, foreign exchange and commodities were removed from the credit risk framework and given explicit capital charges related to the bank's open position in each instrument.

According to the guidelines, the banks will have to identify their Tier 1 and Tier 2 capital and assign risk weights to the assets. The 1988 capital adequacy framework requires banks to have a Tier 1 ratio of at least 4% and a total capital ratio of at least 8% with the contribution of Tier 2 capital to total capital not exceeding 50%, i.e., the following inequalities must hold:

$$Tier\ 1\ ratio = \frac{Tier1 \quad Captial}{RWA} \quad \geq 4\% \qquad (2.3.2)$$

$$Total\ Capital\ ratio = \frac{Total \quad Capital}{RWA}$$

$$= \frac{(Tier1 \quad Capital + Tier2 \quad Captial)}{RWA} \quad \geq \ 8\% \qquad (2.3.3)$$

$$Tier\ 1\ Capital \ \geq \ Tier\ 2\ Capital \qquad (2.3.4)$$

The regulation also limits general loan-loss reserves and subordinated debt which are eligible for inclusion in Tier 2 capital. It can be seen from Table 2.3.1 below presenting the framework of Basel I transitional and implementing arrangements in 1990 to 1992. The implementation of the Basel I guidelines in G-10 countries occurred in two steps. Interim standards of 7.25% for the total capital ratio and 3.25% for the Tier 1 ratio had to be met by the end of 1990, whereas full compliance with the definitive standards was expected by year-end 1992.

Table 2.3.1 The 1988 Basel Accord (transitional and implementing arrangements)

	Arrangements	**End-1990**	**End-1992**
1.	Total capital ratio	7.25%	8%
2.	Tier 1 ratio	3.25%	4%
3.	Limit on general provision (or general loan loss reveres) in Tier 2 capital	Maximum 1.5% or, exceptionally, up to 2% of Tier 2 capital	Maximum 1.5% or, exceptionally and temporarily, up to 2% of Tier 2 capital
4	Limit on term subordinated debt in Tier 2 capital	No limit (at discretion)	Maximum 50% of Tier 1 capital
5.	Deduction for goodwill	Deducted from Tier 1 capital (at discretion)	Deducted from Tier 1 capital

Note: 1. In the event that no agreement was reached on the definition of unencumbered resources eligible for inclusion in Tier 2 capital
2. Source: Basel Committee on Banking Supervision (1988)

For reaching minimum capital requirement or for other non-regulatory reasons, it allows bank to use three type of adjustment in balance sheet that is (a) increasing from capital level (b) decreasing in risk-weighted assets or (c) sell of their assets. The way of adjustment can be viewed from equation (2.3.5) decomposed so that the growth rate of the capital requirement ratio of bank *i* formed into three terms of the growth rate of capital *(K),* the growth rate of the credit risk ratio *(RISK)* and the growth rate of total assets *(A)*

$$\frac{\Delta CAR_{i,t}}{CAR_{i,t}} = \frac{\Delta K_{i,t}}{K_{i,t}} - \frac{\Delta RISK_{i,t}}{RISK_{i,t}} - \frac{\Delta A_{i,t}}{A_{i,t}} \qquad (2.3.5)$$

where $CAR = K / RWA$ = capital adequacy ratio (Tier 1 ratio or total capital ratio)
K = capital (Tier 1 capital or total capital);
$RISK = RWA / A$ = credit risk ratios;
A = total assets;
t = time.

2.4 Basel I Discussion

The fact is that a major focus of Basel I was to distinguish the lower risk weights on credit risk of sovereign, bank, and mortgage obligations from the highest risk weights on nonbank private sector or commercial loan obligations. There was little or no attempt to differentiate the credit risk exposure within the commercial loan classification. All commercial loans implicitly required an 8 % total capital requirement (Tier 1 plus Tier 2) as noted by Saunders and Allen (2002) who point out that Basel I (1998) regulatory capital was regardless of the inherent creditworthiness of the borrower, its external credit rating, the collateral offered, or the covenants extended. Early discussion by the international Swaps and Derivatives Association (ISDA, 2000) comments on Basel Accord (1998) capital regime had serious weaknesses. Its major flaw was absence of an appropriate link between regulatory bucketing system and true credit risk. ISDA suggests Basel Accord to propose the new standards for credit risk, which go beyond the current Basle I approach to allow greater differentiation of risk weightings through the use of credit ratings and to permit the use of internal credit assessments for unrated entities. Jones (2000) provides a discussion of regulatory capital arbitrage activities and points out that the capital requirement was set too low for high risk business loans and too high for low risk loans, therefore the mispricing of commercial lending risk created an incentive for banks to shift portfolios toward loans that were more underpriced from a regulatory risk capital perspective, thus the Basel I had the unintended consequence of long-term deterioration in overall credit quality of bank portfolios.

An indication of Basel I mispricing of credit risk for commercial loans is obtained from Flood (2001) who examines the distribution in charge-off and delinquency rates for loans held by U.S. banks and thrifts institution from 1984 to 1999. The results show that collateralised loans generally pose the smallest credit risk and commercial loans in particular appear to be under-burdened by the Basel weights, while mortgages are relatively overburdened. He points out that the Basel risk weights do not accurately track the historical credit experience of U.S. loan portfolios, suggesting that some loans may be relatively overburdened by the current standards.

Although the Basel I framework helped to promote the soundness and stability of the international banking system, the shortcomings of Basel I meant that regulatory capital ratios were increasingly becoming less meaningful as measures of true capital adequacy, particularly for larger, more complex institutions. In addition, various types of products (e.g. derivatives, balance sheet securitisations) were developed primarily as a form of regulatory capital arbitrage to overcome those rules. It is notable that Basel I suffered from several problems that became increasingly evident over time.

There are the major problems of Basel I:[2]

(1) For individual loans assigned risk weights generally lacked sufficient risk differentiation (Saunders and Allen 2002), for example, “the capital charge for all corporate exposures was the same irrespective of the borrower’s actual rating. This implied that banks with the same capital adequacy ratio (CAR) could have very different risk profiles and degrees of risk exposure” (Saunders and Allen 2002; Stephanou and Mendoza 2005).

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[2] World Bank Policy Research Working Paper 3556, April 2005

(2) "*Building Buckets* approach, there was no distinction in capital treatment between a well-diversified and therefore less risky loan portfolio from one that is very concentrated exposures and hence riskier in capital structures" (Stephanou and Mendoza 2005).
(3) "Capital treatment for sovereign exposures created perverse incentives which led to the mispricing of risks. For example, lending to OECD governments became more attractive because it incurred no regulatory capital charge (i.e. *Bucket 1*), even though this group included developing countries e.g. Turkey, Mexico and South Korea are member countries of OECD, however, they are obviously different countries risk rating." "It led to claim the national central government also enjoyed a zero risk weight, encouraging many banks (particularly in developing countries) to ignore basic diversification principles and lend heavily to their sovereigns (directly or through state-owned enterprises), thereby reducing financial intermediation" (Stephanou and Mendoza 2005).
(4) The lack of emphasis on other risk types (e.g. interest rate, operational, business) , and it may not reflect on the increased competitiveness of credit markets, particularly in the high default risk categories, and the trading of credit risk through credit derivative, collateralised loan obligations (Saunders and Allen 2002).

The proposed goal of the new Basel Capital Accord is to correct the mispricing inherent in Basel I and incorporate more risk-sensitive credit exposure measure into bank capital requirement. Also New Accord provides three different approaches that can be used to obtain a risk weighting of assets. The intention is that this will provide improved assessments of risk and make the resulting capital ratios more meaningful.

2.5 Framework of New Basel II Capital Accord

Since January 2001, the New Basel Capital Accord (Basel II) that should replace the 1988 Capital Accord has been discussed extensively and the New Accord Consultative Paper 3 ("CP3") published by the Basel Committee in April 2003 (BCBS 2003). A more differentiated assessment of banks' risk exposures and the provision of incentives to banks to improve their risk measurement and management capabilities are the key objectives of the new proposal. With regard to the level of overall capital, the Basel Committee has explicitly declared that in the standardised approach minimum capital requirements have to bring about a level of capital that is on average equal to the current requirement (8%), while banks applying the more advanced approaches should receive on average a small capital incentive.

The Basel Committee members agreed in mid-2004 on a revised capital adequacy framework (Basel II)[3]. The framework is to be implemented in most G-10 countries as of year-end 2006, although its most advanced approach will require one further parallel running and will be available for implementation in the year-end 2007. For bank adopting the Internal Ratings-Based (IRB) approach for credit or the Advance Measurement Approach (AMA) for operational risk, there will be a capital floor following implementation of the framework as an interim prudential arrangement.

The new framework of Basel II (BCBS 2005, 2006) is intended to align regulatory capital requirements more closely with underlying risks, and to provide banks and their supervisors with several options for the assessment of capital adequacy. The proposal is based on three mutually reinforcing pillars that allow banks and supervisors to evaluate properly the various risks that banks face. The New Basel Capital Accord focuses on:

− Minimum capital requirements which seek to refine the measurement framework set out in the 1988 Accord that will be required to cover credit, market and operational risk.
− Supervisory review of an institution's capital adequacy and internal assessment process and evaluation of an institution's overall risk profile, to ensure that it holds adequate capital.
− Market discipline through effective disclosure to encourage safe and sound banking practices.

[3] See Basel Committee on Banking Supervision (June, 2004)

The BCBS revised Framework is intended to promote the adoption of stronger risk management practices by the banking industry, and this is viewed as one of its major benefits. The concept and rationale of the three pillars (minimum capital requirements, supervisory review, and market discipline) approach forms the basis of the revised Framework. More generally, there have been expressed supports for improving capital regulation to take into account changes in banking and risk management practices while at the same time preserving the benefits of a framework that can be applied as uniformly as possible at the national level.

2.5.1 The First Pillar – Minimum Capital Requirements

As regards Pillar 1 of Basel II (2006), the purpose of creating a more risk-sensitive framework is pursued through a range of options for addressing credit risk, including:

"(a) a standardised approach, under which risk weights are based on the evaluation of credit quality by external credit assessment institutions (rating agencies and other institutions authorised according to a set of specified criteria);

(b) a foundation internal ratings-based (IRB) approach, based on both banks' internal assessments of risk components and supervisory parameters; and

(c) an advanced IRB approach, in which all risk components are estimated internally by banks."

2.5.2 The Second Pillar – Supervisory Review Process

This section discusses the key principles of supervisory review, risk management guidance and supervisory transparency and accountability produced by the Committee with respect to banking risks, including guidance relating to, among other things, the treatment of interest rate risk in the banking book, credit risk (stress testing, definition of default, residual risk, and credit concentration risk), operational risk, enhanced cross-border communication and cooperation, and securitisation.

There are four key principles of supervisory review[4] in "(1)[5] banks should have a process for assessing their overall capital adequacy in relation to their risk profile and a strategy for maintaining their capital levels; (2)[6] supervisors should review and evaluate banks' internal capital adequacy assessments and strategies, as well as their ability to monitor and ensure their compliance with regulatory capital ratios. Supervisors should take appropriate supervisory action if they are not satisfied with the result of this process; (3)[7] supervisors should expect banks to operate above the minimum regulatory capital ratios and should have the ability to require banks to hold capital in excess of the minimum; (4)[8] supervisors should seek to intervene at an early stage to prevent capital from falling below the minimum levels required to support the risk characteristics of a particular bank and should require rapid remedial action if capital is not maintained or restored."

2.5.3 The Third Pillar – Market Discipline

The regulators included market discipline as the third pillar of the proposed rule on the theory that, if banks are required to publicly disclose substantial information regarding their risk management processes, then the potential effect of such disclosures on the market for their securities would encourage them to have well developed risk management processes. In adopting the proposed rule, the regulators brushed aside complaints that such disclosure would be too burdensome, not comparable across banks, and likely to be misinterpreted by the public. The Basel II approach is akin to that suggested by Turnbull Report (1999)[9] on Risk Management. Disclosure requirement are either general or specific (i.e. depending on the selected

[4] The discussion on the principles for supervisory review excerpts from Paragraphs 725 to 760 in June 2006 update of Basel II (BCBS 2006).
[5] BCBS (2006) paragraph 725.
[6] BCBS (2006) paragraph 745.
[7] BCBS (2006) paragraph 756.
[8] BCBS (2006) paragraph 758.
[9] The Institute of Chartered Accountants in England & Wales (www.iacew.co.uk) has published the final guidance on the implementation of the internal control requirements of the Combined Code on Corporate Governance. The guidance *Internal Control: Guidance for Directors on the Combined Code is* also called The Turnbull Report. First issue was in 1999. For the Revised Turnbull guidance (October 2005).
TurnbullReport (2005), The Turnbull Report, Revised version: The guidance internal control: Guidance for directors on the combined code., visit http://www.frc.org.uk/corporate/internalcontrol.cfm.

approach), and include information on the scope of application, capital structure and adequacy, risk exposure and assessment by risk type. Some other requirements also represent qualifying criteria for the use of particular methodologies or the recognition of particular instruments or transactions in the calculation of regulatory capital.

2.6 Basel II Capital Adequacy

Basel II reflects improvements in banks' risk management practices, for example by the introduction of the internal ratings based approach (IRB). The IRB approach allows banks to rely to a certain extent on their own estimates of credit risk. One of the key changes in Basel II is the addition of an operational risk measurement to the calculation of minimum capital requirements. The Basel II (2006) comprehensive version of proposal states that overall capital adequacy will be measured as:

Regulatory total capital = (1) Credit risk capital requirement + (2) Market risk capital requirement + (3) Operational risk capital requirement.

(1) The credit risk capital requirement depends upon the bank's choice of either the standardised approach or an internal ratings-based one that can be Foundation Internal Based (F-IRB) or Advance Internal Based (A-IRB).
(2) The market risk capital requirement depends on the bank's choice of either standardised approach or internal model such as CreditMetrics, historical simulation, or Monte Carlo simulation. This capital requirement was introduced in 1996 in the European Union and in 1998 in the United States.
(3) The operational risk requirement is a new proposal in Basel II and relies on the bank's choice among a basic indicator approach, a standardised approach, and an advanced measurement approach (AMA). The proposed new operational risk requirement aims to separate out operational risk from credit risk

Market risk is defined as the risk of losses in on and off-balance-sheet positions arising from movements in market prices.[10] "The risks subject to this requirement are: (1) The risks pertaining to interest rate related instruments and equities in the trading book; (2) Foreign exchange risk and commodities risk throughout the bank."

[10] The framework of market risk models in BCBS (2006) are discussed from Paragraphs 683 to 687.

The extent to which a market risk exposure can be marked-to-market daily by reference to an active, liquid two-way market depends for exposures that are marked-to-model, on the extent to which the bank can: “(i) Identify the material risks of the exposure; (ii) Hedge the material risks of the exposure and the extent to which hedging instruments would have an active, liquid two-way market; (iii) Derive reliable estimates for the key assumptions and parameters used in the model”.

As for the operational risk new proposal by the Committee, it is concerned with recognition that developing banking practices and the growing sophistication of financial technology meant that banks were facing new and more complex risks other than credit and market risk. For example, the greater use of more highly automated technology and a greater reliance on globally integrated systems transforms risks from manual processing errors to system failure. Basel II defines an operational risk as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, such as exposure to fines, penalties and private settlements. It does not, however, include strategic or reputational risk. It also introduces the Advanced Measurement Approach (AMA) which allows banks to include their operational risks in assessing capital adequacy.

The Committee listed a number of operational risk events which were identified as having the potential to result in substantial losses, see BCBS (2003):[11]

“(i) Internal fraud: for example, intentional misreporting of positions, employee theft, and insider trading on an employee’s own account.

(ii) External fraud: for example, robbery, forgery, cheque kiting, and damage from computer hacking.

(iii) Employment practices and workplace safety: for example, workers compensation claims, violation of employee health and safety rules, organised labour activities and discrimination claims.

(iv) Clients, products and business practices: for example, misuse of confidential customer information, improper trading activities on the bank’s account, money laundering, and sale of unauthorised products.

[11] BCBS (2003) Sound Practices for the Management and Supervision of Operational Risk

(v) Business disruption and system failures: for example, hardware and software failures, telecommunication problems, and power failures.

(vi) Execution, delivery and process management: for example, data entry errors, incomplete legal documentation and unapproved access given to client.

(vii) Damage to physical assets: for example, terrorism, vandalism, earthquakes, fires and floods."

2.7 Internal Rating-Based (IRB) Approach for Credit Risk

For banks using the IRB approach for credit risk, there will be a capital floor derived by applying an adjustment factor to the following amount: "(i) 8% of the risk-weighted assets, (ii) plus Tier 1 and Tier 2 deductions, and (iii) less the amount of general provisions that may be recognised in Tier 2".[12]

"The adjustment factor for banks using the foundation IRB approach for the year beginning year-end 2006 is 95%. The adjustment factor for banks using (i) either the foundation and/or advanced IRB approaches, and/or (ii) the AMA for the year beginning year-end 2007 is 90%, and for the year beginning year-end 2008 is 80%" (BCBS 2006). The following Table 2.7.1 illustrates the application of the adjustment factors.[13]

Table 2.7.1 Application of the IRB and AMA approach adjustment factors.

	From year-end 2005	**From year-end 2006**	**From year-end 2007**	**From year-end 2008**
Foundation IRB approach[14]	Parallel Calculation	95%	90%	80%
Advanced approaches for credit and/or operational risk	Parallel calculation or impact studies	Parallel calculation	90%	80%

Source: BSBC (2006) paragraph 46.

[12] For banks using the IRB approach for credit risk or the Advanced Measurement Approaches (AMA) for operational risk, there will be a capital floor following implementation of this Framework. Refer to BCBS (2006) paragraphs 45 and 46.

[13] Additional transitional arrangements including parallel calculation are set out in BCBS (2006) paragraphs 263 to 269.

[14] The foundation IRB approach includes the IRB approach to retail.

The Basel Committee Banking Supervision (BCBS) intended the Framework set out here to be available for implementation as of year-end 2006. However, the Committee felt that one further year of impact studies or parallel calculations would be needed for the most advanced approaches, and these therefore would be available for implementation as of year-end 2007. A new EU system has been put in place under a revised EU Directive on Capital Requirements. Also proposals of the Commission have been presented in early 2004. This Directive was implemented in the Member States by the end of 2006 (in parallel with Basel II) and advanced IRB approach would be implemented by the end of 2007.

2.8 Basel II Credit Risk Components

In this section the main elements required for assessing the credit risk will be described. Credit risk can be defined as the risk of loss arising from the failure of counterparty to make a contractual payment. In terms of the New Basel II Accord (2006) describing the framework of IRB approach to credit risk implementation is a more sophisticated methodology, since it is primarily based upon the credit risk building blocks. Banks that have received supervisory approval to use the IRB approach may rely on their own internal estimates of risk components in determining the capital requirement for a given exposure.[15]

The risk components include measures of the probability of default (PD), loss given default (LGD), the exposure at default (EAD), and effective maturity (M). In some cases, banks may be required to use a supervisory value as opposed to an internal estimate for one or more of the risk components.

2.8.1 Probability of Default (PD)

The probability of default (PD), measures the likelihood that the borrower will default over a given time horizon. All banks whether using the foundation or the advanced methodology have to provide an internal estimate of the PD associated with the borrowers in each borrower grade. Each estimate of PD has to represent a

[15] Refer to BCBS (2006) paragraph 211.

conservative view of a long-run average PD for the grade in question and has to be grounded in historical experience and empirical evidence. The preparation of the estimates, the risk management processes, and the rating assignments that lay behind them have to reflect full compliance with supervisory minimum requirements to qualify for the IRB recognition. For corporate and bank exposure, Basel II defines PD as the greater of a one-year PD estimate or 0.03%[16]. One-year PD must be estimated using at least 5 years of data.

2.8.2 Loss Given Default (LGD)

The loss-given-default (LGD) which measures the proportion of the exposure that will be lost if default occurs; while the PD which is associated with a given borrower, does not depend on the features of the specific transaction, LGD is facility-specific. Basel II requires LGD be measured as a percentage of the EAD, with the following minimum requirements for LGD under the AIRB: “A bank must estimate an LGD for each facility that aims to reflect economic downturn conditions where necessary to capture the relevant risks. This LGD cannot be less than the long-run default-weighted average loss rate given default calculated based on the average economic loss of all observed defaults within the data source for that type of facility.”[17]

The LGD value can be determined in two ways: In the first way, respectively under the foundation methodology, LGD is estimated through the application of standard supervisory rules. In the second way, under the advance methodology, the bank itself determines appropriate LGD to be applied each exposure, on the basis of robust data and analysis which is capable of being validated both internally and by supervisors. Thus a bank using internal LGD estimates for capital purpose might be able to differentiate LGD value on the basis of a wider set of borrower characteristics.

[16] BCBS (2006) paragraph 285.
[17] BCBS (2006) paragraph 468.

2.8.3 Exposure at Default (EAD)

The exposure at default which includes the on-balance sheet exposure and an estimate of the off-balance sheet one (as an example, for loan commitments the purpose is to measure the amount of the facility that is likely to be drawn if a default occurs). As with LGD, EAD is also facility specific. Under Basel II IRB guidelines, EAD and LGD are inter-related; LGD is measured as a percentage loss relative to EAD. "EAD for an on-balance sheet or off-balance sheet item is defined as the expected gross exposure of the facility upon default of the obligor. For on-balance sheet items, banks must estimate EAD at no less than the current drawn amount, subject to recognising the effects of on-balance sheet netting as specified in the foundation approach."[18]

2.8.4 Maturity (M)

The maturity (M) is defined as "the greater of 1 year and the remaining effective maturity in years"[19] The maturity (M) of the exposure, which measures the remaining economic maturity of the asset where maturity is treated as an explicit risk component, like in the advanced approach, banks are expected to provide supervisors with the effective maturity of their exposures.

2.9 Credit Risk Exposures

Under the IRB approach, banks must categorise banking-book exposures into broad classes of assets with different underlying risk characteristics, subject to the definitions set out below. The classes of assets are (a) corporate, (b) sovereign, (c) bank, (d) retail, and (e) equity. Within the corporate asset class, five sub-classes of specialised lending are separately identified.[20] Within the retail asset class, three sub-classes are separately identified. Within the corporate and retail asset classes, a distinct treatment for purchased receivables may also apply provided certain

[18] BCBS (2006) paragraph 474.
[19] BCBS (2006) paragraph 320.
[20] Refer to BCBS (2006) paragraph 215.

conditions are met. Banks are required to apply the appropriate treatment to each exposure for the purposes of deriving their minimum capital requirement. Furthermore, banks will be permitted to distinguish separately exposures to small and medium sized enterprises (SMEs) for which Basel II offers a special treatment as corporate or retail entities. For the purpose of research on SMEs credit risk measurement, therefore, it is necessary to interpret and compare the differences between categorised exposures of corporate, retail and SMEs as described following sub-section under Basel II (2006) definition.

2.9.1 Definition of Corporate Exposures

In general, a corporate exposure is defined as a debt obligation of a corporation, partnership, or proprietorship. Within the corporate asset class, five sub-classes of specialised lending (SL) are identified. Such lending possesses all the following characteristics, either in legal form or economic substance:

"(i) The exposure is typically to an entity (often a special purpose entity (SPE)) which was created specifically to finance and/or operate physical assets;

(ii) The borrowing entity has little or no other material assets or activities, and therefore little or no independent capacity to repay the obligation, apart from the income that it receives from the asset(s) being financed;

(iii) The terms of the obligation give the lender a substantial degree of control over he asset(s) and the income that it generates; and

(iv) As a result of the preceding factors, the primary source of repayment of the obligation is the income generated by the asset(s), rather than the independent capacity of a broader commercial enterprise."[21]

Furthermore, banks are permitted to distinguish separately exposures to small- and medium-sized entities (SMEs), as defined in corporate exposures with annual sales of less than 50 Million Euros, banks will permitted to make use of a firm size adjustment to the corporate IRB risk weight.[22]

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[21] BCBS (2006) paragraph 218 and 219 defined corporate exposure.

[22] Banks are permitted to distinguish separately exposures to small- and medium-sized entities (SME), as defined in BCBS (2006) paragraph 273.

2.9.2 Definition of Retail Exposures

Under New Basel II Accord (2006) an exposure is categorised as a retail exposure if it meets all of the following criteria: (1) nature of borrower or low value of individual exposures (2) large number of exposures (3) revolving retail exposures.[23]

2.9.2.1 Nature of borrower or low value of individual exposures

"(i) Exposures to individuals: such as revolving credits and lines of credit (e.g. credit cards, overdrafts, and retail facilities secured by financial instruments) as well as personal term loans and leases (e.g. instalment loans, auto loans and leases, student and educational loans, personal finance, and other exposures with similar characteristics).

(ii) Residential mortgage loans (including first and subsequent liens, term loans and revolving home equity lines of credit) are eligible for retail treatment regardless of exposure size so long as the credit is extended to an individual that is an owner occupier of the property (with the understanding that supervisors exercise reasonable flexibility regarding buildings containing only a few rental units — otherwise they are treated as corporate).

(iii) Loans extended to small businesses and managed as retail exposures are eligible for retail treatment provided the total exposure of the banking group to a small business borrower (on a consolidated basis where applicable) is less than €1 million. Small business loans extended through or guaranteed by an individual are subject to the same exposure threshold."

2.9.2.2. Large number of exposures

"The exposure must be one of a large pool of exposures, which are managed by the bank on a pooled basis. Supervisors may choose to set a minimum number of exposures within a pool for exposures in that pool to be treated as retail." Small and

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[23] Retail exposure categorised in BCBS (2006) paragraphs 231 and 232.

Medium Sized enterprises may be treated as retail exposure while "small business exposures below 1 Million Euros may be treated as retail exposures if the bank treats such exposures in its internal risk management systems consistently over time and in the same manner as other retail exposures. This requires that such an exposure be originated in a similar manner to other retail exposures."[24]

2.9.2.3 Definition of qualifying revolving retail exposures

"A sub-portfolio to be treated as a qualifying revolving retail exposure (QRRE) which criteria must be applied at a sub-portfolio level consistent with the bank's segmentation of its retail activities."[25] In general, the exposures are revolving, unsecured, and uncommitted; the exposures are to individuals; the maximum exposure to a single individual in the sub-portfolio is €100,000 or less; and the asset correlation assumptions for the QRRE risk-weight function are markedly below those for the other retail risk-weight function at low PD values, therefore, banks must demonstrate that the use of the QRRE risk-weight function is constrained to portfolios that have exhibited low volatility of loss rates, relative to their average level of loss rates, especially within the low PD bands.

2.10 Basel II Treatment of SMEs Exposures

This section summarises changes in the final version (Basel II 2006) with respect to the effect on capital requirements for small and medium sized enterprises (SMEs). Generally, SME borrowers are defined as companies with less than 50 Million Euros in annual sales. In recognition of the different risks associated with SME borrowers, under the IRB approach for corporate credits, banks will now be permitted to separately distinguish loans to SME borrowers from those to larger firms. Banks that manage small-business-related exposures in a manner similar to retail exposures will be permitted to apply the less capital requiring retail IRB treatment to such exposures, provided that the total exposure of a bank to an individual SME is less than 1 Million Euros. Such exposures are then treated the same way as credits to private customers.

[24] BCBS (2006) paragraph 232 defined small business exposure.
[25] Definition of qualifying revolving retail exposures refer to BCBS (2006) paragraph 234.

The committee assumes that this should result in an average reduction of approximately ten percent across the entire set of SME borrowers in the IRB framework for corporate loans. Furthermore, several changes in the benchmark risk weight function that will be described later in section 2.13 were especially designed to reduce regulatory capital for exposures to SMEs.

2.11 Credit Risk Capital Requirements

2.11.1 Standardised Approach

This approach measures credit risk similar to Basel I, but has a greater risk sensitivity because it uses the credit ratings of external credit assessment institutions (ECAIs) such as Moody's, Standard & Poor's and Fitch IBCA to define the weights used when calculating *RWAs.* Table2.11.1 indicates an example of the risk weighting for claims on corporates. Assets that represent claims against corporations (including insurance companies) are assigned a risk weight according to credit rating given to the corporation or the asset.

The credit rating must be assigned by an external recognised rating agency that satisfies certain criteria described in the Accord.[26] For unrated exposures, the risk weight is 100%. For rated exposures, the following Table 2.11.1 correlates the credit rating and the risk weight:

Table 2.11.1 Risk weightings for rated corporates

Credit assessment	**AAA to AA-**	**A+ to A-**	**BBB+ to BB-**	**Below BB-**	**Unrated**
Risk weight	20%	50%	100%	150%	100%

For corporates, sovereigns and banks, unrated exposures will normally be given a risk weighting of 100%, which translates into a capital requirement of 8%. Supervisors may adjust the risk-weights according to their previous experience with

[26] For example, the credit rating agency must be independent, the methodology used should be publicly available, and the rating should be rigorous, systematic and subject to some form of validation.

that type of exposure. The standardised approach also allows for credit risk mitigation, which will reduce the capital requirements according to the type and extent of the collateral instrument.

Table 2.11.2 presents the risk weights summarised by type of counterparty and credit rating. It is notable that claims to non-central government public sector entities can be treated either as claims on banks or the relevant sovereign claims. As off-balance sheet risk weight, its items will be converted to credit exposure equivalents using credit conversion factors. As an alternative to ECAIs rating, the country risk scores assigned by Export Credit Agencies (ECAs) recognised by national supervisors, or the consensus risk scores published by the OECD in the "Arrangements on Guidelines for officially Supported External Credits", may be used. To qualify, an ECAs must publish its risk scores and subscribe to the OECD-agreed methodology. Countries are given two options, but must apply the same option to all banks within their country. The first option is to risk weight claims on banks and securities firms at one risk weight category below the country's risk weight.[27] The second option is to risk weight banks and securities firms based on an external credit assessment score, and with lower risk weights for short term obligations (originally maturity of 3 months or less). As Basel I, it assigns a 20 % basket to claims on banks and securities firms organized in OECD member countries.

In particular, this approach for claims in Retail Exposure, Residential Real Estate and Commercial risk weight provided lower risk compared with Basel I described as below:

2.11.1.1 Retail exposures (Loans to Individuals and Small Businesses)

Under Basel II standardised approach, loans to individuals and small businesses, including credit card loans, instalment loans, student loans, and loans to small business entities are risk weighted at 75 %, if the bank supervisor finds that the bank's retail portfolio is diverse (for example, no single asset exceeds 0.2 % of the

[27] Subject to a cap of 100 percent risk weighting, unless the country has a below B- credit score.

entire retail portfolio, and no loan exceeds 1 million Euros.[28] According to Basel I, risk weights in retail and small business loans are placed in the 100% risk weight basket.

2.11.1.2 Residential real estate

"Lending fully secured by mortgages on residential property that is or will be occupied by the borrower, or that is rented, will be risk weighted at 35%."[29] In applying the 35% weight, the supervisory authorities should satisfy themselves, according to their national arrangements for the provision of housing finance, that this concessionary weight is applied restrictively for residential purposes and in accordance with strict prudential criteria. According to Basel I, residential mortgage loans are placed in the 50 % basket.

2.11.1.3 Commercial real estate loans

In general, loans secured by commercial real estate are assigned to the 100% risk basket. However, the Accord (Basel II) permits regulators the discretion to assign mortgages on office and multi-purpose commercial properties, as well as multi-family residential properties, in the 50 % basket subject to certain prudential limits.[30] According to Basel I, commercial real estate is assigned to the 100% basket.

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[28] BCBS (2006) paragraph 69.
[29] BCBS (2006) paragraph 72.
[30] BCBS (2006) paragraph 74.

Table 2.11.2 Risk weights under the standardised approach for credit risk

Type of Claims	**AAA to AA-**	**A+ to A-**	**BBB+ to BB-**	**BB+ to B-**	**Below BB-**	**Unrated**
Sovereigns & Central Banks	0%	20%	50%	100%	150%	100%
Banks-Option 1 (based on sovereign treatment by supervisors)	20%	50%	100%	100%	150%	100%
Banks-Option 2 (based on rating from ECAI) for longer-term claims	20%	50%	50%	100%	150%	50%
Bank-Option 2 (based on rating from ECAI) for short-term claim*	20%	20%	20%	50%	150%	20%
Regulatory retail portfolios**	75%					
Secured by residential property	35%					
Secured by commercial real estate	100% (lower risk weight allowed under strict conditions)					
Past due loans (unsecured portions net of specific provisions)	100% or 150% (depending on degree of provisions coverage)					
All other assets	At least 100%					

Source: Basel Committee on Banking Supervision (2006).
* Short-term claims must have an original maturity of three months or less.
** In order to qualify, claims must meet criteria relating to orientations, products, granularity and low value of individual exposures.

2.12 Internal Rating-Based (IRB) Approach

The key elements of implementation of IRB have summarised by Saunders and Allen (2002). Furthermore, Basel II (2006) comprehensive version describes for each of the asset classes covered five key elements under the IRB framework, there are:

1. Risk exposures: a classification of the obligation by credit risk exposure that is the internal ratings model.
2. Risk components: estimates of risk parameters provided by banks some of which are supervisory estimates.
3. Risk-weight functions ─ the means by which risk components are transformed into risk-weighted assets and therefore capital requirements.
4. Minimum requirements ─ the minimum standards that must be met in order for a

bank to use the IRB approach for a given asset class and supervisory review of compliance with the minimum requirements.

5. Validation of IRB approach: A set of minimum requirements of legibility to apply the IRB approach that is validation that the bank maintains the necessary information systems to accurately implement the IRB approach.

In order to qualify for the IRB approach, banks must have adequate facilities for accurately assessing risk, and meet a stringent list of requirements. In some cases, banks may be required to use a supervisory value as opposed to an internal estimate for one or more of the risk components. The IRB approaches are described below.

2.12.1 Foundation IRB Approach

Under the internal ratings-based (IRB) model, each bank is required to establish an internal ratings model to classify the credit risk exposure of each activity such as commercial lending, consumer lending whether on or off the balance sheet. For the foundation IRB approach, the required outputs obtained from the internal ratings model are estimates of one-year probability of default (PD) and exposure at default (EAD) for each transaction. For banks using the foundation approach for corporate exposures, effective maturity (M) will be 2.5 years except for repo-style transactions where the effective maturity will be 6 months. EAD is estimated through the use of standard supervisory rules and is determined by the banks themselves in the advanced methodology. In most cases, EAD is equal to the nominal amount of the exposure but for certain exposures such as undrawn commitments it includes an estimate of future lending prior to default. Senior claims on corporates, sovereigns and banks not secured by recognised collateral will be assigned a 45% LGD. All subordinated claims on corporates, sovereigns and banks will be assigned a 75% LGD.

2.12.2 Advanced IRB Approach

Under the advanced approach, banks provide their own estimates of PD, LGD and EAD, and their own calculation of M, subject to meeting minimum standards. “For retail exposures, banks must provide their own estimates of PD, LGD and EAD." There is no distinction between a foundation and advanced approach for this asset class.[31] Thus, banks using internal LGD estimates for capital purposes are able to differentiate LGD values on the basis of a wider set of transaction and borrower characteristics. The Basel II guidelines also do not set a lower bound on the LGD that banks can use in the AIRB approach for corporate credits. *M* is defined as the greater of one year and the remaining effective maturity in years as defined below. In all cases, *M* will be no greater than 5 years.

For an instrument subject to a determined cash flow schedule, effective maturity *M* is defined as:

Effective Maturity $M = \text{Min}\left(\frac{\sum_{\forall t} t \times CF_t}{\sum_{\forall t} CF_t}, 5\,years\right)$ where CF_t denotes the cash flows (principal, interest payments and fees) contractually payable by the borrower in period *t*, where *t* is measured in years.[32]

If a bank is not in a position to calculate the effective maturity of the contracted payments as noted above, it is allowed to use a more conservative measure of *M* such as that it equals the maximum remaining time (in years) that the borrower is permitted to take to fully discharge its contractual obligation (principal, interest, and fees) under the terms of loan agreement. Normally, this will correspond to the nominal maturity of the instrument.

2.13 Minimum Capital Requirement under IRB Approaches

Under the IRB approach, a bank estimates each borrower's creditworthiness, and the results are translated into estimates of a potential future loss amount, which form the basis of minimum capital requirements. The framework allows for both a foundation method and more advanced methodologies for corporate, sovereign and bank, retail exposures. In the foundation methodology, banks estimate the probability of default associated with each borrower, and the supervisors supply the other inputs.

[31] BCBS (2006) paragraph 252.
[32] BCBS (2006) paragraph 320 defined Maturity

In the advanced methodology, a bank with a sufficiently developed internal capital allocation process is permitted to supply other necessary inputs as well. Under both the foundation and advanced IRB approaches, the range of risk weights is far more diverse than those in the standardised approach, resulting in greater risk sensitivity. With regard to the IRB approach, the regulatory capital requirement is sufficient to address underlying risks and contains incentives for banks to migrate from the standardised approach to this IRB approach.

The formula for derivation of Risk-weighted assets under IRB approach are described as following section 2.13.1 interpreting detail of capital charge for corporate, sovereign and bank exposures, and retail exposures.

2.13.1 Formula for Derivation of Risk-weighted Assets

The derivation of risk-weighted assets is dependent on estimates of the PD, LGD, EAD and, in some cases, effective maturity (M), for a given exposure.[33] Throughout this section, PD and LGD are measured as decimals, and EAD is measured as currency (e.g. Euro), except where explicitly noted otherwise. For exposures not in default, the following formula is used for calculating risk-weighted assets:[34]

2.13.1.1 Risk-weighted assets for corporates, sovereign and bank exposures

The BCBS (2006) formula for calculating AIRB capital requirements for Corporate, Sovereign and Bank exposure are $EAD \times K$, where K, is given by

$$K = \left[LGD \times N\left[\frac{1}{\sqrt{1-R}} N^{-1}(PD) + \sqrt{\frac{R}{1-R}} N^{-1}(0.999) \right] - PD \times LGD \right] \times \left(\frac{1+(M-2.5)b}{1-1.5b} \right)$$

where, $Correlation(R) = 0.12 \times \left[\frac{(1-\exp^{-50PD})}{(1-\exp^{-50})} \right] + 0.24 \times \left[1 - \frac{(1-\exp^{-50PD})}{1-\exp^{-50}} \right]$

[33] BCBS (2006) paragraph 271.
[34] BCBS (2006) formula for derivation of risk-weight assets calculation in paragraph 272, paragraphs 318 to 324 discuss the circumstances in which the maturity adjustment applies.

Maturity adjustment $(b) = (0.11852 - .05478 Ln(PD))^2$

where: N^{1} (z) is the inverse cumulative distribution function *(c.d.f.)* for a standard normal random variable, i.e. the value of y such tha*t N(y) = z*

$N(y)$ is the *c.d.f.* for a standard normal variable

ln (PD) is the natural logarithm of the *PD*

M is effective (remaining) maturity.

Formally speaking, the formula is based on a one-factor model,[35] meaning that there is only one systematic factor as a proxy for general economic conditions that drives correlations across borrowers. This is important because together with the infinite granularity assumption, it gives rise to additive, portfolio-invariant contributions to capital, i.e. the IRB capital requirements only depend on each individual loan's own characteristics and do not have to be calibrated for each portfolio based on it particular composition. A common characteristic is that lower quality (higher PD) assets have lower correlations. This corresponds to the empirical finding that lower quality exposure are driven mainly by idiosyncratic (borrower-specific) factors and thus relatively less by broader market events (systematic risk).

PD is a credit's probability of default expressed as a percentage, LGD is a credit's expected loss given default expressed as percentage, *M* is the credit's maturity measured in years, and *K* represents the percentage capital requirement per Euro of EAD exposures. When *M* = 1, the maturity adjustment, $\frac{1+(M-2.5)b}{1-1.5b} = 1$. If for any credit $K< 0$, regulatory capital requirements are set to zero. Foundation Internal Rating based (F-IRB) approach capital requirements are calculated by using the A-IRB capital equipment formula with senior claims on corporates will be assigned a 45% LGD. All subordinated claims on corporates, will be assigned a 75% LGD. For retail exposures only the advanced IRB approach is available.

[35] See Wilde (2001) and Gordy (2002) for a technical, and Fitch Ratings (2004) for a non-technical, description of this formula.

Risk-weighted Assets (RWA) = K × 12.5 × EAD

Capital Charge = 8% × RWA

The capital requirement (*K*) for a defaulted exposure is equal to the greater of zero and the difference between its LGD and the bank's best estimate of expected loss The risk-weighted asset amount for the defaulted exposure is the product of *K*, 12.5, and the EAD.

2.13.1.2 Risk-weighted assets for retail exposures

An exposure is categorised as a retail exposure if it meets the criteria as nature of borrower or low value of individual exposures (defined as previous section 2.9.2.1) and large number of exposures (defined as previous section 2.9.2.2), that are not in default and are secured or partly secured by residential mortgages, risk weight will be assigned based on the following formula:[36]

$$Correlation(R) = 0.15$$

Capital requirement

$$(K) = LGD \times N[(1-R)^{-0.5} \times N^{-1}(PD) + (\frac{R}{1-R})^{0.5} \times N^{-1}(0.999)] - PD \times LGD$$

The criteria must be satisfied for a sub-portfolio to be treated as a qualifying revolving retail exposure (QRRE) (defined as previous section 2.9.2.3). These criteria must be applied at a sub-portfolio level consistent with the bank's segmentation of its retail activities generally. Risk weights are defined based on the following formula:[37]

$$Correlation(R) = 0.04$$

Capital requirement

$$(K) = LGD \times N[(1-R)^{-0.5} \times N^{-1}(PD) + (\frac{R}{1-R})^{0.5} \times N^{-1}(0.999)] - PD \times LGD$$

[36] BCBS (2006) paragraph 328.

[37] BCBS (2006) paragraph 329.

For all other retail exposures that are not in default, risk weights are assigned based on the following function which allows correlation to vary with PD:

$$Correlation(R) = 0.3 \times \left[\frac{(1-\exp^{-35PD})}{(1-\exp^{-35})} \right] + 0.16 \times \left[1 - \frac{(1-\exp^{-35PD})}{(1-\exp^{-35})} \right]$$

Risk-weighted Assets (RWA) = K × 12.5 × EAD
Capital Charge = 8% × RWA

2.13.2 Requirements Specific LGD Estimates

Standards for all asset classes in relation to the requirements specific to own-LGD estimates was discussed by BCBS (2006). “A bank must estimate an LGD for each facility that aims to reflect economic downturn conditions where necessary to capture the relevant risks. This LGD cannot be less than the long-run default-weighted average loss rate given default calculated based on the average economic loss of all observed defaults within the data source for that type of facility.”[38]

It was notable that appropriate estimates of LGD during periods of high credit losses might be formed using either internal and/or external data. Meanwhile, supervisors will continue to monitor and encourage the development of appropriate approaches to this issue. Also LGD should be estimated conservatively. “LGD estimates must be grounded in historical recovery rates and, when applicable, must not solely be based on the collateral’s estimated market value. This requirement recognises the potential inability of banks to gain both control of their collateral and liquidate it expeditiously. To the extent, that LGD estimates take into account the existence of collateral, banks must establish internal requirements for collateral management, operational procedures, legal certainty and risk management process that are generally consistent with those required for the standardised approach.”[39]

[38] BCBS (2006) paragraph 468.
[39] BCBS (2006) paragraph 470

Additional standards estimated LGD for corporate exposure described by BCBS (2006) paragraph 472: "Estimates of LGD must be based on a minimum data observation period that should ideally cover at least one complete economic cycle but must in any case be no shorter than a period of 7 years for at least one source. If the available observation period spans a longer period for any source, and the data are relevant, this longer period must be used." Whilst additional standards for retail exposures was discussed as paragraph 473: "The minimum data observation period for LGD estimates for retail exposures is 5 years. The less data a bank has, the more conservative it must be in its estimation. A bank need not give equal importance to historic data if it can demonstrate to its supervisor that more recent data are a better predictor of loss rates."

2.13.3 Firm-size Adjustment for Small and Medium Sized Entities (SMEs)

Under the IRB approach for corporate credits, banks will be permitted to separately distinguish exposures to SME borrowers (defined as corporate exposures where the reported annul sales for the consolidated group of which the firm is a part is less than €50 million) from those to large firms. A firm-size adjustment is $0.04 \times \left(1 - \frac{(S-5)}{45}\right)$ made to the corporate risk weight formula for exposures to SME borrowers. S is expressed as total annual sales in millions of Euro and fall in range of $5 \le S \le 50$. Reported sales of less than €5 million will be treated as if they were equivalent to €5 million for the purposes of the firm-size adjustment for SME borrowers.[40]

$$Correlation(R) = 0.12 \times \left[\frac{1-\exp^{-50PD}}{1-\exp^{-50}}\right] + 0.24 \times \left[1 - \frac{(1-\exp^{-50PD})}{1-\exp^{-50}}\right] - 0.04 \times \left(1 - \frac{(S-5)}{45}\right)$$

Subject to national discretion, supervisors may allow banks, as a failsafe, to substitute total assets of the consolidated group for total sales in calculating the SMEs threshold and the firm-size adjustment. Total assets should be used only when total sales are not a meaningful indicator of firm size.

[40] BCBS (2006) Firm-size adjustment for small- and medium-sized entities (SME)in paragraph 273

2.14 Implementation Treatment of Exposure under IRB Approach

Once a bank adopts an IRB approach for part of its holdings, it is expected to extend it across the entire banking group via a phased rollout. The bank's implementation plan must specify the extent and timing of the roll-out, and must be agreed with the supervisors. These requirements apply across all asset classes and IRB approaches, and are summarised in Table 2.14.1. It is expected to continue to use IRB approach once the banks has adopted it, nevertheless, a voluntary return to another approach is permitted only in extraordinary circumstances and must be approved by supervisor. Therefore, to be eligible for the IRB approach, banks must demonstrate to their supervisors[41] that they meet certain minimum requirements at the outset and on-going basis. As framework of Basel II implementation, therefore, minimum requirements for IRB approach summarised as several dimensions in Table 2.14.2 below[42].

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[41] A Bank applies IRB approach has to based on regulatory of the Second Pillar – Supervisory Review Process

[42] BCBS (2006) Section III.H paragraph 387

Table 2.14.1 Classification and treatment of exposure under the IRB approach

Asset Classes	Asset Sub-Classes/ Categories	IRB Approach	Formula for Risk-Weighted Assets
Sovereign	N/A	Foundation or Advanced	Same as Corporate formula
Bank	N/A	Foundation or Advanced	Same as Corporate formula
Corporate	Standard corporate	Foundation or Advanced	Corporate formula (BCBS paragraph. 272)
	SMEs	Foundation or Advanced	Corporate formula with firm-size adjustment (BCBS paragraph. 273)
	Eligible purchase receivables	Foundation or Advanced	Corporate formula with different (top-down) procedure for deriving PD and LGD; firm-size adjustment might also apply; additional adjustment in formula to account for dilution risk
	Specialised Lending (project finance object finance, commodities finance, income-producing real estate, high-volatility commercial real estate)	Supervisory slotting criteria or Foundation or Advanced	Separate formula fro supervisory slotting criteria approach; Corporate formula for Foundation or Advanced Approach; adjustments to both formulas for high-volatility commercial real estate exposures (BCBS paragraph 283, 284, 284(i), 284(ii))
Retail *	Secured by residential property (e.g. residential mortgages)	No distinction (only one approach)	Separate formula for residential mortgage exposures (BCBS paragraph 328)
	Qualifying revolving retail (e.g. credit cards)	No distinction (only one approach)	Separate formula for revolving retail exposures (BCBS paragraph 329)
	All other retail exposures (e.g. consumer loans)	No distinction (only one approach)	Separate formula for other retail exposures (BCBS paragraph 330)
	Eligible purchased receivables	No distinction (only one approach)	One of the three Retail formulas, depending on composition of receivables; Retail formula with highest capital requirements to be used for hybrid(mixed) pools; adjustment to selected formula to account for dilution risk
Equity **	N/A	Market-based or PD/LGD	Two distinct formulas for market based approach (simple risk weight or internal models methods); separate formula for PD/LGD approach (BCBS paragraph. 343, 344)

Source: Basel Committee on Banking Supervisor (2006); World Bank Policy Research (2005)

* Applies to each identified pool of exposures as apposed to individual exposures.

* *Applies to equity holdings in the banking book; equity assets in the trading book are subject to market risk capital rules.

Table 2.14.2: Minimum requirement for IRB approach

Dimensions	Key Minimum Requirements
Rating system design	• Separate borrower creditworthiness and transaction-specific dimensions • Meaningful distribution of exposures across grades • Plausible, consistent and detailed rating definitions, processes and criteria for assigning exposures to grades within a rating system • Written documentation of rating system design, default and loss definitions etc.
Risk rating system operation	• Independence of rating assignment process • All borrowers and facilities must be re-rated at least on an annual basis • Data collection and storage of key borrower and facility characteristics • Stress testing used in assessment of capital adequacy.
Corporate governance and oversight	• All material aspects of rating and estimation processes to be approved by senior management and (all of a subset of) the Board of Directors • Independent credit risk control unit responsible for design/ selection, implementation and performance of internal rating systems • Internal audit (or an equally independent function) to review the rating system and the credit function's operations at least annually
Use of internal ratings	• Internal ratings and default/loss estimates to play an essential role in credit approval, risk management, internal capital allocation and corporate governance • Rating system broadly in line with minimum requirements for at least three years prior to qualification.
Risk quantification	• PD estimates must be long-run average of one-year default rates (except for retail exposures) and must be based on at least a five-year observation period • Internal estimates must reflect all relevant, material and available data, and must be grounded in historical experience and empirical evidence • Specific reference definition of default and indications of inability to pay • LGD and EAD estimation should incorporate cyclical variability when important for certain types of exposures, and must be based on minimum data observation period of at least seven years (five years for retail exposures) • The risk-mitigating effect of guarantees and single-name credit derivatives can be used to adjust own estimates of PD or LGD, but the adjusted risk cannot be lower than that of a comparable, direct exposure to the guarantor • Minimum requirements (legal certainty, effectiveness of monitoring, control and work-out systems, compliance with internal policies and procedures) for eligible purchased receivables making use of the top-down treatment of default risk and /or IRB treatment of dilution risk.
Validation of internal estimates	• Systems to periodically validate and document the accuracy and consistency of rating systems, processes and the estimation of all relevant risk components
Supervisory LGD and EAD estimates	• Minimum operational and risk management requirements for recognition of additional (to those eligible under the Standardised Approach) collateral types including leases
Calculation of capital change for equity exposures	• Quantitative and qualitative minimum requirements (capital change and risk quantification, risk management process and controls, validation and documentation) to be eligible for the internal models market-based approach for recognition of additional
Disclosure requirements	• Banks must meet the disclosure requirements of Pillar 3

Source: Basel Committee on Banking Supervisor (2006); World Bank Policy Research (2005)

2.15 Basel II Impact on SMEs Access to Finance

The amendment of proposal embodied in the Basel II takes account of the possible impact that SMEs would face on financing conditions as a consequence of the new approach. For instance, loans to SMEs up to 1 million Euros are included in the regulatory retail portfolio when certain conditions are met. That means lower capital requirements under the IRB approaches as well as under the standard approach, where SMEs attract a risk weighting of only 75%.

There is recent research in relation to SMEs and Basel II capital requirements calculation when banks categorise SMEs as retail or corporates exposures and adopt IRB approach. With respect to SME loan portfolios, Dietsch and Petey (2004) propose two parametric methods for estimating credit risk. They establish, when applying these methods that actual capital requirements are significantly lower than those derived under Basel II. They also find that SMEs are riskier than large businesses and that PDs and asset correlations are not negatively, as assumed by Basel II, but positively related to each other. Glennon and Nigro (2006) analyse small businesses' repayment behaviour on Small Business Administration loans and determine that default characteristics can vary widely within the SME segment, depending on the original maturity of the loan.

Jacobson, Lindé and Roszbach (2006) explore a sub-sample of all borrowers that have been assigned an internal rating by bank and compare the credit loss distributions for the three credit types, retail, SMEs and corporates. They compute the credit loss distributions using different threshold values for total sales to divide the banks' loan portfolios into SME and corporate loans and different thresholds for the credit exposure to split up the data into retail and corporate credit. Both economic and regulatory capital under Basel II are computed and tested if conclusions are sensitive to the definitions of retail and SMEs credit. It is found that retail and SMEs portfolios are usually riskier than corporate credit, therefore, special treatment under Basel II is thus not justified.

The likely competitive effects of implementation of Basel II capital requirements on banks in the market for credit to SMEs in the U.S. was examined by Berger (2006). Similar competitive effects from Basel II may occur for other credits and financial instruments in the U.S. and other nations. In this article, Berger addresses whether reduced risk weights for SME credits extended by large banking organisations that adopt the Advanced Internal Ratings-Based (A-IRB) approach of Basel II might significantly adversely affect the competitive positions of other organisations. The analyses suggest only relatively minor competitive effects on most community banks because the large A-IRB adopters tend to make SME loans to different types of borrowers than community banks. There may be significant adverse effects on the competitive positions of large non-A-IRB banking organisations because the data do not suggest any strong segmentation in SME credit markets among large organisations.

Glennon and Nigro (2006) examine sample data on SMEs made through the U.S. Small Business Administration (SBA) lending program. SBA loans receive partial government guarantees to lenders in the case of default. While they recognise the limitations of applying estimates from SBA loans to the general population of SMEs, their paper address methodological issues that are important for any researcher in this area. Moreover, while it is likely that point estimates derived from this sample of loans cannot be generalised to the broader SME population, the risk factors identified are likely to be factors for all SMEs. It is found that SBA loan maturity length is an important factor in default behaviour for their sample of SMEs. Overall, it is concluded SME default are closely tied to the regional and industrial economic health in which the borrower operates. These regional and industrial factors will influence the correlation of defaults for a given SME portfolio as well as the LGD for the portfolio in a period of stress.

The likely effects of Basel II on the capital requirements for SMEs was examined by Altman and Sabato (2006) using primary data for the U.S., Italy, and Australia to estimate one-year probabilities of default (PDs). They combine these PDs with reasonable assumptions for inputs into the Basel II capital formulas to generate the likely capital requirement for SMEs under both the corporate and retail framework. The results indicate that there will be substantial reductions in required capital relative to current requirements if SMEs receive retail treatment under Basel II. Alternatively, it is estimated that if all SMEs are classified as SME corporate exposures, then capital requirements will increase. Furthermore, it is estimated that approximately 20 percent of SME loans would need to be categorised as retail loans to generate a capital requirement no greater than the current regulatory requirement. In this study, they conclude that Basel II will provide incentives for banks to update their internal systems through more extensive use of small-business credit scoring or similar automated mechanisms so that an increasingly larger portion of their SME portfolio will qualify as retail credits. They argued that banks will be faced with the choice of incurring higher regulatory capital requirements for SME corporate exposures or incurring additional organisational and technical costs to meet the Basel II risk management standards for retail treatment of SMEs.

These studies discussed Basel II impact on credit risk of SMEs loan and in some case SMEs exposure treatment to estimate capital requirement. It could be found the focus is on distinguishing exposure to SMEs on the basis of two criteria, the size of the SME or the management of the exposure, and thus include them as a separate subset of either the corporate exposures portfolio or the retail portfolio. As a result, a different amount of minimum regulatory capital is required depending on the size of a firm or how a bank management SMEs exposures to firms.

2.16 Conclusion

The comprehensive version Basel II (2006) increases the granularity of risk weightings and shifts the responsibility of risk assessment on to individual banks. The new approach not only reduces the adverse credit effects that regulator imposed risk weightings but also creates an incentive for the development of more accurate risk assessment and avoidance techniques. The Basel Capital Accord was designed to raise levels of capital internationally, and thereby introduce a greater degree of stability into internationally active banks.

The fact that a very large proportion of small loans are granted to SMEs is an additional reason for paying special treatment to exposure to these firms within the new Basel II Accord (Berger and Udell 1996; Saurina and Trucharte 2004). Basel II has accepted the inclusion of large portfolios composed of SMEs with small loans into the retail asset class.

Basel II reflects improvements in banks' risk management practices by the introduction of the internal ratings based approach (IRB). The IRB approach allows banks to rely to a certain extent on their own estimates of credit risk. Financial institutions are able to use the more sophisticated approaches, such as advanced IRB approach for implementing capital requirement. It is expected under these arrangements that lending to SMEs and retail customers should see falling capital requirements for credit risk.

CHAPTER THREE

Review of the Literature

3.1 Introduction

In this chapter, the various model types used in credit risk are reviewed. The development of banking instruments, the market for credit derivatives and the Basel II process has generated a lot of interest in quantitative credit risk models in industry, academia and among regulators, so that credit risk modelling is at present a very active subfield of quantitative finance and risk management.

Credit risk models can be classified into two broad groups based on the area of their application: models for retail credit products such as personal loans, credit cards, mortgages, etc. and models for corporate sector. Retail models have received a generic name of credit scoring and generally consist of empirical predictive models that take into account associations between borrower's various characteristics that can be observed at the point of application and default.

The corporate world relies mainly on market-based models for credit risk measurement which are represented by two main schools of thought: options structural approach rooted in a seminal work by Merton (1974) and a reduced-form approach based on estimation of stochastic hazard rates (Jarrow and Turnbull 1995b). However, within corporate risk modelling there is also a stream of models, similar in essence to credit scoring, that goes back to the work by Altman (1968). These models (often referred to as accounting-based), use accounting variables from financial statements to distinguish between defaulting and non-defaulting firms and to predict corporate bankruptcy. More detailed overview of credit risk models can be found in Allen, DeLong and Saunders (2004), and Saunders and Allen (2002).

Statistical methods for credit risk measurements are broadly reviewed in literature. There are various statistical techniques for credit risk prediction. They are mostly used as binary classifiers in the traditional credit risk studies. Their purpose is to classify credit obligators into default or non-default accurately. Discriminant analysis and logistic regression have been the most widely used techniques for building credit risk models. The idea of employing survival analysis for building credit-scoring models has been shown by Narain (1992) who applies the technique to estimate the time to default or early repayment. The survival analysis can provide more information than the binary classifiers (Banasik, Crook and Thomas 1999). It can determine the timing when customers become bad as well as the default possibility of credit applicants or existing customers.

The Chapter explores the Market-based models and the Accounting-based approaches. Depending on their formula inputs, market-based models can be divided into structural models based on Merton type models and reduced-form models, this division cuts across that of dynamic and static models. Then Accounting-based models based on financial information, accounting data and using techniques such as discriminant analysis, logistics models, hazard models, hybrid models and machine learning are introduced later in this chapter. Parts of the new minimum capital requirements for credit risk that are closely linked to the structures of existing portfolio credit risk models will be explained. Several proprietary portfolio credit risk models have received a great deal of public attention, including J.P. Morgan's CreditMetrics/CreditManager, Credit Suisse Financial Products' CreditRisk+, McKinsey & Company's CreditPortfolioView, and KMV's PortfolioManager. These new models allow the user to comprehensively measure and quantify credit risk at both the portfolio and internal credit rating models.

Given the framework of these models, the comparison of methodologies and use of models in credit risk analysis are provided. Furthermore, comprehensive reviews of Direct and Indirect Approaches for Measuring Credit Risk and Merton-typed models for estimating SMEs credit risk and credit scoring in UK are provided.

3.2 Statistical Methods for Credit Risk

Statistical methods based on data mining techniques can be used to analyse or determine risk levels involved in credit, i.e. default risk levels. There are two schools of thought in the use of statistical methods to predict default. One holds that default can be modeled using accounting data; and the other recommends using market information.

Default risk levels of credit can be systematically determined by using accounting data or historical records to explore predictive models. It is known as predictive modelling based on statistical methods and credit scoring is one example of it. Customer data used in developing models may consist of historical data such as payment record and credit quality. Past default history will be the most important information to include. Credit scoring requires modelling techniques that can take numerical data as a target or predicted variable to generate predictive segmentation and statistical probability.

Generally many statistical models like logistic regression and discriminant analysis have been used to make credit risk models. Although these methods are useful to make a binary classifier based on static status, they do not provide information on the timing of events and cannot handle time-dependent covariates. These limitations can be overcome by the survival analysis method that will provide the probability of surviving past a certain time as well as the timing of events.

Market-based models can be further classified into structural models and reduced form models. The hybrid approach uses accounting data as well as market information to predict probability of default. Furthermore, machines learning techniques have been proposed in conducting credit risk modelling and default prediction.

These various types of models are reviewed in the following sections

3.3 Market Based Models

Market based credit risk models can be divided into two main categories: structural form model and reduced form models. The market based approach to default risk and the valuation of contingent claims, such as debt, starts with the work of Merton (1974). Since then, Merton's model, termed the structural approach, has been extended in many different ways. However, implementing the structural approach faces significant practical difficulties due to the lack of observable market data on the firm's value. To circumvent these difficulties, Jarrow and Turnbull (1995a), Jarrow and Turnbull (1995b) infer the conditional probabilities of default from the term structure of credit spreads. In the Jarrow–Turnbull approach, termed the reduced form approach, market and credit risk are inherently interrelated. These two main market-based approaches are reviewed in the following sections both from theoretical and practical viewpoint.

3.3.1 Structural Approach Models

The structural approach is best exemplified by Merton (1974) model developed from the Black-Scholes model (Black and Scholes 1973). Many extensions of this model have been developed over the years, but Merton's original model remains an influential benchmark and is still popular with practitioners in credit risk analysis.

Consider a firm whose asset values follows some stochastic process (V_t). The firm is financed by issuing shares i.e. equity and by debt. In Merton model debt has a very simple structure that consists of one single debt obligation or zero-coupon bond with face value X and maturity T. The value at time t of equity and debt is denoted by E_t and X_t and if assumed that market are frictionless (no taxes or transaction costs), the value of the firm's assets is simply as $V_t = E_t + X_t$, $0 \le t \le T$.

At maturity, if the value of the firm's assets is greater than the amount owed to the debt holders i.e. the face value X, then the equity holders pay off the debt holders and retain the firm. If the value of the firm's assets is less than the face value, the equity holders default on their obligations. There are no costs associated with default and the absolute priority rule is obeyed. In this case, debt holders take over the firm and the value of equity is zero, assuming limited liability.

This analogy between option pricing and capital structure builds the foundation of the default prediction model. A number of variations followed the leading work in this area that was done by Black and Cox (1976) who value corporate securities and point out specific form of bankruptcy cost and also the influence of other factors such as taxes, which would have to be introduced into the analysis to justify the existence of debt in a world with positive bankruptcy costs. Geske (1977) studies valuation of corporate liabilities as compound options. Jones, Mason and Rosenfeld (1984) consider various debt structures in their research in order to address the complexity of a company's financial structure. Nielson, Saá-Requejo and Santa-Clara (1993), Longstaff and Schwartz (1995a, 1995b) take an alternative method in an attempt to avoid some of these practical limitations such as insufficiency of asset relative to liabilities, volatility measures, and market equity prices. In their approach, capital structure is assumed to be irrelevant. Bankruptcy can occur at any time and it occurs when an identical but unleveled firm's value hits some exogenous boundary and in default the firm's debt pays off some fixed fractional amount.

Shimko, Tejima and van Deventer (1993), Leland and Toft (1996), Collin-Dufresne and Goldstein (2001) studies took into account the floating interest rates or stochastic interest rates in the pricing model instead of the assumption of the fixed interest rate of Merton type models. Longstaff and Schwartz (1995) derive closed-form expression for fixed and floating rate debt and provide a number of insights about pricing and hedging of corporate debt securities. Anderson and Sundaresan (2000) empirically compare a variety of firm-value-based models of contingent claims on study of structural models of corporate bond yields. Also Gemmill (2002) has shown that Merton's model works well in the particular case when zero-coupon bonds are used for funding. In addition, Campbell and Taskler (2003), in their recent empirical work find that the level of volatility explains well the cross-sectional variation in corporate bond yield. On the other hand, it has been found that equity market variables play an important role in explaining credit spread changes, see Huang and Huang (2003). Recent work by Hull, Nelken and White (2005) has highlighted the fact that the performance of the Merton's model could be improved by calculating spreads using the implied volatility of two equity options in contrast to a more traditional approach that involves the estimation of the instantaneous equity volatility and the debt outstanding.

A model slightly more general than that of Merton (1974) is used by Moody's KMV developed by Crosbie and Bohn (2003). The distance-to-default measure used in the Moody's KMV-Merton credit risk measures represents the number of standard deviations (or distance) between the market value of a firm's assets and its relevant liabilities. This measure combines a firm's liabilities, market value, and volatility of assets into a single measure that determines the probability of default for a public firm.

3.3.2 Reduced Form Models

The reduced form models also called the intensity models when a suitable context is possible describe default by means of an exogenous jump process. More precisely, the default time is the first jump time of a Poisson process with deterministic or stochastic intensity that is Cox (1955) process. One of the earliest examples of the reduced form approach is Jarrow and Turnbull. (1995) who allocate firms to credit risk classes. The reduced form (also called hazard rate models) indicated the default time is the first jump time of a point process. These models do not try to explain why default happens, rather they model default explicitly by an intensity or compensator process. This makes the default a totally inaccessible stopping time. The reduced form approach was expanded by Duffie and Singleton (1999) and Lando (1994 and 1997) to employ for modelling term structures of defaultable bonds and credit risky securities. Reduced-form models are more commonly used in practice on account of their tractability and because fewer assumptions are required about the nature of the debt obligations involved and the circumstances that might lead to default. An explanation of this approach is provided by Caouette, Altman and Narayanan (1998) to interpret default as a point process, for example, over the interval $(t, t+\Delta t]$ the default probability conditional upon no default prior to time t is approximately $\lambda(t)\Delta t$ where $\lambda(t)$ is the intensity (hazard) function. Using the term structure of credit spreads for each credit class, they infer the expected loss over $(t, t+\Delta t]$, that is the product of the conditional probability of default and the recovery rate under the equivalent martingale which is also called risk neutral measure. In essence, this approach uses observable market data such as credit spreads to infer the market's assessment of the bankruptcy process and then price the credit risk derivatives. An essential part of the theory of these models is the risk neutral valuation under the absence of arbitrage opportunities. A theme of default is not triggered by basic market observable data but has an exogenous component that is independent of all the default free market information. Monitoring the default free market does not give complete information on the default process, and there is no economic rationale behind default.

This family of models is particularly suited to model credit spreads and in its basic formulation is easy to calibrate to Credit Default Swap (CDS) data. Das and Tufano (1996) keep the intensity function deterministic and assume that the recovery rate is correlated with the default free spot rate which depends upon state variables in the economy and subject to idiosyncratic variation. Lando (1994 and 1997) derive a simple representation for the valuation of credit risk derivatives which allows for dependence between market risk factors and credit risk.

Lando (1994 and 1997) reduces the technical issues of modelling credit risk to the same issues faced when modelling the ordinary term structure of interest rates. It is shown how to generalise a model of Jarrow, Lando and Turnbull (1997) to allow for stochastic transition intensities between rating categories and into default. Moreover, reduced form approach to model default correlation, contagion models, relies on the works by Davis and Lo (2001), Jarrow and Yu (2001) based on the idea of default contagion in which, when a firm defaults, the default intensities of related firms jump upwards.

3.3.3 Hazards Models

The most common models used for survival analysis are the Cox (1972) proportional hazard model and the accelerated failure time model. The models allow for the inclusion of explanatory inputs, which may influence the survival time.

Survival analysis has been applied in a few cases for company failure analysis. Lane, Looney and Wansley (1986) have applied survival analysis to predict bank failure. Keasey, McGuinness and Short (1990) employ survival analysis for analysing company failure. Survival analysis sets the survival time or the hazard rate as a dependent variable and provides a possibility to model dynamic aspects of the default process. Lando (1994) introduces proportional hazard, survival-analysis model to estimate the time until a bond defaults.

Hazard models (which may be a type of reduced form models) resolve the problems of single period static models by explicitly accounting for time. The dependent variable in a hazard model is the time spent by a firm in the healthy group. A firm's risk for bankruptcy changes through time and its health is a function of its latest financial data and its age. Duffie and Singleton (1994) propose the model in which the default is specified by a hazard rate process connected with the distribution of default time and it is possible to price the defaultable and non-default claims. Davis and Mavroidis (1997) study the valuation of credit default swap by supposing that the hazard rate is a Gaussian model with time dependent deterministic drift and considered the default model taking the hazard rate as principal factor input models.

The advantage of hazard model is that they incorporate time-varying covariates, or explanatory variables that change with time and can be used for bankruptcy forecasting. Denis, Denis and Sarin (1997), Pagano, Panetta and Zingales (1998) derive hazard models based on multiple-period logit methods.

Hazard models for multi-period assessment has been employed by Shumway (1999), where multiperiodicity is understood as the joint use of many past observations for each firm. In this study multiperiodicity consists of calculation of the set of bankruptcy probabilities at various time intervals in the future. Thereafter, Shumway (2001) compares hazard models to single-period models and suggests that hazard models are more appropriated for forecasting bankruptcy. He suggests that both accounting ratios and market driven variables should be used to produce forecasts that are more accurate than those of alternative models.

Madan and Unal (2000) propose a two-factor hazard rate model, in closed form, to price risky debt. The likelihood of default is captured by the firm's non-interest sensitive assets and default-free interest rates and determines hedge positions. Credit spreads generated by their model are consistent with empirical observations.

3.4 Accounting Based Models

A series of models have been considered using the accounting data to predict company default. One of the first known attempts to distinguish companies based on their accounting data was made by Fitzpatrick (1932). In this work, he tries to check financial ratios that are useful in differentiating successful industrial enterprises from those that failed. The methodology of accounting-based approach is based on Multiple Discriminant Analysis (MDA) and logistic models which are the most useful in accounting-based variables for classifying company default prediction.

3.4.1 Multiple Discriminant Analysis (MDA)

The earliest discriminant approach is Naïve Bayes, and Beaver (1966) introduces the univariate approach of discriminant analysis in bankruptcy prediction, he also conducts an analysis of likelihood ratios based on the Bayesian approach. Beaver (1966) uses a dichotomous classification test to determine the error rates a potential creditor would experience if he classified firms on the basis of individual financial ratios as failed or non-failed. He analyses 14 financial ratios and uses a matched sample consisting of 158 firms (79 failed and 79 non-failed). Later, Altman (1968) uses a multiple discrminant analysis technique (MDA) to solve the inconsistency problem of the Beaver's univariate analysis and to asses a more complete financial profile of firms. His analysis is based on a matched sample containing 66 manufacturing firms (33 failed and 33 non-failed) that filed a bankruptcy petition during the period 1946-1965. Altman examines 22 potentially helpful financial ratios and ended up selecting five of them as doing the best overall job together in the prediction of corporate bankruptcy.

In this study, Altman (1968) has expanded it to a multivariate context and developed the Z-Score model with the following five have been selected for having the most discriminatory power:

$Z = 0.12\ X_1 +.0.14\ X_2 + 0.033\ X_3 + 0.006\ X_4 + 0.999\ X_5$

X_1= Working capital / Total assets

X_2= Retained earnings / Total assets

X_3= EBIT / Total assets

X_4= Market value of equities / Book value of liabilities

X_5= Ratio of sales to total assets

The critical value of 2.675 discriminates between the bankrupt and non-bankrupt firms. The discriminant ratio models achieved extremely accurate prediction with 94% and 95% of bankrupt firms and non-bankrupt assigned correctly respectively.

Unfortunately, private companies can not use the Z-score model, because the ratio X_4 assumed that company is publicly traded. Altman (1993) revises the model for private firms by substituting book value for market value $X_{4,}$ in the calculation of the ratio of market value of equities to the book value of liabilities. The revised model is probably somewhat less reliable than the original, but only slightly less.

There have been many subsequent studies investigating the predictive power of financial ratios within a regression, or multivariate framework. These have improved the financial variables used for the Z-score calculation, expanded its range beyond industrial firms, or expanded upon the limited sample data sets of earlier researchers. These studies include Deakin (1972) who applies discriminant analysis of predictors of business failure as well as Edmister (1972) who studies an empirical test of financial ratio analysis for small business failure prediction.

Altman, Haldeman and Narayanan (1977) have developed the ZETA models based on a combined sample of 113 manufacturers and retailers. The ZETA model is based on the following 7 variables: return on assets; stability of earnings; debt service; cumulative profitability; liquidity/current ratio; capitalisation (five year average of total market value); size (total tangible assets).

For many years thereafter, Multiple Discriminant Analysis (MDA) was the prevalent statistical technique applied to the default prediction models and it has been used by many authors Eisenbeis (1978), Taffler and Tisshaw (1977), Bilderbeek (1979), Micha (1984), Lussier (1995).

Altman and Narayanan (1997) survey the works by academics and practitioners in 21 countries and bring together these studies and highlight classification models design and present the economic forces shaping the outcomes in various countries that may diverge.

In Japan, bankruptcies are concentrated in the small and medium size firms. Takahashi, Kurokawa and Watase (1984) use multiple discriminant analysis with 8 financial variables and spend considerable effort to discuss the derivation of cutoff scores based on various assumptions of prior probabilities and cost of errors. Ko (1982) compares standard linear model design against a model with first order interactions and quadratic models and find that each sign was in agreement with each variables' economic meaning and that three of five financial variables in Ko's model are similar to in Altmans' (1968). Because of multiple discriminant analysis importance and widespread use, a number of studies have been addressed in developed counties. For example, Altman and Lavallee (1981) generate Canada Z-score model. Bilderbeek (1979) and Van Frederslut (1978) create discriminant analysis models in Netherlands. Izan (1984) structures Australia corporate models which were quite similar to the Altman (1968).

Weibel (1973) uses univariate statistical parametric and non-parametric tests applied to Swiss firms and utilises cluster analysis to reduce colinearity and arrives at the conclusion that the types of liquidity measures with one variable i.e. (near monetary resource assets minus Current liabilities) / Operation expenditures prior to depreciation performing best, Inventory Turnover and Debt/Asset ratios are good individual predictors. In his models, the results present quite accurate classification.

In Germany Baetge, Muss and Niehaus (1988) derive multiple discriminant analysis drawing samples from both bad and good enterprises representative of the line of business, legal form and size. Principal component analysis was used to reduce the initial universe of 42 financial measures to 7 factors and these factors in turn lead to 3 variables (i.e. capital structure, profitability and financial strength). The discriminate function tested with about 40,000 financial statements of all corporate customers of the bank and the model provided very stable when tested using simulation model developed at Gutting University. Von Stein and Ziegler (1984) combine non-parameteric and parametric methods and recommend all three components of analysis balance sheet, account behaviour and management be pursued to assess company inter-related perspectives. Thirteen financial ratios were identified as the most discriminating of the 140 ratios initially considered.

However, in most of these studies, authors pointed out that two basic assumptions of MDA are often violated when applied to the default prediction problem. The MDA is based on two restrictive assumptions: (1) the independent variables included in the model must be multivariate normally distributed; (2) the group dispersion matrices (or variance-covariance matrices) have to be equal across the failing and the non-failing group. See Barnes (1982), Karels and Grakash (1987) and McLeay and Omar (2000) study for further discussions about this topic of MDA default prediction assumptions and applications. Zmijewski (1984) is the pioneer in applying probit analysis to predict default, but, until now, logistic analysis has given better results in these fields.

3.4.2 Logistic Models

Considering these MDA's problems, Ohlson (1980), for the first time, applies the conditional logit model to the default prediction's study known as O-Score. Ohlson uses a data set with 105 bankrupt firms and 2,058 non-bankrupt firms gathered from the Compustat database over the period 1970-1976. He chooses nine predictors (7 financial ratios and 2 binary variables) to carry out his analysis, mainly because they appear to be the ones most frequently mentioned in the literature. The performance of his models, in terms of classification accuracy, is lower than Altman (1968) and Altman et al. (1977) reported in the previous studies based on MDA, but the reasons to prefer the logistic analysis over MDA are that logistic approach does not require that the variance-covariance matrices of the predictors should be the same for both groups (failed and nonfailed firms); and does not require normally distributed predictors which certainly mitigated against the use of dummy independent variables.

Ohlson (1980) model produces more than 90% correctly predicted. The nine financial ratios in the final O-score model are:

X_1: SIZE = log (total asset/GNP price-level index);
X_2: TLTA = Total liabilities divided by total assets,
X_3: WCTA =Working capital divided by total asset
X_4: CLCA = Current liabilities divided by current assets,
X_5: OENEG = One if total liabilities exceeds total assets, zero otherwise,
X_6: NITA = Net income divided by total assets.
X_7: FUTL = Funds provided by operations divided by total liabilities,
X_8: INTWO = One if net income was negative for the last two years, zero otherwise,
X_9: CHIN = $(NI_t-NI_{t-1})/(|NI_t|+|NI_{t-1}|)$, where NI_t is net income for the most recent period.

After the work of Ohlson's logit models, most of the academic literature was presented by Zavgren (1983), Gentry, Newbold and Whitford (1985), Keasey and Watson (1987), Aziz, Emanuel and Lawson (1988), Platt and Platt (1990), Ooghe, Joos and De Bourdeaudhuij (1995), Mossman, Bell, Swartz and Turtle (1998), Becchetti and Sierrs (2003) who use logit models to predict default. Despite the theoretic difference between MDA and logit analysis, studies show that empirical results are quite similar in terms of classification accuracy.

Logistic regression has also been explored by Laitinen (1999) in building credit scoring models for personal loan, business loan, and credit card applications. Moreover, logistic regression models have been widely used in bankruptcy prediction, market segmentation, and customer behaviour as studied by Laitinen and Laitinen (2000).

Keasey, McGuinness and Short (1990) point out that the logistic regression model does not assume multinormality and also gives an estimate for the probability of failure. This methodology assumes that the predicted values of the probability are cumulatively constrained by the logistic function. Srinivasan and Kim (1987) include logistic regression in a comparative study with other methods for a corporate credit granting problem. They provide comparative analysis of the ability of statistical classification models to replicate the decisions of a corporate credit expert. The empirical evidences show that (nonparametric) recursive partitioning methods provide slightly superior classification results.

From statistical point of view, logistic regression seems to fit perfectly the characteristics of the default prediction problem, where the dependant variable is binary (default and non-default) and with the groups being discrete, non-overlapping and identifiable. The logistic model yields a score between zero and one which easily gives the probability of default of the obligators. Lastly, the estimated coefficients can be interpreted separately as the importance or significance of each of the independent variables in the explanation of the estimated PD.

3.5 Credit Scoring Models

Credit scoring is the process of assigning a single quantitative measure, or score, to potential borrower representing an estimate of the borrower's future loan performance (Feldman 1997). As far as the retail finance credit risk prediction models are concerned, the techniques used are essentially statistical methods, such as discriminant analysis or logistic regression analysis, and more recently, neural networks and support vector machine (SVM). Credit scoring methods are used for estimating the probability of default based on historical data on loan performance and characteristics of the borrower. If the consumer data produce a score above the cut-off score, the application is approved. The basic assumption is that there exists a metric, which can distinguish between good and bad credits and segregate them into two separate distributions.

Feldman (1997) discusses the credit scoring models used in micro business lending tend to be more complex than those used in consumer lending and tend to place considerable weight on factors associated with the financial history of the entrepreneur. Some recent academic studies, Frame, Srinivasan and Woosley (2001), Berger, Frame and Miller (2005) have found that credit scoring is associated with an increase in overall lending because of inclusion of more marginal classes of borrowers.

Clearly it is possible to use standard corporate models in SMEs, but there exist a number of issues relating to the adequacy of the data on which to build the models. Akhavein, Frame and White (2001) indicate that whilst credit scoring methods research have been widely used in consumer lending for three decades, credit scoring has only recently been applied to SME and micro-enterprise lending in the U.S. by large banks, although the rate of adoption by large banks appears to depend on the bank organisational structure.

To facilitate the mortgage underwriting process, reduce costs, and promote consistency, Avery, Bostic, Calem and Canner (1996) point out credit scoring models have been developed that numerically weigh or score some or all of the factors considered in the underwriting process and provide an indication of the relative risk posed by each application. DeYoung, Hounter and Udell (2003) in US tackle both the Federal Home Loan Mortgage Corporation and the Federal National

Mortgage Corporation have encouraged mortgage lenders to use credit scoring, which should encourage consistency across underwriters.

3.5.1 Survival-based Credit Scoring Model

Survival analysis is a specialised method used for measuring the time to occurrence of some event or response. Luoma and Laitinen (1991) point out that the aim of the survival analysis technique is to quantify the relationship between survival and a set of explanatory variables. There are additional benefits for financial institutes to investigate the timing when customers become ‘bad’. Using the estimated timing, the financial institution can compute the profitability over a customer’s lifetime and perform profit scoring. It has been shown previously by Narain (1992) and Banasik, Crook and Thomas (1999) that survival analysis can be applied to estimate the time to default or to early repayment.

The idea of employing survival analysis for building credit scoring models is introduced by Narain (1992) applying the accelerated life exponential model to 24 months of loan data. In his article, it is shown that the proposed model estimated the number of failures at each failure time well. Then multiple regression is used to build a scorecard and it is shown that a better credit-granting decision could be made if the score was supported by the estimated survival times. Also it is found that survival analysis adds a dimension to the standard approach. It is suggested these methods could be equally well applied to any area where there are predictor variables and the time to some event is of interest.

Further work is developed by Banasik, Crook and Thomas (1999) comparing performance of exponential, Weibull and Cox’s nonparametric models with logistic regression. In their study, the idea of competing risk is employed when two possible outcomes are considered i.e. default and early payoff. Therefore, it is found that survival analysis methods are competitive with, and sometimes superior to, the traditional logistic regression approach.

Further study by Stepanova and Thomas (2002) show how using survival-analysis methods for building credit scoring models to assess aspects of profit as well as default. In their study, it looks at three extension of Cox's proportional hazard models applied to personal loan data. A new way of coarse-classifying of characteristics using survival-analysis methods is proposed. Several diagnostic methods are used to check adequacy of the model fit tested for suitability with loan data. It also proposes time-by-characteristic interactions as possible way methods to improve model's predictive power.

It is notable that binary classifying approaches appear not to have fully taken into account several important time-varying factors. That is, the survival-based credit scoring model for predicting may provide financial institutions with an estimate of the default levels over time. Such an estimate is useful for debt provisions and may help to decide on the term of the loan (Banasik, Crook and Thomas 1999; Thomas, Edelman and Crook 2002).

3.5.2 Credit Scoring Studies in UK Corporate Sector

Marais (1979) utilises discriminant analysis to quantify relative firm performance in UK industrial using flow of funds variables with conventional balance sheet and statement measures. His results present that firms whose score fell below a certain cutoff point should be regarded as possible future problems. Later work by Earl and Marais (1982) expand on this work and find that single ratio of Cash Flow / Current Liabilities is a successful discriminator. Subsequent test revealed a very low Type I error (Type I error is referred to as the error to classify a default firm as a non-default firm) but an unacceptably high Type II error (Type II error is defined as the error to predict a non-default firm as a default firm) assessment.

Taffler (1982) uses discriminant analysis and financial ratio data forecasting company failure in the UK corporate sector, which performs well in terms of classification accuracy and becomes widely accepts tools for practical financial analysis in the UK. In Taffler model, a large list of almost 150 potential variables is reduced to just five. These five variables are: (1) Earning before interest and taxes (EBIT) / Total assets (2) Total liabilities/ Net capital employed (3) Quick assets/Total assets (4) Working capital /Net worth, and (5) Stock inventory turnover.

Peel, Peel and Pope (1986) attempt to refine the financial ratio-based failure model, they add a number of non-conventional ratios and variables and are among the first to apply logit analysis in the UK. They are the first to incorporate the new non-financial variables based on (a) The lag and changes in the lag in reporting accounts (b) Director resignations and appointments (c) Director shareholdings which could contribute to corporate failure together with conventional financial ratios in a failure prediction model. The significance of eight financial and non-financial independent variables are tested against a sample of 34 failed and 44 non-failed companies using conditional logit analysis at a 5% level of significance. It is found that the addition of non-financial variables to a conventional failure prediction model leads to a marked improvement, both in terms of explanatory and predictive ability, of the model. In particular, the lag in publishing the financial statement was identified as a significant predictor when combined with conventional financial ratios.

Keasey and Watson (1986) apply a similar framework in order to predict small company failure. They use a sample of 146 firms with financial statement data and information on the age of company, the directors and auditors, lags in reporting to Companies House and whether or not any of the firm s assets secure a bank loan. The results presented show that these additional variables improve the bankruptcy prediction model significantly and the authors conclude that it is possible to develop cost effective monitoring procedures for small companies when predicting failure.

Lennox (1999) demonstrates that the industry sector, company size and the economic cycle have important effects on the likelihood of corporate failure, which is expected to increase when the company in question is unprofitable, is highly leveraged and it has liquidity problems. He also compares discriminant analysis with the logit/ probit approach and concludes that well specified logit and probit models can identify failing companies more accurately than discriminant analysis.

Charitou, Neophytou and Charalambous (2004) examine the incremental information content of operating cash flows in predicting financial distress and develop reliable failure prediction models for UK public industrial firms. The other variables were categorised in financial leverage, liquidity, profitability, activity and market data ratios. They refine prior UK studies by using a more recent company sample and employ logistic regression to develop a classification model. They also examine the predictive ability of the Altman (1968) Z-score model for UK dataset but it did not perform well compared to other models, and thus these five financial ratios variables contained in Z-score models may not be that appropriate of predicting UK business failure.

Table 3.5.1 summaries credit scoring studies in the UK corporate sector. Table 3.5.2 presents the summary of the main features of credit scoring methods in the major US and some other developed countries. Specifically, features include financial ratio variables and the technique used.

3.5.1 The summaries of UK studies on credit scoring methods

Country	Authors	Model	Explanatory Variables
Untied Kingdom	Marais (1979), Earl and Marais (1982)	Univariate and Multivariate Techniques	X_1=Current assets/Gross total assets; X_2=1/Gross total assets; X_3=Cash flow/Current liabilities; X_4= (Funds generated from operations – net change in working capital)/Debt.
Untied Kingdom	Taffler (1982)	MDA	(1) Earring before interest and taxes (EBIT)/Total assets (2) Total liabilities/Net capital employed (3) Quick assets/Total sets, (4)Working capital/Net worth (5) Stock inventory turnover
Untied Kingdom	Peel et al. (1986)	Logit Model	Refine the financial ratio-based failure model, they added a number of non-conventional ratios and variables which were among the first to apply logit analysis in the UK. The new non financial variables are based on (a) The lag and changes in the lag in reporting accounts (b) Director resignations and appointments (c) Director shareholdings
Untied Kingdom	Keasey and Watson (1986)	MDA	Financial statement data and information on the age of company, the directors and auditors, lags in reporting to Companies House and whether or not any of the firm s assets secure a bank loan.
Untied Kingdom	Lennox (1999)	MDA, Probit, Logit Model	1. The number of employees (EMP_{it}) is used as a measure of company size, 2. SIC data are used to create industry dummies (D_j). 3. The debtor-turnover ($DBTN_{it}$), 4.gross cash flow (GCF_{it}) and 5.cash ratio ($CASHRAT_{it}$) variables are used as measures of cash flow. $DBTN_{it}$ captures the effect of debtor repayment on cash flow; if $DBTN_{it}$ is low, the company may have experienced problems in receiving payment for past sales. 6.GCF_{it} is a measure of profit-generated cashflow.7.$CASHRAT_{it}$ captures the ability of the company to meet its short-term liabilities through cash reserves
Untied Kingdom	Charitou, Neophytou & Charalambous (2004)	Logit Model; Neural Networks	Operating cash flows ; Financial leverage, Liquidity, Profitability, Activity and Market data ratios.

Table 3.5.2 The summaries of main feature of credit scoring methods (other developed countries)

Country	Authors	Model	Explanatory Variables
United States	Altman (1968)	MDA	X_1=Working capital/Total asset; X_2= Retained Earnings/Total asset, X_3=Embittering before interest and taxes)/Total assets; X_4=Market value (MV) equity/book value of debt, X_5=Sale/Total assets. Z=Overall Index Z=0.12X1+0.14X2+0.033X3+0.006X4+0.999X5
United States	Altman (1968)	MDA	Adaptation for Private Firms' Application. Substituting the book values of equity for the Market Value in X_4. The results of revised Z-Score model with a new X_4 variable is: $Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$
United States	Altman, Haldeman & Narrayman (1977)	MDA	The ZETA model is based on the following variables: X_1=Return on assets; X_2=Stability of earnings; X_3=Debt service; X_4=Cumulative profitability;X_5=Liquidity/Current ratio;X_6= Capitalisation (five year average of total market value); X_7=Size (total tangible assets)
United States	Ohlson (1980)	Logit Model	1. SIZE(-)=Log (total asset/ GNP price-level index); 2. TLTA(+) = Total liabilities divided by total assets, 3. WCTA(-) =Working capital divided by total asset 4. CLCA(+) = Current liabilities/ Current assets, 5. OENEG(I)= One if total liabilities exceeds total assets, zero otherwise, 6. NITA(-) = Net income/Total assets. 7. FUTL(-) =Funds provided by operations/ total liabilities, 8. INTWO(+) = One if net income was negative for the last two years, zero otherwise, 9. CHIN(-) = $(NI_t-NI_{t-1})/(\|NI_t\|+\|NI_{t-1}\|)$.
United States	Altman and Sabato (2006)	Logistic Regression	SMEs credit risk model with non-logarithm and logarithm transformed predictors as 1. EBITDA/Total Assets 2. Short term Debt/Equity Book Value 3. Retain Earnings/Total Assets 4. Cash/Total Assets 5. EBITDA/Interest Expense
Japan	Takahashi, et al. (1979)	MDA	Net worth/Fixed assets; Current liabilities/Assets; Voluntary reserves plus inappropriate surplus/Assets; Interest expense/Sales; earned surplus; Increase in residual value/Sales; Ordinary profit/Assets; Sales - Variable costs.
Japan	Ko (1982)	Linear model; Quadratic model	X_1=EBIT/Sales; X_2=Inventory turnover 2 years prior/ Inventory turnover 3 years prior; X_3=Standard error of net income (4 years), X_4=Working capital/Debt, X_5=MV equity/Debt; Japanese Model $Z_J = 0.868X_1 + 0.198X_2 -0.048X_3 + 0.436X_4 + 0.115X_5$

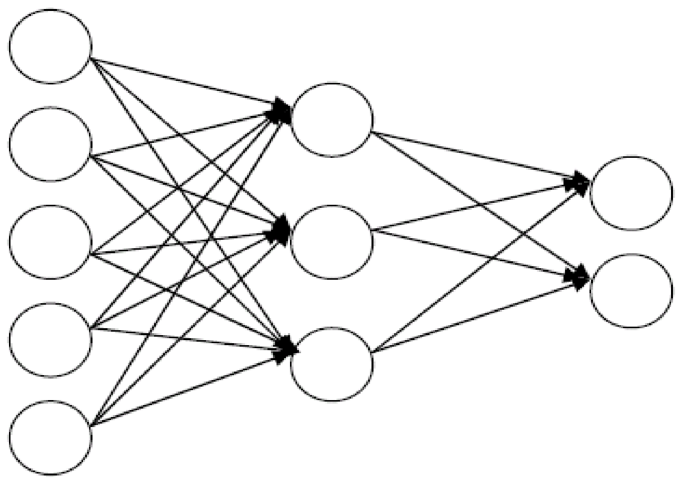
Table 3.5.2 The summaries of main feature of credit scoring methods (other developed countries) continued.

Country	Authors	Model	Explanatory Variables
Switzerland	Weibel (1973)	Univariate Analysis	Liquidity (near monetary resource asset – Current liabilities)/Operating expenses prior to depreciation; Inventory turnover; Debt/Assets.
Germany	Baetge, Huss & Niehaus (1988)	MDA	Capital structure: net worth/(total assets – quick assets – [property & plant without equipment]); Profitability: (operating income + ordinary depreciation + addition to pension reserves)/assets; Financial Strength: (cash income – expenses)/short term liabilities
Germany	Von Stein and Ziegler (1984)	Non-parametric and Parametric methods	Capital borrowed/Total capital; short-term borrowed capital/output; Accounts payable for purchases & deliveries /Material costs; (bill of exchange liabilities + accounts payable)/Output; (current assets – short-term borrowed capital)/Output; Equity/(total assets – liquid assets – real estate); Equity/(tangible property – real estate); Short-term borrowed capital/Current assets; (working expenditure – depreciation on tangible property)/(liquid assets + accounts receivable – short-term borrowed capital); Operational result/ Capital; (operational result + depreciation)/Net turnover; (operational result + depreciation)/ Short-term borrowed capital; (operational result + depreciation) /Total capital borrowed.
Canada	Altman and Lavallee (1981)	DMA	X_1= Sales/Total assets, X_2= Total debt/Total assets, X_3=Current assets/current liabilities; X_4= Net after-tax profits/Debt; X_5= Rate of growth of equity – Rate of asset growth; Debt/Assets; Sales/Assets. Z_C = Canadian Z-score. Z_C=-1.626+0.234X_1-0.531X_2+1.002X_3*0.972X_4+0.612X_5
The Netherlands	Bilderbeek (1979)	DMA	X_1=Retained earnings/Assets; X_2= Added value/ Assets; X_3=Accounts payable/Sales; X_4= Sales/Assets; X_5= Net profit/Equity. Z=Z-score (Netherlands, Bilderbeek) Z_{NB} = 0.45-5.03X_1-1.57X_2+4.55X_3+0.17X_4+0.15X_5
The Netherlands	Van Frederikslust (1978)	DMA	X_1= Liquidity ratio (change in short term debt over time); X_2= Profitability ratio (rate of return on equity). Z_{NF}= Z-score (Netherlands, Frederikslust) Z_{NF} = 0.5293+0.4488X_1+0.2863X_2
Australia	Izan (1984)	MDA	EBIT/Interest; MV equity/Liabilities; EBIT/Assets; Funded debt/ Shareholder funds; Current assets/Current liabilities.

3.6 Machine-learning Methods

The machine-learning methods, or AI systems, were introduced in the recent 90s, when computing technology became affordable and widespread along with the successful implementation of artificial neural networks for solving optimisation problems in several technical fields. Artificial neural networks (ANN) were developed to mimic the neurophysiology of the human brain to be a type of flexible non-linear regression, discriminant, and clustering models. They use the same data employed in the econometric techniques but arrive at the decision model using alternative implementations of a trial and error method. The architecture of ANN can usually be represented as a three-layer system, named input, hidden, and output layers.

The input layer first processes the input features to the hidden layer. The hidden layer then calculates the adequate weights by using the transfer function such as hyperbolic tangent, softmax, or logistic function before sending to the output layer. Combining many computing neurons into a highly interconnected system, we can detect the complex nonlinear relationship in the data. The simple three-layer perceptron, which is most used in credit scoring problems, can be depicted as shown in Figure 3.6.1.



Input Layer Hidden Layer Output Layer

Figure 3.6.1 Three-layer Neural Networks

Anderson and Rosenfeld (1988) edit a collection of papers that chronicled the major developments in neural network modelling. Empirical tests of the accuracy of neural networks produce mixed results. A supervised artificial neural network to predict default applied by Kim and Scott (1991) who present that the system performs well with 87% prediction rate but its predictive accuracy decreases over time. The test results in Coats and Fant (1993) study suggesting that the neural network approach is more effective than MDA for the early detection of financial distress developing in firms. It is found that the NN models consistently correctly predict firms of distress at least 80% of the time over an effective lead time of up to four years.

Podding (1994) applies neural networks approach for default prediction. In this study, he claims that neural networks outperform credit scoring models in bankruptcy prediction. He finds that not all artificial neural systems are equal, and notes that the multi-layer perceptron (or back propagation) performs well in bankruptcy prediction. Altman, Marco and Varetto (1994) examine Italian industrial firms and find that neural networks have about the same level of accuracy as credit scoring models. Trippi and Turban (1998) discuss other application of neural networks to credit risk, including consumer loans, home mortgages, and banking.

Hand and Henley (1997) review statistical classification methods in consumer credit scoring and interpret that neural network is normally applied to credit scoring problems can be viewed as a statistical model involving linear combinations of nested sequences of non-linear transformations of linear combinations of variables. Jagielska and Jaworski (1996) use neural networks as a decision support tool for credit card risk assessment within a major bank. In their study, the results show that that such neural network can help in discovering the potential problems with credit card applicants at the very early stage of the credit account life cycle. Richeson, Zimmermann and Barnett (1994) study on predicting consumer credit performance including neural networks approach. The results present that neural network outperforms traditional statistical methods such as discriminant analysis and logistic regression techniques. Torsun (1996) uses a neural network for a loan application scoring system based on a large data set of 310,000 from a building society. His study presents that neural network can be applied for predicting the type of customers who may go into arrears with their mortgage payment. Yang, Platt and Platt (1999) use a sample of oil and gas company debt to show that the back propagation neural network obtained the highest classification accuracy overall, when compared to the probabilistic neural network, and discriminant analysis.

Also, ANN has been widely used in credit scoring problems and provided a new alternative to LDA and logistic regression, particularly in situations where the dependent and independent variables exhibit complex nonlinear relationships. It has been reported by Jensen (1992), Desai, Crook and Overstreet (1996), Desai, Conway and Overstreet (1997), Piramuthu (1999), and Mahlhotra and Malhotra (2003) that its accuracy is superior to the traditional statistical methods such as discriminant analysis and logistic regression.

However, as mentioned previously, ANN has been criticised for its poor performance when there exist irrelevant attributes or small data sets. Although many methods have been proposed by Nath, Rajagopalan and Ryker (1997), Feraud and Cleror (2002) to deal with the problem of variable selection, it is time consuming and makes the model more complicated. Craven and Shavlik (1997), Chung and Gray (1999) point out the limitations of its long training process in designing the optimal network's system in credit scoring problems.

The machine learning property of the neural networks is very attractive; however, it poses a few problems as well. The most obvious one is that the system may need to go through a large number of iterations to reach the target level of accuracy. As a result the system proves to be expensive in terms of time and system resources. The network may result in over fitted models due to small variation of input values and it is difficult to check beforehand. The models lack explanation of reason for decisions and it is difficult to justify results.

3.7 Expert System

Historically, banking lending has relied on loan officer expert systems such as 5 Cs of credit to asses credit quality Allen (2002): character (reputation), capital (leverage), capacity (earnings volatility), collateral, and cycle (macroeconomic) condition. However, evaluation of the 5 Cs is performed by human experts might be inconsistent and subjective in their assessments. Moreover, the limitation of traditional expert systems is no specified weighting scheme for the 5 Cs in terms of forecasting PD. Recently, a few banks have adopted expert systems, which are also known as one type of the artificial intelligence (AI) systems. Rule-based or expert systems are used to try to mimic in a structured way the process that an experienced analyst uses to arrive at the credit decision. As the name indicates, such a system tries to make a replica of the process used by a successful analyst so that manager expertise is available to rest of the organisation. Caouette, Altman and Narayanan (1998) summarise the main components of expert systems:

(1) A consultation module that interacts with the user by asking questions, providing intermediate answers and hypotheses, and asking further questions until enough evidence has been collected to support a final recommendation.
(2) A knowledge base consisting of data, algorithms for financial simulation, and statistical forecasting and a set of production rules in systems.
(3) A knowledge acquisition and leaning module for creation of production rules and other rules based on the judgmental inputs of the user.

In general, expert system is based on the characteristics by a set of decision rules which is a theoretical or practical understanding of subject or a domain. An example of lending decision expert system is a knowledge base consisting of data such as industry financial ratios, and a structured inquiry process to be used by the analyst in obtaining data on a particular borrower. Also such system is often used in fraud models because their ‘rules’ based nature reflects on behaviour patterns. Saunders and Allen (2002) interpret that the development of expert systems has given banks and financial institutions the opportunity to test high powered modelling techniques.

3.8 Hybrid Approach Models

A hybrid model is the combination of the structural approach based on Merton's theory and an accounting-based statistical model similar to Altman's discriminant approach. In general, hybrid models try to combine market information along with fundamental information of the firm based on a detailed examination of a firm's balance sheet, income statement and projected cash flows to predict default.

Hybrid systems using direct computation, estimation, and simulation are driven in part by a direct causal relationship, the parameters of which are determined through estimation techniques. Sobehart, Stein, Mikityanskaya and Li (2000) present a summary of the approach Moody's used to validate and benchmark a series of quantitative default risk models and construct a hybrid default risk model for US non-financial public firms. In this study, they use an early warning system to monitor changes in the credit quality of corporate obligors. Crosbie and Bohn (2003) derive KMV Merton-type model. They use an option theoretic formulation to explain default and then derive the form of the relationship through estimation. In this method, migration probability matrices are data summaries which help to predict the tendency of a credit to migrate to lower or higher quality based on historical migration patters. Such matrices are derived by using the cohort component analysis that is, observing a group of bonds or companies through time from inception to end.

Benosa and Papanastasopoulosb (2007) demonstrate a hybrid approach extending the Merton model to assess credit quality. They use financial ratios, other accounting based measures and risk neutral distance to default metric of structural model as explanatory variable and estimate the hybrid model with an ordered probit regression methods. In this study, the main conclusion is that financial ratios and accounting variables contain significant and incremental information, however, the risk neutral distance to default metric does not reflect all available information regarding the credit quality of a firm.

3.9 Portfolio Credit Risk Models

Quantitative credit risk modelling at the portfolio level developed as the credit migration approach proposed by JP Morgan with CreditMetrics (1997), the option pricing, or structural approach, as initiated by KMV Merton model (1997) which is based on the asset value model originally proposed by Merton (1974). Credit Suisse Financial Products (CSFP) with CreditRisk+ (1997) proposes the actuarial approach making no assumptions with regard to causality which only focuses on default. McKinsey proposed CreditPortfolioView (2001) which is a discrete time multi-period model where default probabilities are conditional on the macro-variables like unemployment, the level of interest rates, the growth rate in the economy, which to a large extent drive the credit cycle in the economy. KPMG's Loan analysis system (LAS) and Kamakura's risk manager (KRM) may be categorised as type of reduced form models which decompose risky bond yields into the risk-free rate plus a credit risk premium. The framework of theses models are broadly reviewed in this following section.

3.9.1 CreditMetrics/ CreditManager Model

CreditMetrics (1997) provides an exposition of framework for quantifying credit risk in portfolios of traditional credit products (loans, commitments to lend, financial letters of credit), fixed income instruments, and market driven instruments subject to counterparty default (swaps, forwards, etc.). CreditMetrics use ratings not only as indicators of probabilities of default but also as the basis for choosing discount rates for use in valuing the end-of-period remaining cash flows of each portfolio exposure. Joint probabilities that any given pair of borrowers will have any given pair of ratings at the end of the analysis period are used to simulate the aggregate portfolio market value over a range of scenarios, with the estimated portfolio credit loss distribution being traced out by the estimated loss rates for the scenarios.

The methodology of credit risk is based on credit migration analysis that is the probability of moving from one credit quality to another including default, which is often taken arbitrarily as 1 year. CreditMertics relies on Monte Carlo simulation to create a portfolio loss distribution at the horizon date. Each obligor is assigned a credit rating, and a transition matrix is used to determine the probabilities that the obligor's credit rating will be upgraded or downgraded, or that it defaults. The values of any bond or loan portfolio, say 1 year forward, where the changes in values are related to credit migration only, while interest rate is assumed to be deterministic. Taking this approach, independent scenarios are generated in which the future credit rating of each obligor in the portfolio is known and correlations are reflected so that highly correlated obligors, for example, default in the same scenario more frequently than less correlated obligors. In each scenario, the credit rating of the obligors determines the value of the portfolio and accumulating the value of the portfolio in each scenario allows to estimate descriptive statistics for the portfolio or to examine the shape of the distribution itself. CreditMetrics risk measurement framework is summarised by Figure 3.9.1.

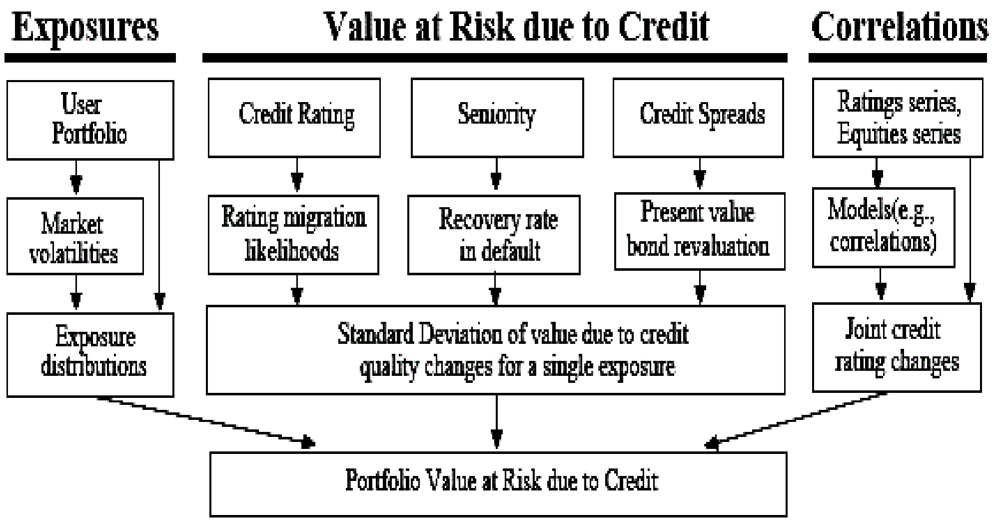


Figure 3.9.1 CreditMetrics risk measurement; Source: JP Morgan

3.9.2 KMV/ Portfolio Manager Model

KMV-Moody's (1997) approach differs from CreditMetrics as it relies upon the Expected Default Frequency (EDF) for each issuer, rather than upon the average historical transition frequencies produced by the rating agencies, for each credit class.

KMV's model is based on the option pricing approach to credit risk as originated by Merton (1974) and thus, credit risk estimated by KMV models is essentially driven credit risk by the dynamics of the assets value to the firms. That is, given the current capital structure of the firm which is composition of its liabilities: equity, short-term and long-term debt, convertible bonds, once the stochastic process for the asset value have been specified, then actual probability of default for any time horizon, 1 year, 2 year etc. can be derived.

In Figure 3.9.2 there are six variables that determine the default probability of a firm over some horizon, from now until time H. These are main elements of KMV model's estimated default probability.

1. The current asset value.
2. The distribution of the asset value at time H.
3. The volatility of the future assets value at time H.
4. The level of the default point, the book value of the liabilities.
5. The expected rate of growth in the asset value over the horizon.
6. The length of the horizon, H.

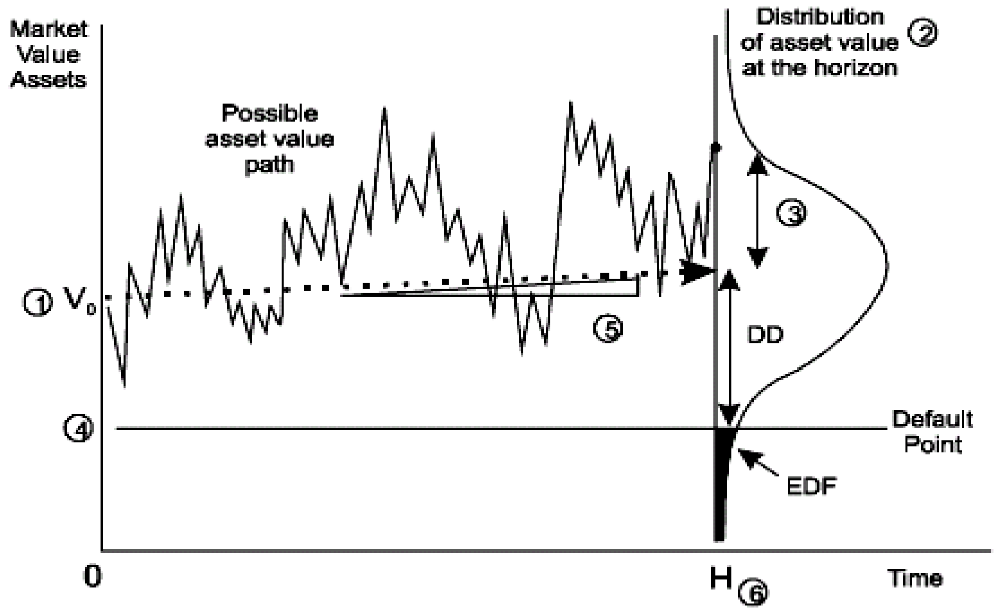


Figure 3.9.2 KMV-Merton type model default risk methodology;
Source: Moody's KMV (2003)-Modelling default risk

Figure 3.9.2 depicts how the probability of default relates to the distribution of asset returns and the capital structure of the firm in the simple case where the firm is financed by equity and a zero-coupon bond. KMV applies distance to default (DD) to publicly traded companies for which the value of equity is market determined. The default probability i.e. Expected Default Frequency (EDF) would simply be the likelihood that the final asset value was below the default point (the shaded area in Figure 3.9.2).

3.9.3 CreditRisk+ Model

Credit Suisse Financial Products (CSFP) developed the CreditRisk+ Model (1997). It is a statistical model of credit default risk that makes no assumptions about the causes of default. This approach is similar to that taken in market risk management, where no attempt is made to model the causes of market price movements. The model considers default rates as continuous random variables and incorporates the volatility of default rates in order to capture the uncertainty in the level of default rates. Often, background factors, such as the state of the economy, may cause the incidence of defaults to be correlated, even though there is no causal link between them. The effects of these background factors are incorporated into the CreditRisk+ through the use of default rate volatilities and sector analysis rather than using default correlations as explicit inputs into the model.

CreditRisk+ assumes as necessary conditions: 1) a Poisson distribution instead of a Binomial one, 2) a small magnitude for the default rate, and 3) a large number of obligors. Other conditions, such as independence and no conditionality, are necessary no matter what distribution is chosen.

Mathematical techniques applied widely in the insurance industry are used to model the sudden event of an obligor's default. This approach contrasts with the mathematical techniques typically used in finance. In financial modelling one is usually concerned with modelling continuous price changes rather than sudden events. Applying insurance modelling techniques, the analytic CreditRisk+ Model captures the essential characteristics of credit default events and allows explicit calculation of a full loss distribution for a portfolio of credit exposures. CreditRisk+ risk measurement framework is summarised as Figure 3.9.3.

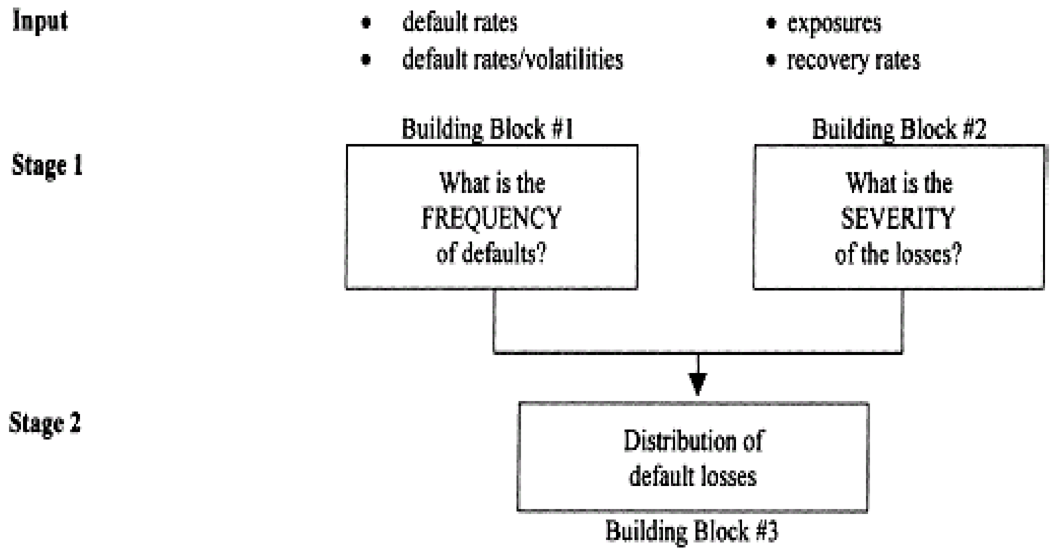


Figure 3.9.3 CreditRisk+ risk measurement framework; Sources: Credit Risk+

3.9.4 CreditPortfolioView Model

CreditPortfolioView Models proposed by McKinsey (2001) takes into account the current macroeconomic environment. Rather than using historical default rate averages calculated from decades of data, CreditPortfolioView uses default probabilities conditional on the current state of the economy. Therefore an obligor rated triple B would have a higher default probability in a recession than in an economic boom. The portfolio loss distribution is conditioned by the current state of the economy for each country and industry segment.

CreditPortfolioView is a multi-factor model which is used to simulate the joint conditional distribution of default and migration probabilities for various ratio groups in different industries, for each country conditional on the value of macroeconomic factors such as the employment rate, the rate of growth in GDP, the level of long-term interest rate, foreign exchange rates, government expenditures and the aggregate saving rate. The model is based on the causal observation that default probabilities, as well as migration probabilities, are linked to the economy. When the economy worsens both downgrade as well as defaults increase. It is the contrary when the economy becomes stronger. In other words, credit cycles follow business cycles closely. Since the state of the economy is, to a large extent, driven by macroeconomic factors, Credit Portfolio View proposes a methodology to link those macroeconomic factors to the default and migration probabilities.

3.9.5 Loan analysis system (LAS) and Kamakura's risk manager (KRM)

LAS and KRM models may be categorised as type of reduced form models. KPMG's Loan analysis system based on current market debt price uses a net present value (NPV) approach to credit risk pricing that evaluates the loan's structure. The loan's value is computed for all possible transitions through various states, ranging from credit upgrades and prepayments, to restructurings, to default. In these models default dependencies arise from direct links between firms. Input to the LAS includes the credit spreads for 1 year option-free zero coupon primary bonds for each of the S&P or Moody's ratings classification. LAS obtains risk neutral default rates by using iterative arbitrage pricing methods to price to state of default or non-default reference loans as contingent claims on the one-year loan. Kamakura' Risk Manager (KRM) is based on Jarrow and Yu (2001) derived approach of reduced form models. Credit spreads are decomposed into PD and LGD by the use of both debt and equity prices in order to better separate the default intensity process from the loss recovery process. The default hazard rate is modelled as a function of stochastic default-free interest rates, liquidity factors, and lognormal risk factors, such as a stochastic process for the market index. Saunders and Allen (2002) summarise that inputs of KRM is the benchmark of five explanatory variables used to parameterised system. They are (1) return on asset (ROA) = (net income/ total assets) (2) leverage = total liabilities / total asset (3) relative size = firm equality value/ total market value of the NYSE and AMEX; (4) monthly excess return over the CRSP[45] NYSE/AMES index return and (5) monthly equity volatility.

[45] Centre for Research in Security Price (CRSP) Contains security-level historical pricing, returns, and volume data on more than 20000 stocks (inactive and active companies) from the NYSE, AMEX, and NASDAQ markets.

3.9.6 Comparing Studies Portfolio Credit Risk Models

Saunders and Allen (2002) also point out that reduced form models decompose risky bond yields into the risk-free rate plus a credit risk premium. The credit spread consists of the risk neutral probability of default (PD) multiplied by the loss given default (LGD). KPMG's Loan Analysis uses this information to price untraded risk debt securities or loans. Kamakura's Risk Manager extends the analysis by estimating the liquidity premium and carrying cost included in bond spread to back out estimates of credit spreads. The primary advantages of reduced form models compared to structural models like Moody's KMV are their relative ease of computation and better fit to the observed credit spread data.

A number of studies describe and compare these credit portfolio models in the literature. Surveys of the techniques employed may be found in Basel Committee on Banking Supervision BCBS (1999) and Crouhy, Galai and Mark (2000). Koyluoglu and Hickman (1998) examine credit risk portfolio models i.e. CreditMertics, CreditPortfolioView and CreditRisk+, placing them within a single general framework and demonstrating that there is little difference between them in either theory or results, provided that input parameters are harmonised. It is found that these new techniques are accepted in credit risk modelling amongst both practitioners and regulators. Gordy (2000) offers a comparative anatomy of two especially influential benchmarks for credit risk models, CreditMetrics and CreditRisk+. Simulations are constructed for a wide range of plausible loan portfolios and correlation parameters. He points out that direct comparison often is not straightforward, because different models may be presented within rather different mathematical frameworks. In his study, it is found that the two models perform very similarly on an average quality commercial loan portfolio when the CreditRisk+ volatility parameter σ is given a low value. Both models demand higher capital on lower quality portfolios, but CreditRisk+ is somewhat more sensitive to credit quality than the CreditMetrics. Crouhy, Galai and Mark (2000) in their analysis of the different credit risk models also compare the Value at Risks (VaRs) implied for the similar portfolios at one point in time by different models, mainly, CreditMetrics, KMV, CreditRisk+ and CreditPortfolioView Models. It is suggested that the calibration of these portfolio credit risk models which need reliable default data for estimating probability of default. Hence, KMV is adopted when market value of firm assets are available while CreditPortfolioView is based on macroeconomics factors default and migration probability. It is notable that the revision of the transition probabilities is based on the internal expertise build up by the credit department of the bank, and the internal approval as well as the quality of the bank's credit portfolio.

Empirical investigations of these models have so far been limited. Lopez and Saidenberg (2000) suggest techniques for assessing models through cross-sectional evaluation of their risk measures but do not implement their suggestions on actual data. Gordy (2000) and Kiesel, Perraudin and Taylor (2002) implement rating-based models on stylised portfolios, studying how the risk measures vary across different type of portfolios. Lopez and Saidenberg (2000) derive the methods for evaluating credit risk models. Frey and McNeil (2003) review credit modelling methodologies analysing the mathematical structure of portfolio credit risk models with particular regard to the modelling of dependence between default events in these models. They explore the role of copulas in latent variable models underlying KMV and CreditMetrics and use non-Gaussian copulas to present extensions to standard industry models, as well as exploring the role of the mixing distribution in Bernoulli mixture models which is the approach underlying CreditRisk+ and derived large portfolio approximations for the loss distribution. In their article, it is found that maximum likelihood estimation of parametric mixture models generally outperform simple estimation methods. A broad discussion and comparison of these models can be found in Saunders and Allen (2002) who review portfolio credit risk models and compare these models across different measurement and modelling techniques. These models are summarised in Table 3.9.1 which compares different credit portfolio models that seek to offer alternative approaches to measuring the credit risk of a loan or a portfolio of loans.

Table 3.9.1 Comparison of different credit portfolio risk models measurement

	Merton KMV/Moody's	CreditMetrics	CreditRisk+	CreditPortfolioView	KPMG/Kamakura
Measuring Default	Mark to Market or Default Losses	Mark to Market	Default Losses	Mark to Market or Default Losses	Mark to Market
Risk Drivers	Asset values, Asset Volatility, Continuous default probabilities	Assets Values	Expected default values	Macroeconomic factors	Debt and equity prices, Downgrade
Data Requirement	Equity price, Equity Volatility, defined debt term, credit spreads, correlations, exposures	Historical transition matrix, credit spreads and yield curves, LGD, correlation, exposures	Default rates and volatility, Macroeconomic factors, LGD, exposures	Historical transition matrix, Macroeconomic variables, credit spreads, LGD, exposures	Debt term and equity price, historical transition matrix, correlations, exposures
Transition Probabilities	Distance to default (DD), structural and empirical, Term structure of EDF and assets	Credit migration	Actuarial random default rate	Migration conditional on macroeconomic factor	Driven by Default intensity
Volatility of Credit Event	Variables	Constant or variables	Variables	Variables	Variables
Correlation of Credit Events	Multivariate normal asset returns	Multivariate normal asset returns	Independence assumption or correlation with expected default rate	Gamma distributional form with Macroeconomic factor loadings	Poisson intensity processes with joint systemic factors
Measuring Correlation	Assets Values	Assets Values	Default rate volatilities	Default rate volatilities	Debt and Equity Prices
Modelling Correlation	Sophisticated factor model for assets return	Equity returns	Correlated default process	Correlation of default probability across industry segments	Poisson Intensity with joint systemic factors
Recovery Rates	Exogenously defined beta distribution	Exogenously defined Beta distribution	Constant within band	Random	Constant or Exogenously defined Stochastic distribution
Numerical Approach	Analytical (historical) and Econometric	Simulation and Analytical	Analytic (historical)	Simulation	Econometric
Interest Rates	Constant	Constant	Constant	Constant	Stochastic
Risk Classification	Empirical EDF	Ratings	Exposure bands	Ratings	Ratings /credit spreads

Source: Saunders and Allen (2002)

3.10 Credit Risk Models Comparison

It is difficult to say conclusively, which of the credit risk methods discussed have the best ability to predict default, each approach having their assumptions and limitations. A number of studies on credit risk models comparison reveal a larger degree of consistency in underlying structure. Different parameter assumptions and functional forms can produce different credit risk estimate across different models.

The simple KMV-Merton model in comparison with the Hazard model is studied by Bharath and Shumway (2004). It is found that KMV-Merton model does not produce a sufficient statistic for the probability of default, and it appears to be possible to construct such a sufficient statistic without solving the simultaneous nonlinear equations required by the KMV-Merton model. From their empirical study, it was concluded that the Hazard model performed marginally better than the KMV Merton model.

Altman, Marco and Varetto (1994) analyse the comparison between traditional statistical methodologies for distress classification and prediction which are linear discriminant (LDA) or logit analyses, with an artificial intelligence algorithm known as neural networks (NN). The data set comprised over 1000 Italian firms from 1982 to 1992. Interestingly, both approaches predicted acceptable 90% classification of distressed and non-distressed firms from a hold-out sample.

Lee and Urrutia (1996) compare the performance of the logit and hazard models in predicting insolvency and detecting variables that have a statistically significant impact on the solvency of property and liability insurers. The empirical results indicate that the hazard model identifies more significant variables than the logit model and that both models have comparable forecasting accuracy. It was concluded that the combined use of both models provides a more complete analysis of the insurance insolvency problem.

Desai, Crook and Overstreet (1996) compare the ability of neural networks such as multilayer perceptrons and modular neural networks, and traditional techniques such as linear discriminant analysis and logistic regression, in building credit scoring models in the credit union environment. The results indicate that customised neural networks offer a promising avenue if the measure of performance is percentage of bad loans correctly classified. However, logistic regression models are comparable to the neural networks approach if the measure of performance is percentage of good and bad loans correctly classified. Mossman, Bell, Swartz and Turtle (1998) provide an empirical comparison of four types of bankruptcy prediction models based on financial statement ratios, cash flows, stock returns, and return standard deviations. The results indicate the cash flow model discriminates most consistently two to three years before bankruptcy if considered in isolation. By comparison, the ratio model is the best single model during the year immediately preceding bankruptcy.

Hu and Ansell (2005) construct retail financial distress prediction models based on five credit scoring techniques-Naïve Bayes, logistic regression, recursive partitioning, artificial neural network, and sequential minimal optimisation (SMO), and compare these methods classification ability. Analyses provide sufficient evidence that the five credit scoring methodologies have sound classification ability. In the time period of one year before financial distress, logistic regression model shows identical performance with neural network model based on the accuracy rate and shows the best performance in terms of Area Under the Receiver Operating Characteristic (AUROC) value.

3.11 Modelling Credit Risk of SMEs

3.11.1 The Definition of SMEs

The role of small and medium-sized enterprises (SMEs) in economy is crucial for strengthening economic performance of many countries all over the world. SMEs represent over 95% of enterprises in most OECD countries and are continuing source of dynamism for the economy, producing two-third of all jobs and often more than one-third of the country's GDP. The Small Business Service (SBS), an executive agency of the Department of Trade and Industry, published Small and Medium-sized Enterprise (SME) Statistics for the UK in 2005.

There were an estimated 4.3 million business enterprises in the UK, 99.9% were small to medium sized. At the start of 2005, Small and medium-sized enterprises (SMEs) showed an increase of 59,000 (1.4 percent) as compared to the start of 2004. Almost all of these enterprises (99.3 percent) were small (0 to 49 employees). Only 27,000 (0.6 percent) were medium-sized (50 to 249 employees) and 6,000 (0.1 percent) were large (250 or more employees). Small and medium-sized enterprises (SMEs) together accounted for more than half of the employment (58.7 percent) and turnover (51.1 percent) in the UK.

New definition of SMEs in EUROPA (2005) is given as follows: Micro SMEs are defined as enterprises which employ fewer than 10 persons and whose annual turnover or annual balance sheet total does not exceed €2 million. Small SMEs are defined as enterprises which employ fewer than 50 persons and whose annual turnover or annual balance sheet total does not exceed €10 million. Medium-sized SMEs consists of enterprises which employ fewer than 250 persons and which have either an annual turnover not exceeding €50 million, or an annual balance sheet total not exceeding €43 million. Basel II (2005, 2006) describes SMEs borrowers as companies with less than Euro 50 Million in annual sales. In recognition of the different risks associated with SME borrowers under the IRB approach for corporate credits, banks are now permitted to separately distinguish loans to SMEs from those to large firms. The Basel II definition of SMEs does not entirely match the definition put forward by the European Commission. Under Basel II, SMEs are defined as companies with an annual turnover of less than €50M (regardless of any other criteria). The annual sales criterion can be substituted by total assets at the discretion of the national supervisor.

Within the SME category, there is then a further distinction between corporate and retail SMEs. Exposures to SMEs can be classified as retail exposures if the banking group's total exposure to the consolidated entity is less than €1M. Otherwise, they are treated as corporate exposures but benefit from a size adjustment in terms of their capital requirements, i.e. a reduction in the risk weights for corporate exposures based on the size (expressed in terms of annual turnover) of the counterparty. This can lead to a reduction in capital requirements of up to 20% when compared to a corporate counter-party with similar risk parameters (i.e. PD and LGD).

Not only do the criteria used to define firm size vary from country to country and within common economic zones such as in the United States, UK or in the European Union, but they also depend on the economic measure or variable used to establish that definition for instance annual turnover, total assets, number of employees or even capital. These discrepancies are presented on Table 3.11.1 in relation to the definition of SMEs in research studies, and in different countries.

There are several studies on SMEs issue that have used different definitions. Dietsch and Petey (2004) study SME exposures which should be treated as retail or corporate exposures and design three classes of SMEs in French and German companies: small SMEs with turnover between €0.15 and €1 million, medium-size SMEs with turnover between €1 and €7 million, and large SMEs with turnover between €7 and €40 million. The large firms were with turnover higher than €40 million. Fabi, Laviola and Reedtz (2003) address new Basel capital accord-IRB approach loans by risk classes and firms' sales and separate small SMEs with turnover less than € 5 millions and medium SMEs set between € 5-50 million. OECD Small and Medium Enterprise Outlook OECD (2002) categorise that small SMEs turnover is less than €7 million and medium-sized SMEs less than €40 million.

There is a quite different definition of small business in USA. Small Business Administration (SBA) Size Standards Office define small business for different industries, and main categories are (1) 500 employees for most manufacturing and mining industries (2) 100 employees for wholesale trade industries (3) $6 million of annual receipts for most retail and service industries (4) $28.5 million of annual receipts for most general and heavy construction industries (5) $12 million of receipts for all special trade contractors (6) $0.75 million of receipts for most agricultural industries.

Table 3.11.1 The summary of definition of SMEs

Authors	**SME Thresholds**			**Large Firms**
Dietsch & Petey (2004)	Group 1 SMEs 0.15-1 M€	Group 2 SMEs 1-7 M€	Group 3 SMEs 7 -40 M€	Large firms > 40 M€
Fabi, Laviola & Reedtz (2003)	Micro n.a.	Small Firms < 5 M €	Medium firms 5-50 M €	Large firms > 50 M €.
Basel II (2005, 2006), Altman and Sabato (2006), Jacobson et al. (2006)	SMEs annual sales less than 1M€ as retail entity	SMEs annual sales less than 50 M € as corporate entity		Corporate exposures
OECD Small and Medium Enterprise Outlook Reports (2002)	Micro SMEs n.a.	Small SMEs ≤7 (M€	Medium-SMEs ≤ 40 M€	
EUROPA (2005) (the portal site of the European Union)	Micro SMEs Employees < 10 Annual turnover ≤ 2 M€ (or Annual balance sheet total ≤ 2 M€)	Small SMEs Employees <50 Annual turnover ≤ 10M€ (or Annual balance sheet total ≤ 10 M€)	Medium SMEs Employees <250 Annual turnover ≤ 50M€ (or Annual balance sheet total ≤ 43 M€)	
UK	Employees 0-9	Employees 10-49	Employees 50-250	Employees > 250
USA: Small Business Administration (SBA) Size Standards Office	(1) 500 employees for most manufacturing and mining industries (2) 100 employees for wholesale trade industries (3) $6 million of annual receipts for most retail and service industries (4) $28.5 million of annual receipts for most general & heavy construction industries (5) $12 million of receipts for all special trade contractors (6) $0.75 million of receipts for most agricultural industries			

3.11.2 Estimation of SMEs Credit Risk

New Basel II Accord complete version (BCBS, 2006) describes the model building component around the IRB approach is largely focused on exposure risk modelling and defining the PD and LGD of a particular obligor or facility. To compute risk and capital requirement at portfolio level, one needs to make some assumption about the joint default process or distribution. Under Basel II, loans to small businesses may be designated as corporate loans or as retail loans. For loans to be classified as retail credits under Basel II, loan amounts must be small (under 1 million Euros), and the loans must be managed on a pooled basis. If loans are designated as corporate, they may be considered as loans to small and medium enterprises (SMEs) under Basel II if the loan amount is small and the business meets certain size criteria. A corporate loan receives a lower capital requirement if it is designated as a SME.

To compute risk at portfolio level and capital requirement, it needs to make some assumptions about the joint default process or distribution. Broadly there are two approaches to computing joint losses: direct estimation with data or indirectly through a structural model of firm valuation and default (Saidenberg and Schuermann 2003). The binding constraint typically is data availability: defaults are rare, joint defaults even more so. In general, the direct approach would take a large data set with a long history and proceed to computing default and loss correlations directly within a time window large enough. To do this properly, one really needs large amounts of data, restricting the application of this approach to consumer banking portfolios such as credit scoring. In addition, they reflect on the indirect approach that uses a structural model of default, e.g. the Merton model which looks at evolution of a firm’s balance sheet to arrive at a distance-to-default measure and suggest that since default data is very sparse, the idea is to focus modelling effort instead on the default process in a space where the data is denser.

3.11.2.1 Merton Type Models for SMEs

In Merton model, for example, CreditMetrics and KMV model, both approaches rely on the asset value model, where the default process is endogenous, and relates to the capital structure of the firm i.e. the composition of its liabilities: equity, short-term and long-term debt, convertible bonds, etc., once the stochastic process for the asset value has been specified, then the actual probability of default for any time horizon, 1 year, 2 years, etc. can be derived. The key parameters of Merton type model created for SMEs need to be derived from a consistent set of data and ratings. These data are available directly from banks' internal rating system for SMEs. If banking internal rating is unavailable the credit bureau supervisor's credit rating are used alternatively.

Parameterisation for Merton model using rating data is discussed by Carey and Hrycay (2000). Such method involves mapping each internal grade to a grade on the Moody's or Standard & Poor's (S&P) scale and using the long-run average default rate for the mapped agency grade to quantify the internal grade. The mapping method is useful because of its apparent simplicity and agency grades are familiar to most market participants, as well as Moody's and S&P maintain databases with long histories of default data publicly issued bonds and regularly publish tables of historical average default rates.

Merton-type models such as KMV-Merton model, however, potentially provide alternative modelling choices. Allen, DeLong and Saunders (2004) survey of credit risk modelling of retail markets points out that such Merton-type models focusing on the equity price of the firm. The problem with such models is that retail borrower and small business often do not have public trade stock, and therefore, equity prices may not be available or may be unreliable due to liquidity problems. Therefore, alternative RiskCalc models derived by Moody's seek to determine which private firms will default on loans. An overview of RiskCalc models is provided by Falkenstein, Boral and Carty (2000) who use credit scoring employing financial ratio analysis to determine which firms are likely to default.

3.11.2.2 Credit Scoring for SMEs

Credit scoring methods are based on producing estimated default probabilities (or other risk measures) for individual borrowers, and the characteristics typically used as predictors are borrower financial ratios and other characteristics as predictors. See Hand and Henley (1997), Thomas et al. (2002) for a detailed overview of consumer credit scoring, including the treatment of various data and statistical issues regularly encountered when building these models. Similar approaches are used to evaluate potential applicants for solicitation such as for marketing purposes and evaluating borrowers credit where it has been extended for monitoring purposes.

Credit risk modelling for SME is presented by a statistical model: financial ratios (such as profitability and leverage), the presence of past credit problems (if a business credit report was available from a commercial credit bureau like Dun & Bradstreet[46] or Experian[47]). FairIssac (1995) develops small business credit scoring models using a sample of more than 5000 small business loan applications over five years from 17 large U.S. banks designed to represent a national pool. This model, which is constructed in cooperation with the Robert Morris Associates, was further refined in 1996 using data from 25 banks. Several large banks begin to adopt Small Business Credit Scoring (SBCS) following the introduction of the Fair, Isaac model.

Eisenbeis (1978) notes, for example, that Dun & Bradstreet's small business credit scores were based on a logit model. However, he argues that a hazard/survivorship model may be better suited for the dynamic nature of the problem, given that the probability of default may not be constant throughout the life of the loan. Mester (1997) further notes that alternative methods of evaluating the data, such as the use of neural networks, have also been investigated.

[46] The Dun & Bradstreet (D&B) provides small business report and credit risk solution. D&B Rating assess a firm's size and composite credit appraisal, based on information in a company's interim or fiscal balance sheet and an overall evaluation of the firm's creditworthiness. http://smallbusiness.dnb.com/

[47] Experian provides company's credit report and credit rating including analytical and information services to organisations and consumers to help manage the risk and reward of commercial and financial decisions. http://www.experian.co.uk/

Berger and Udell (2002) analyse the technologies and definition of SMEs lending, and point out credit scoring methods are useful for micro-small business lending. They identify 6 distinct lending technologies for SME are: (1) financial statement lending, (2) relationship lending, (3) credit-scored micro-business lending, (4) asset-based lending, (5) factoring and (6) trade credit. Later, important issues of SMEs lending are addressed by Berger and Udell (2004) who conjectures that the mix of technologies may be an important consideration in addressing policy issues such as SMEs funding gaps, the evolution of SME lending in developing economies, the importance and functioning of the credit channel, and the calibration of Basel II. Berger and Udell (2004) discuss the credit scoring methods for measuring SMEs which is a model that can produce fitted default probabilities for a representative sample of borrowers in each internal grade, averages of the fitted values may be used as estimates of average default probabilities for each grade.

Commercial banks in U.S. are increasingly using credit scoring models to underwrite small business credits, as stated by Berger, Frame and Miller (2005). They focus on small business credit scoring (SBCS), a lending technology used by many financial institutions over the last decade and discuss this technology, evaluate the research findings on the effects of this technology on small business credit availability, and links these findings to a number of research and public policy issues. In this research, they strongly suggests that SBCS has increased small business credit availability in a number of dimensions, including: increasing the quantity of credit extended; increasing lending to relatively opaque, risky borrowers; increasing lending within low-income areas; lending over greater distances; and increasing loan maturity.

3.12 Monte Carlo Simulation for Credit Risk Models

The key to successful credit risk modeling is availability of data to specify and calibrate the model. Traditionally there have been limited data available on credit default and it was difficult to access, therefore, Monte Carlo simulation can be a useful method for conducting research in credit risk modelling.

The Monte Carlo simulation may begin, once the distribution of the independent variables and their correlations are established. The end result of the simulation is a probability distribution of outcomes; an advantage of Monte Carlo simulation is that it makes it possible to model complex relationships without having a closed mathematical solution. A simulation may be used to test the validity of direct solutions because in simulating it is necessary to define all the variables being used and their distributions, all of which may have been hidden or assumed in the direct solutions. Monte Carlo simulations are used in CreditMetrics (1997) and Merton-KMV (1997) models.

Carey (1998) empirically examines two characteristics of private debt portfolios credit loss rate distributions, conditional on individual asset risk and other portfolios characteristics. He estimates both expected losses and the size of loss rates in the bad tail of the conditional loss distribution using Monte Carlo simulation resampling methods. Results show ex ante riskier classes of private debt perform better on average than public debt. Both diversification and the riskiness of individual portfolio assets influence the bad tail of the portfolio loss distribution.

Gordy (2000) explore comparative simulations methods evaluating CreditMetrics and CreditRisk+ models. It is found that the effect of individual and underlying mathematical structures providing intuition for the relationship between the two models and it is described quite precisely where the models differ in functional form, distributional assumptions and reliance on approximation formula.

Altman and Saunders (2001) carry out a set of Monte Carlo simulations which allow estimation of the size of losses in the tail of loan loss distributions conditional only on assumptions made about the composition of bank portfolios. In the simulations, they follow Carey (1998) and look at a number of portfolios.

Crouhy, Galai and Mark (2000) study credit portfolio risk models and point out that Monte Carlo simulation are used in CreditMertics to create portfolio loss distribution at the horizon date. Each obligor is assigned a credit rating and a transition matrix is used to determine the probabilities that the obligor's credit rating will be upgraded or downgraded, or that it defaults. KMV has demonstrated that substantial differences in default rates may exist within the same bond rating class, and the overlap in default probability ranges may be quite large with, for instance, some BBB and AA rated bonds having the same probability of default. KMV has replicated 50 000 times, through a Monte Carlo simulation, Moody's study of default over a 25-year period.

Portfolio losses depend on default events that are relatively rarely addressed by Kreinin (2001) and therefore, efficient Monte Carlo simulation could be based on a transformation of the measure that describes joint evolution of market and credit risk factor for estimating credit risk models. Frey and McNeil (2001) present results from a simulation study showing that, even for asset correlations, assumptions concerning the latent variable copula can have a profound effect on the distribution of credit losses.

3.13 Conclusion

The New Basel II Accord (2006) has proposed credit risk approach that recognised the individualised, quantitative framework adopted by banks to meet their specific requirements. It is notable, new credit risk technology has made a stronger contribution to progress in other aspects of the banking business, making it possible for institutions to increase their prudence on credit exposure and to be more flexible in extending credit because of better information systems.

This chapter has provided broad reviews on credit risk models studies. The choice of the model, however, would depend on the circumstances. Among all the methods surveyed here, there is no single model which may be termed as a standard solution that would suit all banks. A variety of factors determine the best fit for the purpose. Banks need quantitative expertise not only for internal development the methodology, but also for optimally selecting from the available methodologies.

Statistical models that estimate default probabilities for individual borrowers may be used to obtain an estimate of the mean default probability for a grade by averaging model fitted values for a sample of within-grade borrowers (Carey and Hrycay 2000). The two categories of statistical methods i.e. studies on accounting-based models and market-based models have been addressed. A series of models have been considered using the accounting data to predict company default. There are Multiple Dsicriminant Analysis (MDA), Logistic models, Neutral Network (NN) methods.

Credit scoring models retain their important role in credit risk modelling that is they can produce estimated default probabilities (or other risk measures) for individual borrowers, typically using borrower financial ratios and other characteristics as predictors. The main advantages of the credit scoring models are that they are objective and consistent. Moreover, the models can be easily comprehended and are based on traditional and robust statistical principles. In addition, the time horizon and architecture of the model can be made compatible with that of the rating system or the portfolio credit risk model. Moreover, survival analysis for building credit-scoring models has been applied to estimate the time to default or early repayment (Banasik, Crook and Thomas 1999; Narain 1992). The survival analysis can provide more information than the binary classified models. It can determine the timing when customers become bad as well as the default possibility of credit applicants or existing customers.

There are a number of studies that had applied credit scoring models to SMEs. Most importantly, automation of the decision process, which involves a large volume of data, enables the banks to speed up the approval process and, henceforth, achieve more efficient customer servicing. Therefore, it is much easier to build a large and reliable database within a relatively short period where as in the absence of database, the default prediction models would not work properly. The fact is that a very large proportion of small loans are granted to SMEs (Berger and Udell 1996; Saurina and Trucharte 2004), however, a lot of modelling effort in the SMEs segment is still in an experimental stage, where more innovative approaches are needed.

Furthermore, a whole range of modelling techniques has been developed to analyse portfolio credit risk. There are several studies on these models that compared their different measurement and modelling techniques that seek to offer alternative approaches to measuring the credit risk of a loan or a portfolio of loan. It is notable these models may be used to estimate average default probabilities for borrowers assigned to each of a financial institution's internal credit risk rating grades. Such models are increasingly used in setting financial institution capital structure, in internal control and are being considered for use in setting regulatory capital requirements for banks.

These theoretical models are currently used in different segments in banking i.e. corporate and retail banking. From above literature, one may find that models used traditionally have been corporate models but there is a lack of adequate information for these such as the share price information or credit ratings in SMEs. Meanwhile, credit scoring alternatively can use information which is appropriate for consumer credit and individual loans and so might not be appropriate for SMEs. Actually, many criticisms have been raised by governments and SME associations that high capital charge for SMEs could lead to credit rationing of small firms and, given the importance of these firms in economy, could reduce economic growth.

As a consequence, there is a need to demonstrate that banks should develop credit models specifically addressed to SMEs in order to minimise their expected and unexpected losses. Many banks and consulting companies already follow the practice of separating large corporate from small and medium sized companies when modelling their credit risk. In the academic literature, however, a study that demonstrates the significant benefits of such a choice is lacking.

CHAPTER FOUR

SMEs Credit Risk Methodologies

4.1 Introduction

In studies of company default one can often use public data, available from a number of sources. Unfortunately in the area of Small and Medium Sized Enterprises (SMEs) there is greater difficulty in obtaining data and this is particularly true for small businesses in this category. At the initial stage of the research it was felt appropriate to use full and partial simulation methods to compare credit scoring and Merton type models. The main feature is to look at assessment methodology and make some observations on the results obtained from simulations. In some cases the results obtained in the analysis reflect solely the assumptions made, but it demonstrates the ability to apply the appropriate technology when data of the desired form becomes available.

As illustration from literature, it is known that Merton type models were designed primarily for corporate business and are based on the gearing of the business debt to asset ratio and the volatility in the equity price. Accounting-based models require the selection of appropriate financial ratios and accounting measures to act as explanatory variables for predicting default. Many authors have explored the variables that might be used in Accounting-based models (Altman 1968; Ohlson 1980).

It is not clear which of these two models are appropriate to assess the default within Small and Medium Sized Enterprises (SMEs). It is important that this research explores whether information used with Merton type model is equivalent to the Accounting information popularly used. To do this for a sample of SMEs the distance to default (DD) and expected default frequency (EDF) were calculated. The relationship between DD and EDF of Merton type models and financial ratio variables of accounting-based models measures was explored by linear regression.

This Chapter will therefore discuss the studies that have been explored. In the case of credit scoring two simulations are carried out. This will be followed by a study using Merton type model. Furthermore, further simulations are generated for credit scoring model. This will allow comparison of the information base for SMEs. The aim is to assess whether the two models are employing equivalent information.

The Chapter will describe the assessment methodology.

4.2 Data Creation

First a sample set was selected randomly from SMEs company in UK based on Datastream (Datastream included Global Economics, Equities, Bonds, Futures and Options, Financial and Macroeconomic indicators over 50 countries) and Osiris database (Osiris database provides worldwide companies financial statement and stock data of listed companies around the world). SME companies were selected from database of UK businesses based on industry classification benchmark which included Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications and Technology sectors, but excluding Oil & Gas, Utilities and Financial companies (Banks, Insurance, Brokerage, REITs, ect.). The second group was not included because these industries have different financial structures, have a different default environment and appropriate data are, in some cases, difficult to obtain. Secondly, Basel II Accord has specified banking and financial institution counterparties as the category as sovereign and bank exposures. The total 116 companies were selected described later in section 4.6.

Derived from real sample 116 SMEs, two initial simulating samples were created for the credit scoring analysis: the first a full simulation and the second a partial simulation. For the Merton type model further data is collected for a subset of the data collected for the partial simulation.

4.3 Selection of Financial Ratio Variables

It is obvious that an important aspect of credit scoring models (i.e. multiple discriminant analysis and logistic model) is the selection of the appropriate financial ratios and accounting based measures that will be used as explanatory variables. In the default prediction studies which are summarised in Table 4.4.1 appropriate financial ratios and accounting variables were selected according to their ability to increase the prediction accuracy and decrease the misclassification rates. Explanatory variables that commonly have been used in previous studies of company credit fall under one of the following broad risk factors of financial performance:

4.3.1 Profitability Variables

Profitability can be expressed in a variety of accounting ratios that either measure profit relative to assets or relative to sales. Higher profitability should raise a firm's equity value and also implies there may be a longer time until a fall in revenue or costs to rise before losses incur, a company's creditworthiness is positively related to its profitability. They show how successful a firm is in generating returns and profits on its investments. The ratios include Net Income, Net Income less extraordinary items, EBIT (Earning before Interest and Tax), and Operation Profit in the numerator and Total Assets, Fixed Assets and Sales in the denominator.

4.3.2 Leverage Variables

These variables measure the size of firm's debt relative to its asset including liabilities to assets and long-term debt to asset indicating that high leverage increases the probability of default, and the degree to which an investor or business is utilising borrowed money. Companies that are highly leveraged may be at risk of default if they are unable to make payments on their debt; they may also be unable to find new lenders in the future. In addition, leverage variables measure firm's vulnerability to business downturns and economic shocks. Key variables to examine leverage are the Total Liability to Total Assets ratio and Debt to Equity. Those measuring the debt proportion of the assets of the firm should have a positive relationship with default, those measuring the equity ratio a negative one.

4.3.3.Liquidity

These variables are a measure of quality and adequacy of the current assets of a firm to meet its current liabilities if all become payable simultaneously. Some key variables for examining liquidity are Working Capital ratio, Quick Ratio and Current ratio. The high liquidity reduced the probability of default. Liquidity is a common variable in most credit decisions and can be measured by a huge variety of accounting ratios. The most popular ratio is the Current Ratio, calculated as current assets divided by current liabilities. In general the hypothesis is that the higher liquidity, i.e. the higher cash and other liquid positions, or the lower short-term liabilities, the lower is the probability of default.

4.3.4 Debt Coverage Variables

These variables are related to liquidity variables in that they are intended to measure the ability of a firm to service its debt. Most common solvency variables are the Interest Coverage Ratio and the Cash Flow to Interest Expense. Higher debt coverage reduces the probability of default. Debt coverage either measures the earnings before interest and taxes to interest expenses or the cash flow to liabilities ratio. Here liabilities are adjusted by subtracting advances from customers in order to account for industry specificities (e.g. construction), where advances traditionally play an important role in financing.

4.3.5 Growth Rates Variables

Small and medium-sized enterprises (SMEs) would expect growth of their enterprises performance in relation to business success, such as growth of profitability, annual sale and operating revenues, but there is a concern that only a few achieve breakthrough growth and promote continuous improvement profitability and productivity in practice. Therefore, growth variables are thought to be a significant indicator related to SMEs success. They are typically sales growth, EBITDA growth or net profit growth. It is generally better for a firm to grow than to shrink. Companies that grow very quickly often find themselves unable to meet the management challenges presented by such growth especially within smaller firms. Furthermore, this quick growth is unlikely to be financed out of profits, resulting in a possible build up of debt and the associated risks. As Khandani, Lozano and Carty (2001) point out, the relationship between the rate at which companies grow and the rate at which they default is not as simple as that between other ratios and default. Therefore one should expect that the relationship between the growth ratios and default to be non-monotone. The ratios included in Growth categories measure the stability of a firm's performance. Both rapid growth and rapid decline (negative growth) will tend to increase a firm's default probability.

4.3.6 Activity Ratios

A large stock of inventories relative to sales increases the probability of default; other activity ratios have different relationships to default. Activity ratios are accounting ratios that reflect some aspects of the firm that have less straightforward relations to credit risk than other variables, but that nevertheless capture important information. Most of the ratios considered in this study either display the ability of the firm's customers to pay their bills, measured by accounts receivable, or they evaluate the company's own payment habit in looking at accounts payable. For example a firm that suffers from liquidity problems would have higher accounts payable than a healthy one. Therefore the default probability should increase with these ratios. They measure the ability of a firm to turnover its assets, equity, inventories, cash, account receivables or payable. Some important activity variables are the Asset Turnover ratio and the Equity Turnover ratio.

4.3.7 Size Variables

They measure the market position and the competitive position of a firm. Key variables for the measurement of the size of a firm are total sales and total assets. The large firms default less often. Sales or total assets are almost indistinguishable as reflections of size risk. Both items are divided by the consumer price index to correct for inflation. Usually smaller firms are less diversified and have less depth in management, which implies greater susceptibility to idiosyncratic shocks. Therefore larger companies should default less frequently than smaller firms.

4.4 Data Analysis in Credit Scoring Methods

The ratios within each of categories given above can be viewed as alternatives of the same underlying construct. In building a logistic model, it would seem appropriate to include a diverse range of variables. Variable from two sets were not used in analysis these were Debt Coverage variable, and Size Variable. This was due to missing accounting data for firms in the initial study. As explained earlier the larger the Debt Coverage the more likely a firm will survive, not default. In past studies, size has had an impact aspect of survival of firms. A final 15 financial ratio variables were selected from an initial 20 financial ratios. ROE ratio, Change in ROE, Inventory Turnover, Insolvency Ratio, and Quick Ratio are excluded because accounting data is missing for most of SMEs. The final 15 selected financial ratio variables are described below and summarised in Table 4.4.1

Further details of the variables used are given in the list below:

1. TLTA: Total Liability /Total Asset. This ratio indicates that proportion of debt a company has relative to its assets. A Debt Ratio greater than 1 indicates that a company has more debt than assets, and a Debt Ratio less than 1 indicates a company has more assets than debt. Used in conjunction with other measures of financial health, the Debt Ratio can help investors determine a company's level of risk.

2. NPTN: Net Profit and Loss / Turnover. Profit ratios measure the efficiency with which the company uses its resources. The more efficient the company, the greater is its profitability. It is useful to compare a company's profitability against that of its major competitors in its industry. Such a comparison tells whether the company is operating more or less efficiently than its rivals. In addition, the change in a company's profit ratios over time tells whether its performance is improving or declining. A number of different profit ratios can be used, and each of them measures a different aspect of a company's performance.

3. WCTA: Working Capital /Total Assets. This ratio frequently found in studies of corporate problems, is a measure of the net liquid asset of the firm relative to the

total capitalisation. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.

4. EBITTA: Earnings Before Interest & Taxes / Total Asset. The ratio measures the true productivity of the firm's assets. EBIT is an indicator of a company's financial performance calculated as revenue minus expenses excluding tax and interest, also referred to as operating earnings. It shows what returns management has made on the resources made available to them before making any distribution of those returns.

5. ROA: ROA = Net Income / Total Asset is an indicator of how profitable a company is relative to its total assets. ROA gives an idea as to how efficient management is at using its assets to generate earnings. Calculated by dividing a company's annual earnings by its total assets, ROA is displayed as a percentage.

6. CHROA: Change in ROA = $(ROA_t - ROA_{t-1}) / (|ROA_t| + |ROA_{t-1}|)$ based on CHIN variable calculation (see 7. CHIN described as below), it explains the increase or decrease rate of recent period.

7. CHIN = $(N_t - N_{t-1}) / (|N_t| + |N_{t-1}|)$, where N_{it} is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income (the measure appears to be due to Mckibben (1972)) and this variable is used in Ohlson, 1980, O-Score Model.

8. SALEG.: Sale Growth = $(Sale_t - Sale_{t-1}) / Sale_{t-1}$. It presents percentage increase (or decrease) in sales between two time periods. This ratio measures the stability of a firm's performance in sales. Both rapid growth and rapid decline (negative growth) will tend to increase a firm's default probability.

9. CACL: Current Ratio = Current Assets / Current Liabilities. It provides an indication of the liquidity of the business by comparing the amount of current assets to current liabilities. A business's current assets generally consist of cash, marketable securities, accounts receivable, and inventories. Current liabilities include accounts

payable, current maturities of long-term debt, accrued income taxes, and other accrued expenses that are due within one year. A Current Ratio significantly higher than the industry average could indicate the existence of redundant assets. Conversely, a Current Ratio significantly lowers than the industry average could indicate a lack of liquidity.

10. CFCL: Cash Flow / Current Liabilities. Cash flow presents a common measure of internally generated cash and is defined as cash from operations less fixed asset purchases. This ratio measures how well a firm manages its short-term debt with its cash and other liquid assets.

11. TNTL: Turnover / Total Asset. It evaluates the efficiency of managing all of the firm's assets. The higher ratio is the more effective is the use of the firm's investments on total assets.

12. FASF: Fixed Assets / Shareholders Funds. High ratios relative to the industry can indicate low working capital or high levels of debt.

13. ARSL: Account Receivable / Sales. It is a measure of how well the firm collects sales on credit from it customer, just as average collection period measures this in number of days.

14. CHARSL: Change in Account Receivable to Sales. This ratio intends to explain the increase or decrease rate of recent period. A higher or increasing accounts receivable turnover is usually a positive sign showing the firm is successfully executing its credit policies and quickly turning its accounts receivables into cash. A possible negative aspect to an increasing in this ratio indicates the firm may be too strict in its credit policies or decline in potential sales.

15. APSL: Accounts Payable to Sales: This ratio is obtained by dividing the 'Accounts Payables' of a company by its 'Annual Net Sales'. This ratio gives you an indication as to how much of their supplier's money does this company use in order to fund its sales. Higher ratio means that the company is using its suppliers as a

source of cheap financing. The working capital of such companies could be funded by their supplier.

Table 4.4.1 List of SMEs 15 financial ratio variables (for each ratio, the variables name and definition are presented and their major categories along with potential relationship to probability of default; moreover, the ratios are broken down into their major categories)

Category	Variable Name	Variable Definition	Related to Probability of Default
Profitability	NPTN	Net Profit and Loss /Turnover	＋
Profitability	EBITTA	Earnings Before Interest & Taxes / Total Asset	＋
Profitability	ROA	ROA = Net Income / Total Asset	＋
Growth Ratio	CHROA	Change in ROA = $(ROA_t-ROA_{t-1})/(\|ROA_t\|+\|ROA_{t-1}\|)$	＋；－
Growth Ratio	CHIN	Change in Net Income = $(N_t-N_{t-1})/(\|N_t\|+\|N_{t-1}\|)$	＋；－
Growth Ratio	SALEG	Sale Growth= $(Sale_t - Sale_{t-1}) / Sale_{t-1}$	＋；－
Leverage	TLTA	Total Liability/Total Asset	＋
Liquidity	WCTA	Working Capital/ Total Asset	＋
Liquidity	CACL	Current Ratio= Current Assets/Current Liabilities	＋
Liquidity	CFCL	Cash Flow/ Current Liabilities	＋
Activity	TNTA	Turnover/ Total Asset	＋
Activity	FASF	Fixed Asset/ Shareholder Funds	－
Activity	ARSL	Account Receivable/ Sales	－
Activity	CHARSL	Change in Account Receivable to Sales	＋；－
Activity	APSL	Account Payable / Sales	－

Note: Variables (+) is positive; (-) is negative related to default probability (＋ ； －) indicated both rapid growth and rapid decline (negative growth) will tend to increase a firm's default probability.

4.5 Monte Carlo Simulation

Monte Carlo simulation is a widely used tool in finance and allows the modelling of the distribution of portfolio defaults and losses, taking into account default probability and recovery rates as well as the correlation between assets in a portfolio. Glasserman (2004) interprets that principles of Monte Carlo methods are based on the analogy between probability and frequency. The mathematics of measure formalises the intuitive notion of probability, associating an event with a set of outcomes and defining the probability the event to be its frequency or measure relative to that of universe of possible outcome.

In the simplest case, this means sampling randomly from a universe of possible outcomes and taking the fraction of random draws that fall in a given set as an estimate of the set's frequency. The law of large numbers ensures that this estimate converges to the correct value as the number draws increase. The central limit theorem provides information about the likely magnitude of the error in the estimate after a finite number of draws for most situations. It is notable that if variance is infinite there is a problem using central limit theorem.

Consider estimating the integral of a function *f* over the unit interval. It may represent the integral $\alpha = \int_0^1 f(x)dx$ as an expectation E [*f* (*U*)], with *U* uniformly distributed between 0 and 1. A mechanism for drawing points $U_1, U_2, \ldots$ from [0,1] is assumed to be independent and uniform. Evaluating the function *f* at *n* of these random points and averaging the results produces the Monte Carlo estimate $\hat{\alpha} = \frac{1}{n}\sum_{i=1}^{n} f(U_i)$. If *f* is indeed intergrable over [0, 1] then, by the strong law of large numbers, $\hat{\alpha} \to \alpha$ with probability 1 as $n \to \infty$. If f is in fact square intergrable and α_f is derivative of function *f*. We set $\sigma_f^2 = \int_0^1 (f(x) - \alpha)^2 dx$, then the error $\hat{\alpha} - \alpha$ in the Monte Carlo estimate is approximately normally distributed with mean 0 and standard deviation $\alpha_f / \sqrt{n}$, the quality of this approximation improving with increasing *n*.

The parameter α_f would typically be unknown in a setting in which α is unknown, but it can be estimated using the sample standard deviation $s_f = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(f(U_i) - \hat{\alpha}_n)^2}$. Thus, from the function value $f(U_1), \ldots, f(U_n)$, it is obtained not only an estimate of the integral α but also a measure of the error in this estimate. The form of the standard error $\alpha_f / \sqrt{n}$ is a central feature of the Monte Carlo methods.

Monte Carlo simulation methods used to model credit risk remain an active area of research, and the field is currently spread wide over modelling variations. Traditionally credit default frequency has been low and so there is very limited data available and hence it is difficult to assess default. Therefore, Monte Carlo simulation is a useful method in studying credit risk, for example Gordy (2000), Carey (1998), Altman and Saunders (2001), Crouhy, Galai and Mark (2000) employ Monte Carlo methods using set of data for credit risk analysis in their studies.

In this initial study modelling credit risk using Monte Carlo simulation is based on logistic regression to estimate SMEs obligators' default probability. Full and partial simulation methods are used and the credit risk models and predictive percentage are presented in different models described in the following section.

4.6 Full Simulation Data

Using the four categories of SMEs, Micro, Small, Medium and Large, (defined by turnover) a sample is selected from each category and the mean and standard deviation are calculated. For a business to be eligible they must have a marginal turnover between 0.15 millions to 50 millions Euros and to have provided financial statements at least 3 years till 2004. Total 116 selection samples are used in the 4 bands, details are provided in Table 4.6.1.

Table 4.6.1 Samples selection of SMEs

SMEs Size	**Turnover in M€**	**Sample of SMEs Data**
Micro SMEs	0.15~1	13
Small SMEs	1~5	26
Medium SMEs	5~25	46
Large SMEs	25~50	31
Total Samples		116

The mean and standard deviation and descriptive statistics of micro, small, medium and large SMEs are presented in Table 4.6.2. Some comments are presented below on the summary statistics.

1. The mean of these variables TLTA, SALEG, CACL, TNTA, FASF, ARSL, CHARSL and APSL is a positive value in all bands micro, small, medium and large sized of SMEs.
2. Large SMEs show the mean of all the 15 financial ratio variables is positive. For smaller sized SMEs, there are more negative values for the mean of the financial variable. There are 3 negative values for medium SMEs, 5 negative values for small SMEs 7 negative for micro SMEs.
3. Only the mean of CHROA and CHIN is a negative for micro SMEs.
4. NPTL, WCTA, EBITTA and ROA have a negative value of the mean for micro, small and medium SMEs, only large SMEs have positive value of the mean.

Table 4.6.2 The mean and standard deviation of SMEs

	Micro SMEs		**Small SMEs**		**Medium SMEs**		**Large SMEs**	
Explanatory Variables	**Mean (μ)**	**Std. Deviation (σ)**	**Mean (μ)**	**Std. Deviation (σ)**	**Mean (μ)**	**Std. Deviation (σ)**	**Mean (μ)**	**Std. Deviation (σ)**
TLTA	.8075	1.25361	1.4032	2.82403	.5720	.32536	.5721	.26119
NPTL	-6.4954	7.53320	-1.1119	2.08507	-.1424	.45046	.0493	.08786
WCTA	-.0924	.17362	-.0828	1.57924	.0871	.25377	.1570	.23066
EBITTA	-1.2379	1.18107	-.9571	2.14169	-.0504	.19682	.0558	.10169
ROA	-1.4108	1.50524	-1.1028	2.40583	-.0760	.23680	.0322	.10065
CHROA	-.1771	.54225	.2024	.59472	.1994	.61968	.2275	.61307
CHIN	-.1058	.43299	.2419	.44075	.2069	.60675	.3048	.59027
SALEG	.7303	3.07434	1.2602	3.65809	.4489	1.10833	.0228	.37539
CACL	2.5423	1.75249	1.8631	1.54724	1.8937	1.62526	1.6371	.77554
CFCL	-3.8171	4.52311	-.7153	1.49105	.0373	.51814	.2828	.36176
TNTA	.5866	.89326	2.9821	10.51969	1.0977	.70838	1.3352	.91553
FASF	.6818	.77320	1.1055	2.80485	.6290	1.33166	.9361	1.69985
ARSL	.6645	.94297	.3988	.44466	.2158	.17690	.2160	.15299
CHARSL	3.2769	4.81369	1.7631	5.54328	1.1199	5.40621	.4130	1.03026
APSL	.8643	.84527	.4983	.51212	.2679	.25760	.1867	.15095

These means and variances are then used to generate a sample of 100 companies for each SME band. This created a sample of 400 simulated businesses but will not indicate whether they would default or not. To do this for each company it is assumed that the probability of failure is related to equally weighted combinations of the variables using a logistic model as $Prob(\text{failure}) = 1/\{1 + \exp\{S(\mathbf{x})\}\}$, where $S(\mathbf{x})$

is the sum of vector of financial variables. Then using the obtained probability of failure a random number between 0 and 1 is generated if the value is less than the probability the business is defined to have defaulted and if not it is defined as having not defaulted.

4.7 Partial Simulation Data

The partial simulation uses the random sample of firms to provide the financial ratios for the businesses. The assignment of whether the business has defaulted or not is the same as for the full simulation. The probability of failure is assumed to be related to the equally weighted combination of the financial ratios using the logistics model as $Prob(\text{failure}) = 1/\{1 + \exp(\boldsymbol{\beta}'\boldsymbol{x})\}$ where $\boldsymbol{\beta}$ and $\boldsymbol{x}$ are the vectors of coefficient to be estimated and financial variables respectively.

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4.7.1 Merton Type Data

For the Merton Type analysis a sample of 14 are taken from the large SMEs. For each of these businesses the daily share price is obtained. This is used to obtain the default probabilities. This further experiment was carried out using the results of the Merton Type analysis. This created probabilities of default for each of the 14 companies. This measure is related to the distance to default. A model based on the best relationship between time to default and a single financial ratio is built to predict the failure of the other business. Then this is used in a logistic analysis. More details on the simulation analysis conducted in this thesis are given in section 4.10.

4.8 Estimation Procedures

In this section the aim is to consider the alternative approaches to assessing default. Multivariate Discriminant Analysis (MDA), Logistic analysis and Merton model are described below.

4.8.1 Discriminant Analysis

Multivariate Discriminant Analysis (MDA) is based on a linear combination of two or more independent variables that will discriminate best between a prior defined groups: the default from non-defaulted firms. The multiple discriminant approach (MDA) (Altman and Lavallee 1981) is based on the following main assumptions: (a) the independent variables are multivariate normal, and (b) the covariance matrices of the two groups (default and non-default) are equivalent. This is really Linear Discriminant Analysis (LDA).

It weights the independent variables (financial ratios and accounting variables) and generates a single composite discriminant score. The score is then compared to a cutoff value, which determines the group that the firm belongs to. This is achieved by the statistical rule of maximizing the between group variance relative to the within group variance. The cutoff value is usually defined as the midpoint of the distance between the means of the standardized groups. One might note that the choice of the optimal cut-off score can incorporate changes in economic conditions.

Multiple linear DA has following discriminant function with an output in $[-\infty,+\infty]$:

$$CS_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_k X_{ik} \tag{4.8.1}$$

with CSi = discriminant score of firm i, $\beta_0, \dots, \beta_k$ = estimated coefficients, and $X_{i1}, \dots, X_{ik}$ = variables/features of firm i.

The estimation process of the coefficients is aimed at getting the best possible discrimination between both groups. A firm is then classified into the failing or non-failing group by comparing its discriminant score CS_i with a cutoff score between the failing and the non-failing firms.

4.8.2 Logistic Analysis

Logistic regression has the following advantages over MDA models (Mensah 1984; Ohlson 1980): (a) no assumptions need to be made regarding prior probabilities of failure and the distribution of predictor variables, (b) the use of such models permits an assessment of the significance of the individual independent variables included in the model, and (c) the models calculate the weight which each coefficient contributes to the overall prediction of failure or non-failure and produce a probability score, which makes the results more accurate.

In logistic analysis, the conditional probabilities or logistic scores lying between 0 and 1 (on a sigmoidal curve) are determined with the following formula by Hosmer and Lemeshow (2000):

$$P(y=1|X)=P_1 = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+....+\beta_k X_k)}} \qquad (4.8.2)$$

The exponent in equation (4.8.2) expresses the so-called 'logit'. The coefficients are estimated with the *maximum likelihood* method. Therefore, the likelihood function in formula (4.8.3) is maximised:

$$L(P)= \prod_{i=1}^{n} P_1(X_i)^{y_i}[1 - P_1(X_i)]^{1-y_i} \qquad (4.8.3)$$

$P_1\ (X_i)$ = probability of failure of i^{th} firm, β = vector with k estimable parameters $\beta_1, \beta_2, ... , \beta_k$, and X_i = vector with characteristics of i^{th} firm, and Y_i = 1 if i^{th} firm doesn't fail, Y_i = 0 if it fail. Both discriminant analysis and logit models are based on financial ratios and other risk factors of obligors. There are differences between the two models. The explanatory variable coefficients in a discriminant model are not subject to the standard regression test or interpretation. They are estimated to merely compute the discriminant score. Thus, the logit model offers a reasonable complement to analysis. For example, each explanatory variables coefficient β measures the change in log-odds of financial distress with respect to a unit change in the corresponding explanatory variables.

4.9 Theoretical Models of Merton-KMV

The KMV's framework relies on market data as well as accounting data. Its horizon can be chosen from a few days to several years. Indeed, market data can be updated daily assuming the other firm characteristics stay constant until further information becomes available.

The quantitative modelling of default risk, initiated by Merton (1974) shows how corporate liabilities (debt and equity) can be priced and the probability of default can be estimated under some specific assumptions. An important observation in Merton (1974) is that equity can be viewed as a call option on the value of the firm's asset.

Equity holders are the residual claimants to the firm's assets and are only subject to limited liability when the firm is default. Under Black-Scholes (1973) option model framework, the strike price of the call option is equal to the face value of the firm's liabilities and the option expires at time T when the debt matures. At time T, equity holders will exercise their option and pay off the debt holder if the value of the firm's asset is greater than the face value of its liabilities. Otherwise, the equity holders will let call option expire when the value the assets is not sufficient to fully repay the firm's debts. It this case, the firm files for bankruptcy and ownership is assumed to be transferred costlessly to the debt holders while the payoff for equity holders is zero.

The Merton-KMV (MKMV) model applies the framework of Merton, in which the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. The model recognizes that neither the underlying value of the firm nor its volatility are observable, but under the model's assumptions both can be inferred from the value of equity, the volatility of equity and several other observable variables by solving two nonlinear simultaneous equations.

Therefore, MKMV can determine a firm's probability of default. There are essentially three steps in the determination of the default probability of a firm.

1. Estimate asset value and volatility: in this step the asset value and asset volatility of the firm is estimated from the market value and volatility of equity and the book value of liabilities.
2. Calculate the distance-to-default: the distance to default (DD) is calculated from the asset value and asset volatility (estimated in the first step) and the book value of liabilities.
3. Calculate the default probability; the default probability is determined directly from the distance to default (DD) and the default rate for given levels of distance to default (DD).

In this study, the approach to calculate default risk measures using Merton's model is by KMV as outlined in Crosbie (1999), Crosbie and Bohn (2003), Vassalou and Xing (2001) and Bharath and Shumway (2004). It is assumed that the capital structure of the firm includes both equity and debt. The approach is based on Merton (1974) which uses Black-Scholes (1973) Option Pricing model. Let V_A be the value of the firm's underlying asset. It is assumed that follows a Geometric Brownian Motion (GBM) of the form if the market value of a firm's underlying asset (V_A).

$$dV_A = \mu V_A dt + \sigma_A V_A dW \qquad (4.9.1)$$

where μ is an instantaneous drift, and an instantaneous volatility σ_A. W is a standard Wiener process. With appropriate manipulation this can be formed into a parabolic differential equation for $F(V_A,t)$, the function of value and time, of the following form:

$$0 = ½ \sigma^2 V_A^2\, \delta^2 F/\delta V_A^2 + rV_A \delta F/\delta V - rV + \delta F/\delta t \qquad (4.9.2)$$

where r is the instantaneous riskless rate of interest and appropriate boundary conditions prevail.

The second critical assumption of the Merton model is that the firm has issued just one discount bond maturing in T periods. Under these assumptions, the equity of the firm is denoted by X_t the book value of the debt at time t, that has maturity equal T.

The market value of equity, E will then be described by the Black-Scholes (1973) formula for call options,

$$E = V\,N(d_1) - Xe^{-rT}\,N(d_2) \tag{4.9.3}$$

where $d_1 = \dfrac{\ln(V_A / X) + \left(r + \frac{1}{2}\sigma_A{}^2\right)T}{\sigma_A \sqrt{T}}$, (4.9.4)

$d_2 = d_1 - \sigma_A \sqrt{T}$, r is the risk-free rate, and N (.) is the accumulation density function of the standard normal distribution.

The KMV-Merton model is based on two important equations. The first is the Black-Scholes-Meton equation (4.9.3) expressing the value of a firm's equity as a function of the value of the firm. The second is that the volatility of the firm's value is related to the volatility of its equity. Therefore, under Merton's assumption it follows directly from Ito's Lemma that

$$\sigma_E = (V / E)\frac{\partial E}{\partial V}\sigma_A \tag{4.9.5}$$

In the Black-Schole-Merton model, it can be expressed that $\frac{\partial E}{\partial V} = N(d_1)$, so that under Merton model's assumption, the volatilities of the firm and its equity are related by

$$\sigma_E = (V / E)N(d_1)\sigma_A \tag{4.9.6}$$

where d_1 is defined by equation (4.9.4). The most important step of model implementing is to use equations (4.9.3) (4.9.6) simultaneously to iteratively obtain values for E, σ_E , V_A and σ_A .

4.9.1 Estimate Asset Value and Volatility

To calculate σ_A, an interactive procedure is adopted based on Bharath and Shumway (2004), Crosbie and Bohn (2003), Vassalou and Xing (2001).

First step, to estimate asset value and volatility, this is achieved using daily equity price from past 12 months to obtain an estimate of the volatility of equity σ_E, and the value is taken as initial $\sigma_A = \sigma_E E/(E+X)$ and this is used in equation (4.9.3) to infer the market value of each firm assets every day for the previous year and calculate a new estimate σ_A. The procedure is repeated until the new σ_A computed converges, so the absolute difference in less than 10 E-4 to the adjacent σ_A. For most firms, it takes only a few iterations for converges. Once the converged value of σ_A is obtained, it is then used to back out V_A through equation (4.9.3).

Once V_A and σ_A are estimated, the distance to default can be calculated as

$$DD = \frac{\ln(V_A / X) + \left(r - \frac{1}{2}\sigma_A{}^2\right)T}{\sigma_A \sqrt{T}} \tag{4.9.7}$$

The implied expected default frequency (EDF), implied probability of default, is

$$EDF = N(-DD) = N\left(-\frac{\ln(V_A / X) + (r - \frac{1}{2}\sigma_A{}^2)T}{\sigma_A \sqrt{T}}\right) \tag{4.9.8}$$

The input variables to the KMV-Merton model are summarised in Table 4.9.1 for the data input of variables in Merton-KMV model.

Table 4.9.1 Data input in Merton-KMV model

Data in Merton Models	**Vassalou and Xing (2001)**	**Bharath and Shumway (2004)**
E:	Shares outstanding multiplying by the firm's current stock price.	Shares outstanding multiplying by the firm's current stock price.
σ_E:	Daily stock price of firm of pass 12 month	Daily stock price of firm of pass 12 month
X:	Book value of firm's total liability	Current liability + 1/2 Long-term Debt
A:	A: Total Asset of firm	A = E+X
σ_A:	Initial σ_E for estimating iterative calculation to converge to new σ_A	$\sigma_A = \sigma_E$ E/(E+X) iterative calculation to converge to new σ_A
r :	One-year Treasury Bill	1-year Treasury Constant Maturity Rate
T	1 year	1 year

Note: *E*: Equity value of a firm; σ_E: volatility of Equity (Stock return); *X*: face value of the firm's debt; *A*: Total asset of firm; γ: risk-free rate; σ_A: volatility of Asset value of firm; *T*: the time period.

4.10 Empirical Analysis

This section of thesis describes the approach taken in more detail. In the previous sections the methods to be used have been presented. They cover Monte Carlo methods for the full simulation, partial simulation, the Merton Type model and the further experiment using Merton Type data. The sections discuss the estimation procedures using Discriminant Analysis, Logistic Regression and Merton Type analysis. The aim is to investigate the methodologies that are going to be used subsequently to explore credit risk. Hence the objective is to assess the effectiveness of different methods in the context of SMEs.

The aim of this study is to compare across the models not to establish the predictive capability of the individual model. A fair comparison can be achieve through the use of the results on all the data rather than subsets of the data. If, of course, the desire had been to establish the predictive power of the models then there would have been a need to consider either a hold out sample or bootstrap approach.

Given the sample size if a hold out sample had been deployed there would have been greater concern about the reliability of the estimates obtained.

For the full simulation, partial simulation and further simulation the analysis is based on the logistic regression model. Given a known model has been used to define default, interest lies in the relationship between the estimates of the coefficients and the model's coefficients.

For the Merton Type model the interest lies with the implementation of the procedure used. The results obtained indicate some of the issues which will arise in future research using the model.

4.10.1 Full Simulation

The data has been simulated on the basis of a sample drawn from businesses in a database. The data has been grouped into four bands, micro, small, medium and large. For each band the mean and variance of the 15 financial variables are obtained in Table 4.6.2. For each band a 100 businesses are created with each financial variable generate as a normal variate with mean and variance of the band. Hence the data consist of 400 businesses with 15 financial ratios for each business.

For each business a default variable is created by generating a random variable in the following manner. A probability of default is created using the logistic model on assumption that all 15 variables are included as equally weighted. Probability default $= 1/\{1 + \exp(S(\boldsymbol{x}))\}$, where $S(\boldsymbol{x})$ is the sum of the vector of financial ratios. A uniform variate on (0,1) is created. If a random value of this variate is less than the probability then the business is defined as defaulted, if this value is greater than the probability then the business is defined as not defaulted.

Hence the data used consist of 400 businesses each with 15 financial ratios and 1 default variable. A logistic model is then fitted using SPSS using a stepwise approach. It would be expected that the coefficients would be similar in value to each other.

In the full simulation there are 106 generated default case indicated by ‘0’ and 294 non-default cases indicated by ‘1’. The smaller the size of SME the more likely they are to be a default cases. There are 65 default cases in micro SME, 30 in small SMEs, 9 in medium and 2 in large SMEs. Table 4.10.1 shows that the full simulation for default and non-default cases in each band of SEMs.

Table 4.10.1 Full simulation default and non-default cases in each band of SMEs

Band of SMEs	**Simulation cases**	**Default**	**Non-default**
Micro	100	65	35
Small	100	30	70
Medium	100	9	91
Large	100	2	98
Total SMEs	400	106	294

Using SPSS a logistic model was run using forward stepwise approach. The Hosmer and Lemeshow test shows the models fit needed 12 steps. The Hosmer and Lemeshow Goodness-of-Fit Test divides subjects into deciles based on predicted probabilities, and then computes a chi-square from observed and expected frequencies. It can be seen from Table 4.10.2 the *p*-value = 0.950 is computed from the chi-square distribution with 8 degrees of freedom and indicates that the logistic model is a good fit.

Table 4.10.2 Goodness-of- Fit test in full simulation credit scoring model

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	18.936	8	.015
2	15.736	8	.046
3	16.633	8	.034
4	11.291	8	.186
5	4.381	8	.821
6	3.218	8	.920
7	2.427	8	.965
8	4.392	8	.820
9	1.950	8	.983
10	2.165	8	.976
11	.880	8	.999
12	2.736	8	.950

Table 4.10.3 shows that these are the predicted values of the dependent variable based on the full simulation SMEs in logistic regression model. The results show that 99 cases correctly predicted to be 0 and 290 cases correctly predicted to be 1. In this case, the 12 step model produces correct percentage of 97.3%.

Table 4.10.3 Classification in fully simulation credit scoring model

Observed			Predicted		
			PD		Percentage Correct
			.00	1.00	
Model	PD	.00	99	7	93.4
		1.00	4	290	98.6
Step 12	Overall Percentage				97.3

The β (B) coefficients for the logistic regression are presented in Table 4.10.4. There are 12 final variables selected in this model. Wald test shows that the coefficients of TATL, NPTN, WCTA, EBITTA, ROA, SALEG, CACL, CFCL, TNTA , FASF and CHARSL variables are statistically significant at $\alpha = 0.01$. CHROA is statistically significant at $\alpha = 0.05$. Only constant term is insignificant in this case.

Table 4.10.4 Variables in full simulation credit scoring model

Model		B	S.E.	Wald	df	Sig.	Exp(B)
Step 12	TATL	1.148	.357	10.370	1	.001	3.153
	NPTN	1.302	.257	25.626	1	.000	3.677
	WCTA	1.347	.515	6.830	1	.009	3.846
	EBITTA	1.227	.388	10.003	1	.002	3.412
	ROA	.888	.249	12.659	1	.000	2.429
	CHROA	1.310	.549	5.696	1	.017	3.705
	SALEG	1.488	.306	23.652	1	.000	4.427
	CACL	1.345	.316	18.140	1	.000	3.837
	CFCL	1.371	.279	24.167	1	.000	3.940
	TNTA	1.128	.218	26.739	1	.000	3.090
	FASF	1.656	.396	17.443	1	.000	5.236
	CHARSL	1.203	.240	25.041	1	.000	3.330
	Constant	.153	.560	.075	1	.784	1.166

The logistic regression equation of full simulation model is

$$\log\left(\frac{1-p}{p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_{12} X_{12}$$

where p is the probability. Expressed in terms of the variables used in this example, the logistic regression equation is

$$\log\left(\frac{1-p}{p}\right) = 0.153 + 1.148\ TATL + 1.302\ NPTN + 1.347\ WCTA + 1.227\ EBITTA$$
$$+0.888\ ROA + 1.310\ CHROA + 1.488\ SALEG + 1.345\ CACL$$
$$+ 1.371\ CFCL + 1.128\ TNTA + 1.656\ FASF + 1.203\ CHARSL$$

It is interesting to note that 12 variables out of the 15 appear in the model and that the values are generally similar and close to 1. The departures from one may be due to accounting for the other variables not included in the model.

4.10.2 Partial Simulation

The method of generation in the full simulation gives rise to theoretically independent variables for each business. This is clearly unrealistic. Hence as a second analysis it was decided to use the sample itself. The sample is limited compared to full simulation with only 116 businesses. The default variable is created exactly as for the full simulation.

The partial simulation generates SMEs which are 16 default cases indicated '0' and 100 non-default cases indicated '1'. Again a logistic model using forward selection was fitted using SPSS. The Hosmer and Lemeshow test shows step 5 demonstrates good model fit. The Hosmer and Lemeshow Goodness-of-Fit Test presents in Table 4.10.5. The p-value = 0.999 indicates that the logistic model is a good fit.

Table 4.10.5 Goodness-of-Fit test in partial simulation credit scoring model

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9.159	8	.329
2	4.904	8	.768
3	1.705	8	.989
4	1.307	8	.995
5	.863	8	.999

The results of the prediction based on the logistic regression model are presented in Table 4.10.6 which shows that 13 cases are correctly predicted to be 0 and 99 cases are correctly predicted to be 1. In this case, the step 5 model produced overall correctly predicted percentage of 96.6%.

Table 4.10.6 Classification in partial simulation credit scoring model

Observed			Predicted		
			PD		Percentage Correct
			.00	1.00	
Step 5	PD	.00	13	3	81.3
		1.00	1	99	99.0
	Overall Percentage				96.6

The β (B) coefficients for the logistic regression are presented in Table 4.10.7. There are 5 variables in the model and these are one profitability variable, two growth rate variables, and two activity variables. CHROA, SALEG, and FASF are significant at $\alpha = 0.05$. ARSL is significant at $\alpha = 0.1$.

Table 4.10.7 Variables in partial simulation credit scoring model

Model		B	S.E.	Wald	df	Sig.	Exp(B)
Step 5	NPTN	2.353	.837	7.895	1	.005	10.516
	CHROA	4.967	1.980	6.294	1	.012	143.582
	SALEG	.802	.365	4.814	1	.028	2.229
	FASF	.859	.324	7.019	1	.008	2.362
	ARSL	5.051	3.068	2.709	1	.100	156.143
	Constant	4.385	1.647	7.089	1	.008	80.207

$$\log(\frac{1-p}{p}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5$$

Expressed in terms of the variables used in this example, the logistic regression equation is

$$\log(\frac{1-p}{p}) = 4.385 + 2.353 NPTN + 4.967 CHROA + 0.802 SALEG + 0.859 FASF + 5.051 ARSL$$

The results are much more variable with coefficients lying between 0.802 and 5.051 and only 5 out of the 15 variables are included. There are two plausible reasons for this: the sample size and colinearity. Of the two explanations the latter is of more concern. In the full simulation the variables are constructed on an independent basis with each variable having a normal distribution with a mean and variance taken from a sample of companies. Hence there is no theoretical association between variables, see covariance matrix presented in Table 4.10.8. Thus in estimating the individual *βs* there is little impact from the other variables. The values are therefore close to a constant value of 1, which reflects well the original equal weighting of the variables.

In the case of partial simulation only the outcome is simulated. In this case the 'real' covariance ensure there is at least some association between the variables. This has an impact on the estimates obtained with the possibility of inflation and deflation of the coefficients estimated. This is due to colinearity. Hence there is a greater variability in the estimated coefficients away from the expected equal weighting. Obviously it would be possible to carry out standard test for colinearity.

Table 4.10.8 Summary coefficients of variable in full and partial simulation models

Category	**Variable Name**	**Fully Simulation Model for SMEs**		**Partial Simulation Model for SMEs**	
		Coefficients	**(p-value)**	**Coefficients**	**(p-value)**
Leverage	TLTA	1.148	0.001**		
Profitability	NPTN	1.302	0.000**	2.353	0.005**
	WCTA	1.347	0.009		
	EBITTA	1.227	0.002**		
	ROA	0.888	0.000**		
Growth Ratio	CHROA	1.310	0.017	4.967	0.012*
	SALEG	1.488	0.000**	0.802	0.028*
Liquidity	CACL	1.345	0.000**		
	CFCL	1.371	0.000**		
Activity	TNTA	1.128	0.000**		
	FASF	1.656	0.000**	0.859	0.008**
	ARSL			5.051	0.100
	CHARSL	1.203	0.000		
Constant		0.153	0.784	4.385	0.008**

** Significant level in α =0.01in Wald test.
* Significant level in α =0.05in Wald test.

4.10.3 Merton Type Model Estimation

This model was described in the early section 4.9. The data needed for the model is accounting data in terms of debt, the interest rate and valuations of the business, the assets or equity, at regular points. The estimation procedure used is due to Bharath and Shumway (2004). An iterative procedure is used and this was described earlier in this Chapter. It was implemented in Excel and a typical spreadsheet is presented in Appendix A.

It had been hoped to use all 116 businesses but a sample of only 14 which can be seen from Table 4.10.9 was used in the analysis. This was for two reasons. Firstly, gaining the data for all business was difficult since for some companies equity values were not available throughout the period. Secondly for some SMEs where equity prices are available they are so rarely traded that no efficient estimate of the volatility could be obtained. This would have severely affected the analysis.

The results for the selected business are presented below. It is notable that the businesses selected are fairly stable and unlikely to default. This may be due to two factors. The observation period for the equity price is too short to reflect the inherent variability in rarely traded stocks such as SME. Secondly the requirement that the data selected should have financial statements for 3 recent years including 2004. This latter restriction may have biased the sample to non-defaulting businesses.

In this study, the data inputs to KMV-Merton model include *E*: Equity value of a firm; σ_E: volatility of Equity; *X*: face value of the firm's debt; *A*: Total asset of firm; *r*: risk-free rate; σ_A: volatility of Asset value of firm; *T*: the time period.

For *r*, risk-free rate, average one-year Repo (base) rate is obtained from the Bank of England. *E*, the market value of each firm's equity (market price × outstanding common shares), is provided by Datastream. σ_E is the annualised percent standard deviation of returns and is estimated from the prior year stock return data for each month; *X*, the face value of debt, to be debt in current liabilities plus half of long term debt. Then all the data from 14 firms is used to calculate *E* and σ_E to resolve *A* and σ_A.

Table 4.10.9 The firm data of KMV-Merton model

Firms/ Industrial Classification	E:	X:	A:	σ_E :	σ_A :	DD	EDF
1. WLN (2745_ Industrials)	3.0989	8.34	11.0815	0.078218	0.021874	12.98235	0
2. TDC-LN (2757_ Industrials)	0.9903	9.85	10.4185	0.057845	0.005499	10.19560	0
3. SMON-LN (2777- Industrials)	7.2709	19.125	25.576	0.049760	0.014146	20.54057	0
4. HCL-LN (5757_ Consumer Service)	2.055	22.205	23.308	0.044084	0.003887	12.47397	0
5. JCR-LN (5379_ Consumer Services)	0.274	4.425	4.509	0.131821	0.008009	2.352907	0.0093136
6. CSP-LN (5755_ Consumer Services)	2.6408	12.825	14.916	0.168178	0.029775	5.058003	2.122E-07
7. QA.-LN (9533_ Technology)	1.1855	14.68	15.236	0.308274	0.023986	1.676625	0.0468079
8. EMP-LN (9537_ Technology)	0.7046	4.27	4.7916	0.067300	0.009897	11.64059	0
9. AMR-LN (3355_ Consumer Goods)	4.0329	11.085	14.643	0.088506	0.024376	10.85941	0
10. CRG-LN (4535_ Health Care)	11.142	8.405	19.186	0.130889	0.076008	11.05398	0
11. ASE-LN (9535_ Technology)	1.0813	1.19	2.220	0.303226	0.147670	4.149545	1.665E-05
12. EPO-LN (9535_ Technology)	1.1589	6.895	7.758	0.199781	0.029842	3.938447	4.102E-05
13. FAR-LN (2791_ Industrial)	0.4422	1.185	1.576	0.209434	0.058747	4.828704	6.880E-07
14. GRH-LN (5755_ Consumer Services)	0.5853	0.55	1.112	0.137167	0.072213	9.708840	0

Note: E: Equity value of a firm; X: face value of the firm's debt; A: Total asset of firm (E;X;A in million of GBP); σ_E **:** volatility of Equity (σ_E estimated by monthly return); X: face value of the firm's debt; A: Total asset of firm; γ: risk-free rate used average one-year Repo (base) rate r = 0.0438 ; σ_A **:** volatility of Asset value of firm; T: the time period. E, X, A Million GBP

As seen in the last column of Table 4.10.9 the probability of failure is low. Generally this could be explained in terms of sample selection or the lack of volatility in the equity price. The sample was chosen by requiring all business to have 3 recent financial statements including one for 2004. This means the businesses are currently active. Hence there is a bias towards non-defaulting companies. The lack of volatility may be due to the SME stock being rarely traded and/or the period of organisation. If the former is true then it may be necessary to look for other measures of the value of SME. If the latter is true then one can simply extends the period of observation of the equity.

4.10.4 Further Simulation for Distance Default

Initially it had been hoped to generate default probabilities for all 116 business in the sample by use of the Merton Type model. It was then intended to relate these probabilities to the financial ratios using logistic regressions, as in credit scoring. This would have allowed comparison between the two methods. It was decided to generate the equivalent of the default probabilities, distance to default, by alternative route. This meant that further restriction was placed on the analysis, but it does illustrate what might have been done if all probabilities had been available.

Using the 14 businesses the correlation between the distance to default and the financial variables was calculated and the variable with the highest absolute correlation was selected. This was fitted to the data and the model then used to predict the other 102 businesses. Obviously this will mean that the probability of default will be simply related to this variable. A cut off level was used to define those that defaulted or not. Using the data created, a logistic model to predict default from the financial ratio variables was fitted. Table 4.10.10 presents the correlation between the distance to default and the financial variables. The *CFCL* (Cash Flow/ Current Liabilities) ratio is the ratio with the highest absolute correlation of 0.5218 between distance to default (DD).

Therefore, it is used this highest correlation *CFCL* variable to estimate distance default (DD) based on linear regression. The estimated regression contains dependent variable $Y = DD$, and independent variable $X = CFCL$, therefore the linear regression equation is $DD = \alpha + \beta * CFCL$. Table 4.10.11 shows the summary output of regression $\alpha = 8.398232$, $\beta = 2.752815$, residual = 4.757066.

Table 4.10.10 The correlation of financial variables and distance to default (DD)

	TLTA	NPTL	WCTA	EBITTA	ROA	CHROA	CHIN	SALEG	CACL	**CFCL**	TNTA	FASF	ARSL	CHARSL	APSL
TLTA	1														
NPTL	-0.847	1													
WCTA	-0.4877	-0.031	1												
EBITTA	-0.6473	0.9409	-0.3242	1											
ROA	-0.5498	0.9025	-0.4417	0.9901	1										
CHROA	-0.181	0.4163	-0.3385	0.5279	0.5417	1									
CHIN	-0.1194	0.1589	-0.024	0.1739	0.1716	0.8779	1								
SALEG	0.49129	-0.232	-0.5195	0.0016	0.06	-0.097	-0.1994	1							
CACL	-0.4384	0.5491	-0.0465	0.5981	0.5693	0.0538	-0.1643	0.1416	1						
CFCL	-0.2425	0.6475	-0.5934	0.8286	0.8564	0.5344	0.1682	0.2858	0.5444	1					
TNTA	-0.1634	0.1009	0.1349	0.0458	0.0176	-0.309	-0.391	-0.1029	0.0905	-0.165	1				
FASF	-0.2605	0.4163	-0.1158	0.4638	0.4395	0.4621	0.2595	-0.0087	-0.05	0.4022	-0.0519	1			
ARSL	0.4136	-0.552	0.18886	-0.5605	-0.5381	-0.289	-0.0741	0.0707	-0.038	-0.499	-0.3116	-0.3941	1		
CHARSL	-0.2393	-0.264	0.83847	-0.5002	-0.5931	-0.172	0.1897	-0.618	-0.353	-0.638	-0.1296	-0.1388	0.2639	1	
APSL	0.84388	-0.965	-0.0608	-0.8564	-0.8187	-0.29	-0.0837	0.264	-0.497	-0.546	-0.1655	-0.4097	0.5234	0.2308	1
DD	-0.3023	0.3727	-0.1402	0.4067	0.3997	0.133	-0.0001	-0.1634	0.3955	**0.5218**	-0.2207	-0.1339	-0.0792	0.0341	-0.2863

Table 4.10.11 Summary output of regression: CFCL and DD

	Coefficients	Standard Error	t Stat	P-value
Intercept	8.398232	1.272603372	6.599253	2.54E-05
CFCL	2.752815	1.299082434	2.1190456	0.055629

Regression Statistics	
Multiple R	0.52182551
R Square	0.27230187
Adjusted R Square	0.21166035
Standard Error	4.757066
Observations	14

From the second step, *CFCL* is used to estimate distance default $\hat{DD}$ based on linear regression.

Therefore, $\hat{DD}$ = 8.398232+ 2.752815 * *CFCL* + 4.757066 * *NORMSINV (RAND())* where *NORMSINV (RAND ())* is simulation random draw number for generating residual underlying standard normal distribution $\varepsilon \sim N(0,1)$ and linear regression to predict $\hat{DD}$ which is used for generating default ‘0’ and non-default ‘1’ cases in the third step, and the results of $\hat{DD}$ value will be used in logistic regression and 15 financial variables of real 116 SMEs dataset.

The results of the third step for generating *DD* with 15 financial variables of 116 SMEs are based on credit scoring methods, then 116 SMEs cases are ranked and predicted *DD* using Logistic regression are used for comparing credit scoring models and simulation estimated $\hat{DD}$ from Merton-KMV models. Three cutoff values are used for comparing credit scoring and Merton-KMV models.

Table 4.10.12 shows that cut off level for three models. Model 1 assigns top ranked 90 as non-default ‘1’ cases and 26 as default ‘0’cases. Model 2 assigns top ranked 85 cases as non-default and 31 as default cases. Model 3 assigns 80 as non-default cases, and 36 as default cases. The results of models comparison are presented in Table 4.10.12.

Table 4.10.12 Cutoff assigns cases for Model 1, Model 2 and Model 3

Models	**Cut off level cases**	
	‘0’ default cases	**‘1’ non-default cases**
Model 1	26	90
Model 2	31	85
Model 3	36	80

The Hosmer and Lemeshow test is shown in Table 4.10.13. Model 1 has the p-value = 0.783, which indicates that the logistic model is a good fit. Model 2 and 3 are less successful with the Hosmer and Lemeshow test having their p-values of 0.542 and 0.558 respectively.

Table 4.10.13 Comparing Goodness-of Fit test in Model 1, Model 2 and Model 3

Hosmer and Lemeshow Test

Step	**Chi-square**	**df**	**Sig.**
Model 1 (step 1)	4.760	8	.783
Model 2 (step 4)	6.947	8	.542
Model 3 (step 2)	6.803	8	.558

The results shown in Table 4.10.14 indicate in this case that only constant and CFCL are included in Model 1 and p-value both are significant at $\alpha = 0.01$ level.

The logistic regression presented in Table 10.4.14 can be written as an equation for Model 1.

Model 1: $\log(\frac{1-p}{p}) = 1.025 + 1.1816 CFCL$

In Model 2, the four financial variables in logistic regression equation are TATL, ROA, CFCL and ARSL, however, TATL and ROA variables show p-value = 0.119 and 0.062 respectively. CFCL, ARSL and constant term present significance level of 0.001 and 0.05 respectively. The variables of Model 2 as have seen from Table 4.10.14 show that variables TATL and ROA have negative relationship with predicted default (*PD*) and CFCL and ARSL have positive relation with predicted default (*PD*); therefore, the logistic regression equation is constructed as

Model 2: $\log(\frac{1-p}{p}) = 1.098 + (-0.840)TATL + (-1.460)ROA + 2.361CFCL + 3.654ARSL$

In Model 3, financial variables NPTN, CFCL and constant are included in logistic equation. NPTN presents significance level of *p*-value = 0.08, and CFCL, constant term both show p-value less than 0.001 indicating higher significance of level than 1%. The variable, NPTN presents negative relationship with predicted defaults (*PD*). For Model 3, the logistic regression equation is constructed as

Model 3: $\log(\frac{1-p}{p}) = 1.151 + (-0.271)NPTN + 1.557CFCL$

It can be seen from Table 4.10.14 that overall CFCL is the most significant financial variable in all three models.

Table 4.10.14 Variables in logistic regression of Model 1, Model 2 and Model 3

		B	S.E.	Wald	df	Sig.	Exp(B)
Model 1 (Step 1)	CFCL	1.025	.265	14.985	1	.000	2.786
	Constant	1.816	.294	38.220	1	.000	6.146
Model 2 (Step 4)	TATL	-.840	.540	2.425	1	.119	.432
	ROA	-1.460	.783	3.479	1	.062	.232
	CFCL	2.361	.583	16.412	1	.000	10.597
	ARSL	3.654	1.789	4.173	1	.041	38.612
	Constant	1.098	.534	4.228	1	.040	2.997
Model 3 (Step 2)	NPTN	-.271	.155	3.070	1	.080	.763
	CFCL	1.557	.434	12.852	1	.000	4.745
	Constant	1.151	.249	21.414	1	.000	3.160

Classification Table 4.10.15 shows predicted values of the dependent variable (default ‘0’and non-default ‘1’) based on estimated *PD* from full financial variables SMEs logistic regression models. The results show how many cases are correctly predicted and overall percentage predicted correctly in these three models. In Model 1, there are 9 cases correctly predicted to be ‘0’ default and 86 cases correctly predicted to be ‘1’ non-default, therefore, the overall correctly predicted percentage is 81.9% in Model 1. The results in Model 2 present that 16 cases are correctly predicted to be ‘0’ and 83 cases are correctly predicted to be ‘1’, therefore, the overall correctly predicted percentage is 85.3%. The results in Model 3 show there are 16 cases correctly predicted to ‘0’ and 76 cases are correctly predicted to be ‘1’, and overall percentage correctly predicted is 79.3%. As can be seen the Model 2 has higher correctly predicted percentage among these models.

Table 4.10.15 Classification of cutoff levels in Model 1, Model 2, Model 3

Observed			Predicted		
			PD		Percentage Correct
			.00	1.00	
Model 1 (Step 1)	PD	.00	9	17	34.6
		1.00	4	86	95.6
	Overall Percentage				81.9
Model 2 (Step 4)	PD	.00	16	15	51.6
		1.00	2	83	97.6
	Overall Percentage				85.3
Model 3 (Step 2)	PD	.00	16	20	44.4
		1.00	4	76	95.0
	Overall Percentage				79.3

The results for Model 1 are unsurprising. The two other cutoff levels are of more concern where it is possible that there has been over-fitting of the model from introducing other variables. Whilst Model 2 produces slightly better prediction it simply reinforces the concept of over-fitting.

4.11 Information Comparison Merton Model and Accounting Model

The next stage of research explores whether information used by the Merton type model is equivalent to the Accounting information popularly used. The current work explores two types of models for Small and Medium Sized Enterprises (SMEs) with the aim of comparing the information base. The aim is to assess whether the two models are employing equivalent information. To do this for a sample of 116 SMEs the distance to default (DD) and expected default frequency (EDF) were calculated. The relationship between *DD* to financial and accounting measures based on previous 15 financial variables was explored by linear regression.

Linear regression is used to describe relationships between variables. Standard linear regression analysis involves minimising the sum of square differences between a response (dependent) variable and a weighted combination of predictor (independent) variables. The estimated coefficients reflect how changes in the predictors affect the response. The response is assumed to be numerical, in the sense that changes in the level of the response are equivalent throughout the range of the response. The fifteen financial ratios variables of SMEs are considered to be explanatory variables, and distance default (DD), expected default frequency (EDF) are considered to be a dependent variable.

The linear regression model and this relationship are described in the following formula.

$$Y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_{p-1} x_{i,p-1} + \varepsilon_i \quad (i = 1, 2, \dots, n)$$

where Y_i is the value of the i^{th} case of the dependent variable

p-1 = 1, 2, 3, ..., n-1 is the number of predictors

β_j is the value of the j^{th} coefficient, j = 0,1….., p-1

X_{ij} is the value of the i^{th} case of the j^{th} predictor

ε_i is the error in the observed value for the i^{th} case.

there x_{ij} is the i^{th} value of x_j. Writing these n equations in matrix form we have:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \dots \\ Y_n \end{bmatrix} = \begin{bmatrix} x_{10} & x_{11} & \dots & x_{1,p-1} \\ x_{20} & x_{21} & \dots & x_{2,p-1} \\ \dots & \dots & \dots & \dots \\ x_n & x_{n1} & \dots & x_{n,p-1} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_{p-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \dots \\ \varepsilon_n \end{bmatrix}$$

where Y_i is the DD, β_j, is the coefficient, X_{ij} is the j^{th} predictor and ε_i is the error for i = 1, ... , n. Similarly EDF is explored using both log-based transformations of EDF (LGEDF) and square root for EDF (SQRTEDF) for comparative performance. Given the skewed nature of many of the variables then both the raw data and transformed data was used in model fitting. For example, TLTA, CACL, TNTA, ARSL and APSL are transformed into log based variables: Logtlta, Logcacl, Logtnta, Logarsl and Logapsl respectively. The results of 16 models considered are summarised in Table 4.11.1 and Table 4.11.2.

Table 4.11.1 gives the results for the untransformed predictors. The highest R^2 is 0.229 for DD with three variables fitted TLTA, TNTA and WCTA. When outliers are excluded the model with highest R^2 is 0.137 with variables CACL and CFCL. The most frequently occurring predictors across the models are CACL and then FASF. Table 4.11.2 gives results for the models including log transformations. There is more stability but the R^2 is still low. Highest R^2 is 0.233 for log transformations LGEDF with two LGTLTA and LGCACL variables included and with exclusion of outliers it falls to 0.192 for DD with LGTLTA. The variables in the model are more constant with LGTLTA or FASF and LGCACL appearing most often. It may present relevant information between financial variables LGTLTA (log-based Total Liability to Total Assets leverage) and Merton models with one input variable $ln(V_A/X)$ (V_A: Asset value of firm ; X: the debt of firm) for calculation of distance to default (DD).

Linear regression has been used in this work to investigate relationship between Merton type and Accounting models. Overall the results show low R^2 value in these models even with excluded outliers. This indicates there are only weak relationships between the information contained within the Merton type variables, DD and EDF, and the Accounting variables. This may be attributed to the lack of volatility in SMEs' shareprices due to irregularity of trading which leads to an overestimate of the DD. This will require further investigation in future studies. If it is true that the information is different then one possible strategy is to combine both sources to enhance prediction of default.

Table 4.11.1 Summary of relationship between 15 financial variables and DD, EDF, LGEDF, SQRTEDF

116 SMEs and 15 Financial Ratios Variables						**Excluded outliers SMEs and 15 Financial Ratios Variables**					
Model		**Unstandardised Coefficients**				**Model**		**Unstandardised Coefficients**			
Dependent Variables	**Variables in Equation**	**B**	**Std. Error**	**t**	**Sig.**	**Dependent Variables**	**Variables in Equation**	**B**	**Std. Error**	**t**	**Sig.**
DD	(Constant)	11.931	1.161	10.277	.000	**DD**	(Constant)	5.447	.880	6.187	.000
	TLTA	-6.440	1.131	-5.694	.000		CACL	1.510	.368	4.105	.000
	TNTA	.874	.312	2.798	.006						
	WCTA	-4.149	1.845	-2.249	.026						
	R= .479 R Square= .229						R= .364 R Square = .133				
EDF	(Constant)	.156	.034	4.564	.000	**EDF**	(Constant)	.140	.033	4.205	.000
	FASF	-.035	.011	-3.232	.002		FASF	-.033	.010	-3.207	.002
	CACL	-.035	.014	-2.592	.011		CACL	-.031	.013	-2.326	.022
	R= .350 R Square= .123						R= .341 R Square = .116				
LGEDF	(Constant)	-35.914	14.358	-2.501	.014	**LGEDF**	(Constant)	-23.951	10.460	-2.290	.024
	CACL	-13.826	6.038	-2.290	.024		CACL	-17.564	4.462	-3.936	.000
							CFCL	-6.372	3.035	-2.100	.038
	R=.210 R Square= .044						R= .370 R Square = .137				
SQRTEDF	(Constant)	.171	.037	4.659	.000	**SQRTEDF**	(Constant)	.156	.036	4.314	.000
	CACL	-.039	.015	-2.699	.008		CACL	-.035	.014	-2.454	.016
	FASF	-.026	.012	-2.213	.029		FASF	-.024	.011	-2.116	.037
	R= .300 R Square=.090						R= .284 R Square = .081				

Note: Variables Excluded outliers SMEs cases are 2 standard deviations casewise.

Table 4.11.2 Summary of relationship between 10 financial ratios and 5 log-base variables with DD, EDF, LGEDF, SQRTEDF

116 SMEs with 10 Financial Ratios and 5 log-base Variables						**Excluded Outliers with 10 Financial Ratios and 5 log-base Variables**					
Model		**Unstandardised Coefficients**				**Model**		**Unstandardised Coefficients**			
Dependent Variables	**Variables in Equation**	**B**	**Std. Error**	**t**	**Sig.**	**Dependent Variables**	**Variables in Equation**	**B**	**Std. Error**	**t**	**Sig.**
DD	(Constant)	4.181	1.120	3.734	.000	**DD**	(Constant)	6.169	.707	8.731	.000
	LGTLTA	-5.574	1.030	-5.413	.000		LGTLTA	-3.333	.653	-5.105	.000
	R= .455 R Square= .207						R= .438 R Square = .192				
EDF	(Constant)	.116	.023	4.987	.000	**EDF**	(Constant)	.133	.025	5.233	.000
	FASF	-.035	.011	-3.186	.002		FASF	-.034	.010	-3.387	.001
	LGCACL	-.073	.023	-3.134	.002		LGCACL	-.095	.028	-3.424	.001
							EBITTA	.043	.020	2.203	.030
	R= .384 R Square= .147						R= .408 R Square = .167				
LGEDF	(Constant)	-31.023	10.368	-2.992	.003	**LGEDF**	(Constant)	-30.532	9.043	-3.376	.001
	LGTLTA	69.337	11.984	5.786	.000		LGTLTA	38.706	8.355	4.633	.000
	LGCACL	45.856	11.815	3.881	.000						
	R=.482 R Square= .233						R= .404 R Square = .163				
SQRTEDF	(Constant)	.125	.025	4.992	.000	**SQRTEDF**	(Constant)	.146	.028	5.312	.000
	LGCACL	-.078	.025	-3.131	.002		LGCACL	-.107	.030	-3.546	.001
	FASF	-.025	.012	-2.144	.034		FASF	-.025	.011	-2.269	.025
							EBITTA	.048	.021	2.255	.026
	R= .333 R Square= .111						R= .366 R Square = .134				

Note: (1) 5 log variables are Logtlta, Logcacl, Logtnta, Logarsl and Logapsl.
(2) Excluded outliers are 2 standard deviations casewise.

4.12 Conclusion

The aim of the study has been to investigate the methodologies that might be employed in further research into credit risk modelling of SMEs. Two prime methodologies have been considered in this work: a credit scoring approach using logistic regression and a Merton type model. This section of research is based on simulation methods to overcome data limitation because the data set obtained did not include defaulting SMEs. This has been a major limitation to the current study. The study has therefore resorted to simulation to generate data for analysis for credit scoring approach. For the Merton Type model simulation has not been used but the lack of capability to evaluate at regular intervals the value of the business has been a limitation.

This section summarises the results obtained and will review the results and the implications for further study

In Full simulation, the data generated produced theoretical independent normal variates for the financial ratios for each business, which is clearly not realistic. The coefficients as expected are generally close to the expected values. This may be in part due to the size of sample considered. For Partial simulation, financial ratios used were observed values from specified businesses and so there may be dependency between the variables. The sample is obviously smaller than that of the full simulation. The results prove to be more volatile compared to those of the full simulation. Of the two potential reasons, relative sample size and colinearity, the latter seems to be the more likely contributing factor. Hence in future analysis care will have to be taken to effectively deal with colinearity.

The need for a measure of value of the company overtime is problematic for SMEs. It is difficult to obtain equity price or ratings for these businesses especially for the micro and small SMEs. For the 14 business investigated the times to default and the probability of default have been obtained using the approach of Bharath and Shumway (2004). The businesses seem to be stable with probabilities of default close to zero. This may be due either to the selection criteria used or the lack of sufficient volatility in the equity price in the period of observation. The criterion for selection was biased to companies that had survived and hence default probabilities would be expected to be low. Lack of volatility in equity price may be due to lack of trading in SME stock or just the length of period observed.

Whilst it was hoped to be able to evaluate distance to default and probability of default for all businesses for a number of reasons only 14 could be used. Hence it was not possible to make the comparison as desired. The results obtained in this section were, therefore, predictable but did illustrate the analysis that could have been used had full enumeration been possible.

The relationship between DD to financial and accounting measures was explored by linear regression. The results obtained showed a low R^2 with few financial and accounting variables entering a stepwise models. This implies a weak common informational base. There may be, however, explanation for the low R^2, such as the lack of volatility in SMEs' shareprice due to irregularity of trading which leads to an overestimate of the DD.

Overall, the work in this Chapter has achieved the goal of testing the potential methodologies to be used in the research. In subsequent chapter research will be based on a larger sample containing insolvent and solvent companies of SMEs. It has also highlighted some of the important issues faced by researchers in the area of credit risk assessment for SMEs. For the credit scoring approach a larger range of financial variables will be considered than those used in Chapter Four for SMEs modelling. Whilst the results have been mainly predictable the insights gained should allow better analysis of the future data. For Merton type model it might be worth investigating different methods other than equity to value the company. As for comparison of Merton model and Accounting model, it is found that overall the results show low R^2 value in these models even with the exclusion of outliers. Hence, there is only a weak link between Merton type and Accounting models.

CHAPTER FIVE

Extended Data Collection of SMEs

5.1 Introduction

The new Basel II framework on credit risk components, risk exposures, capital requirement has been introduced in Chapter Two. Risk associated with lending to SMEs shares the features of both retail and corporate sectors, and this has been recognised by Basel II provisions. A number of studies on credit scoring methods, accounting based models, are introduced in literature review of Chapter Three. However, research on credit scoring modelling for SMEs sector is scarce, and this is surprising, given the importance of this sector in national economy: Berger, Frame and Miller (2005), for example, state that almost half of the U.S. private-sector employment and non-farm domestic product is accounted for by small/medium sized business. Yet small companies, though, according to Berger, Frame and Miller (2005), experience problems in obtaining credit, since the majority of them do not have publicly traded equity and certified audited financial statements. Problems in obtaining credit could be partially alleviated by increasing the adoption of credit scoring techniques when lending to small business (OECD 2001).

Chapter Four has looked into the methodologies for assessing default for SMEs and tested them on a limited set of data. It has also highlighted some of the important issues faced by researchers in the area of credit risk assessment for SMEs. In addition, it has suggested that a further set of variables should be considered in the Accounting models.

The purpose of this chapter is to provide a detailed description of the data that can serve a source of the potential predictor variables in relation to SMEs performance. To make the model development more robust, the work described in this Chapter concentrates on including data on defaulting and financially distressed firms in SMEs credit risk modelling. Sample composition includes different default definitions that will be presented in the following sections. K-mean clusters and Principle Component Analysis are used to detect structure in the relationships between variables which may provide the first stage to analysis of data for further models construction. Based on this data composition, possible approaches for SME default predictive models will be described further in Chapter Six.

5.2 Data Description

There is a concern that credit risk development based solely on bankruptcy data can significantly underestimate predicted credit risk of companies, even when the outcome of the model is recalibrated to the expected default rate in the population. Accordingly, in this Chapter, extensive work has been carried out to ensure that the definition of default used in the development of SMEs credit risk models is appropriate. Different default definition should be considered, therefore, definition of business bankruptcy, Insolvency terms in UK and Basel II reference definition of default events are illustrated below.

5.2.1 UK Insolvency Act of 1986

The majority of bankruptcy prediction studies defined failure legalistically.
The main reason for a legal definition is that it provides an objective criterion that allows researchers to easily classify the population of firms being examined. The legal definition of failure is also adopted in this study, but other defaulters are also explored.

The definition of default varies in different countries due to legislation and cultural background. For example, in default prediction studies in the United States most definitions of default are based on US federal bankruptcy law which are the code of Chapter 11 (reorganising the company's financial structure and trying to recover from distress) or Chapter 7 (going into liquidation and stopping all business operations). As for the definition of business bankruptcy in UK, the insolvency terms in UK are determined by Insolvency Act of 1986.

According to the UK Insolvency Act of 1986[48], "a company is said to be insolvent if it either does not have enough assets to cover its debts (i.e. the value of assets is less than the amount of the liabilities), or it is unable to pay its debts as they fall due". "An insolvent company, ('the debtor'), might use either an Administration Order or a Company Voluntary Arrangement ('CVA') to reorganise its business and try to become profitable again. Management continues to run the day-to-day business operations in the case of a CVA and an Administrator appointed by the Court will run a company in the case of an Administration Order. If a company goes into liquidation either voluntarily or is formally wound up by the Court, the company stops all operations and goes out of business. A liquidator may be appointed to 'liquidate' (sell) the company's assets and the money is used to pay off the debt, which may include debts to creditors and investors. Alternatively and finally the debtor may have an Administrative Receiver ('a Receiver') appointed under a floating charge".

5.2.2 Definition of Insolvency Terms

Under UK Insolvency Act of 1986, once a company has become insolvent, the Act provides five courses of action: In Administration, In Receivership, Company Voluntary Arrangement (CVA), Liquidation and Dissolution.

"(1) In Administration: an order made in a county court to arrange and administer the payment of debts by an individual; or an order made by a court in respect of a company that appoints an administrator to take control of the company.
(2) In Receivership: the process where an insolvency practitioner is appointed by a debenture holder to realise a company's asset and pay preferential creditors and debenture holder's debt.
(3) A Company Voluntary Arrangement (CVA) is used to rescue companies which are insolvent yet have an underlying business that would be profitable in the

[48] Information is available at http://bankruptcy.org.uk/bkdocs/insolvency-act-1986.pdf

future without having old debts holding it back. A proposal takes effect if it is accepted by a majority of the members and in excess of 75% in value of creditors present and voting.

(4) Liquidation (winding up) applies to companies or partnerships. It involves the realisation and distribution of the asset and usually the closing down of the business. There are three types of liquidation-compulsory, creditors' voluntary and members' voluntary. Voluntary liquidation is not involving the courts or the Official Receiver, and members' voluntary liquidation for solvent companies and creditors' voluntary liquidation for insolvent companies.

(5) Dissolution: having wound-up the company's affairs, the liquidator must call a final meeting of the members, creditors or both. The liquidator is then usually required to send final accounts to the Registrar and to notify the court. The company is then dissolved."

5.2.3 Basel II Reference Definition of a Default Event

Basel II (2006) defined a default with regard to a particular obligor when either or both of the two following events have taken place: (BCBS 2006 paragraph 452)

"(1) The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held).

(2) The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstandings."

The elements to be taken as indications of unlikeliness to pay include: (BCBS 2006 paragraph 453)

"(1) The bank puts the credit obligation on non-accrued status.

(2) The bank makes a charge-off or account-specific provision resulting from a significant perceived decline in credit quality subsequent to the bank taking on the exposure.

(3) The bank sells the credit obligation at a material credit-related economic loss.
(4) The bank consents to a distressed restructuring of the credit obligation where this is likely to result in a diminished financial obligation caused by the material forgiveness, or postponement, of principal, interest or (where relevant) fees.
(5) The bank has filed for the obligor's bankruptcy or a similar order in respect of the obligor's credit obligation to the banking group.
(6) The obligor has sought or has been placed in bankruptcy or similar protection where this would avoid or delay repayment of the credit obligation to the banking group."

5.2.4 Financial Distress

Financial analysis may be used to view some of the indicators of the financial distress. Important ratios to be considered include liquidity ratio and insolvency ratio. The ratios provide indicators on whether the firm is facing financial problems in liquidity meeting both its current and long term debt obligations.

Ross, Westerfield and Jaffe (1999) point out that the definition of financial distress has two bases: as a stock-based insolvency and a flow based insolvency. A stock-based insolvency occurs when a company's total liabilities are greater than its total assets. A flow-based insolvency occurs when a company's operating cash flow cannot meet its routine obligations. Based on financial distress discussion in the above study, Hu and Ansell (2006) in their study of U.S. Europe and Japan retail companies derive performance indicators when developing financial distress prediction models. In connection with sample selection of financially distressed companies in this research, the criteria are based on financial and accounting criteria, hence, a company was regarded as distressed in this research if its insolvency ratio (Shareholders Funds / Total Assets) was negative or if its interest cover based on cash flow (EBITDA/ Interest Payable) was less than one.

To identify a flow-based insolvency the Interest Coverage was defined as:

Interest Coverage = EBITDA / Interest Payable < 1

where EBITDA is Earnings Before Interest, Taxes, Depreciation and Amortisation.

The negative values show that the company does not have enough funds to cover the interest payments, and so this signals the flow-based financial distress.

To identify a stock-based difficulties the Insolvency Ratio was used:

Insolvency Ratio = Shareholders Funds / Total Assets.

Since

Shareholders Funds = Total Assets – Total Liabilities,

the Ratio can be reformed as

Insolvency Ratio = (Total Assets – Total Liabilities) / Total Assets

= 1- (Total Liabilities / Total Assets).

The negative values of Insolvency Ratio mean that Liabilities exceed Assets, and therefore, signal the stock-based insolvency.

5.3 Sample Selection

A sample for analysis was selected from the UK businesses of available from 'Datastream' (the Global Economics, Equities, Bonds, Futures and Options database over 50 countries) and 'Thomson ONE Banker' (Thomson ONE Banker provides access to relevant real-time global market data, news, and authoritative content from industry-leading sources, included company profile integration) on the basis of industry classification, including Oil & Gas, Basic Materials, Industrials, Consumer Good, Healthcare, Consumer Services, Utilities, Telecommunications and Technology sectors.

It should be noted that financial sector such as banks and other financial institutions for example, investment fund companies were excluded from the dataset, since firms in this sector are structurally different and their financial reporting practices generally preclude combining them with non-financial firms in models using financial ratios (Gilbert, Menon and Schwartz 1990). For a business to qualify as a SME from the Basel II perspective, it must have an annual turnover less than €50Million (BCBS 2006).

For default prediction modelling to be possible there should be financial variables selected from financial statement that is balance sheet, income statement, and cash flow. Beresford and Saunders (2005) study on small business start-up process in UK point out that more than half fail within three years of formation. Further, there is a general agreement that for micro business the failure rate is higher, one-third failing within the first year. Taking this into account, SMEs were included in the sample if they had at least more than 3 years financial statements available before the default was observed. This may mean the sample is biased but it seems a realistic basis on which to work, given the data required.

The Basel II definition of default events was not used in sample selection for two reasons. Firstly, because these events such as 90 days past due, charge-off account, loan restructuring and obligor's significant decline in credit quality, are difficult to collect and these are normally not publically generated and maintained within financial institutions. Secondly, Basel II definition of default can be differentiated using the amount overdue or the time that payment is behind. In most publicly available information, however, these detailed measures are missing and more general definitions have to be used. Therefore, Basel II definition of default events are excluded because this information belongs to banks' internal data and difficult to obtain, especially customers historic payment records, delay payment, collection, and bad debt records. The credit control information is not easy to collect from banks also owning to the concern about internal data confidentiality and customer data protection.

The companies that comprised the insolvent sample group for the study followed the three most common routes, i.e. administration, receivership and liquidation. They were identified from the UK Bankruptcy & Insolvency Website[49] and UK-Wire database website[50]. For company to be included in the sample, it had to satisfy the

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[49] The UK Bankruptcy & Insolvency Service operates under a statutory framework – mainly the Insolvency Acts 1986 and 2000, the Company Directors Disqualifications Act 1986 and the Employment Rights Act 1996. Website: http://www.insolvency.gov.uk/

[50] UK-Wire provides Real-time UK Company Press Release service providing the latest regulatory announcements such as trading results and other press releases affecting a Company's financial position). http://moneyextra.uk-wire.com/

following criteria: (a) the company's shares must have been publicly traded, i.e. the company was a public limited one (plc) according to the UK Companies Act of 1985; (b) the insolvent company must have failed between the 4-year period from 2001 to 2004; and (c) it must have had at least three years of full financial statement data prior to its formal failure year.

For default prediction to be possible there should be financial statements (balance sheets, income statement, and cash flow statement) for at least 3 years available before the default was observed. The total 445 SME companies were found to meet these requirements, and were classified into 4 groups of financial health as presented in Table 5.3.1.

The application of the above criteria resulted in a sample of 28 insolvent companies. They were marked in the database as insolvent or 'dead' (delisted from stock registration), however, the remaining 'alive' (still active and listed) companies exhibited different levels of financial health. Group 1 indicates 28 delisted and insolvent companies; Group 2 consists of 32 financially distressed companies that meet both Insolvency Ratio and Interest Coverage definitions; Group 3 comprises 160 companies which only flow-based problems; and Group 4 includes 225 healthy SMEs. So Group Number presents an indication of distress on the ordinal scale of measurement with 1 indicating most distressed and 4 standing for least distressed or healthy companies.

Table 5.3.1 Levels of financial health of SMEs.

Group of SMEs			**Number of SMEs**	
Group 1	Insolvent	Dead and delisted SMEs	Delisted	**28**
Group 2	Flow-Based and Stock-Based Distress	Insolvency Ratio < 0 and Interest Coverage <1	Active	**32**
Group 3	Flow-Based Distress	Interest Coverage < 1	Active	**160**
Group 4	Healthy	Listed healthy	Active	**225**
			Total	**445**

5.4 Financial Categories and Ratios Description

The factors that lead SME businesses to fail vary and they have been discussed in studies by McKinnon (1973) and Shaw (1973), who attribute the phenomenon to high interest rates, recession, declined profits, heavy debt burdens and so on. Moreover, industry-specific characteristics, such as the character of operations and government regulation, can contribute to a firm's financial distress. Studies on business failure in the different countries, commonly found that small, private and newly founded companies with ineffective control procedures and poor cash flow planning are more vulnerable to financial distress than large well-established public firms.

The first 5 categories have been addressed in Chapter Four (section 4.3) and based on (1) Profitability (2) Liquidity (3) Leverage (Structure Ratios) (4) Growth Rate (5) Activity (Efficiency), and the illustration of these five categories.

The economic cost of business failures is significant; evidence shows that the market value of the distressed firms declines substantially prior to their ultimate collapse (Charalambous, Charitou and Kaourou 2000; Warner 1977). Hence, the suppliers of capital, investors and creditors, as well as management and employees, are severely affected by business failures. Therefore, additional four financial categories are included in analysis. These are (6) Asset Utilisation Ratios (7) Cash Flow Related Ratios (8) Employees Efficiency Ratios and (9) Financial Scale. These additional four financial categories are considered in analysis for exploring SMEs default prediction model. The illustration of the reasons for it are presented below.

5.4.1 Asset Utilisation Ratios

An asset utilisation ratio is a financial ratio that measures the speed at which a business is able to turn assets into sales, and hence operating profit and earnings. Main related asset utilisation ratios are composed in relation to total assets, fixed assets, shareholders fund and working capital contribution to employees for measuring either excess assets or reserved capital. So these ratios are able to indicate the ability of companies to operate their resources adaptively. Also known as fixed assets are real estate, physical plants and facilities, leasehold improvements, equipment (from office equipment to heavy operating machinery), that can reasonably be assumed to have a life expectancy of several years. Fixed assets are among the most important assets that a company holds, for they represent major investments of financial resources. Therefore Fixed Asset per Employees value could indicate whether fixed assets can provide for business operating efficiency.

Fixed assets are also very important to small business owners because they are one of the things that are examined most closely by prospective lenders. When examining a business's fixed assets, lenders are typically most concerned with the following factors: 1) The type, age, and condition of equipment and facilities; 2) The depreciation schedules for those assets; 3) The nature of the company's mortgage and lease arrangements; and 4) Likely future fixed asset expenditures.

When a bank or other lending institution is approached by an entrepreneur or small business owner who is seeking a loan to establish or expand a company's operations, loan agents will always undertake a close study of the prospective borrower's assets quality, since they usually are a decisive indicator of the business's financial health and obligations.

5.4.2 Cash Flow Related Ratios

A study by DeThomas and Fredenberger (1985) shows that SMEs are more interested in cash and cash flow than reported earnings and assets. As result, the small sized businesses and newly founded companies with ineffective control procedures and poor cash flow planning are more vulnerable to financial distress than large well-established public firms. Besides, because small business cannot survive without generating cash from their normal everyday operating activities, several operating cash flow related ratios are constructed in order to evaluate their usefulness in predicting corporate failure.

There is a number of studies on operating cash flow variables associated with predicting bankruptcy. Gentry, Newbold and Whitford (1987) investigate that cash-based funds flow ratios could serve as a feasible alternative to financial ratios used to establish the financial health of the firm. The discriminating ability of cash flow variables is demonstrated by Gilbert, Menon and Schwartz (1990) who conclude that cash related ratios can significantly add to the explanatory power of insolvency prediction models.

Bernard and Stober (1989) also argue that operating cash flows rather than accrual earnings are expected to play an important role in predicting the probability of default, as cash flows provide a direct link to the ability of the organisation to repay its debt and interest obligations. On the other hand, a study by Shin (2006), who points out that accrual earnings represent only indirect links to expected cash flows, since accruals are subject to arbitrary allocations and manipulation by managers. Ward (1994) indicates cash flow information is useful in specific industries and his empirical results suggest that cash flow variables might be better predictors of corporate failure in mining and oil and gas sectors. A comparative study of predictive rules based on financial ratios, cash flow variables and market profitability factors was carried out by Mossman, Bell, Swartz and Turtle (1998) who find that financial ratios and cash flow variables yield better predictive efficiency in the last two years prior to bankruptcy. Recently, Charitou, Neophytou and Charalambous (2004) examine the incremental information content of operating cash flows in predicting financial distress and thus develop reliable failure prediction models for UK public industrial firms as yet SMEs have not been included in this analysis.

As presented above, prior studies provided some evidence that cash flow related variables may add to the explanatory power of insolvency prediction models. The definition of Cash Flow defined as cash flows by adding only depreciation to earnings (i.e. traditional Cash Flow). Cash Flow from Operation was defined as operating earnings plus non-cash expenses/revenues (non-current accruals) plus changes in working capital except for changes in cash and cash equivalents (current accruals), see Laitinen (1994).

Cash flow related ratios are structured by Cash Flow and Cash Flow from operation. There are ten ratios in this category included in analysis: 1) Market Capital /Cash Flow from Operation, 2) Cash flow /Operation Revenue, 3) Cash Flow / Current Liabilities, 4) Cash Flow / Interest Expense, 5) Debtors / Cash Flow, 6) Cash Flow from Operation to Total Assets, 7) Cash Flow from Operation to Current Liabilities, 8) Cash Flow from Operation to Sales, 9) Cash Flow from Operation to Shareholders Funds and 10) Cash Flow from Operation to Total Liabilities.

5.4.3 Employees Efficiency Ratio

It has been shown that SMEs contribute greatly to the development of the economy, with a great number of employees working in SMEs, especially in such sectors as service and high technology industries. With organisations placing increasing emphasis on knowledge and recognition of human capital as their most important asset, the measurement of management efficiency in utilising human capital is one of key elements to operate business successfully. Hence, the need for a financial performance tool is essential to determine how an organisation is managing its workforce, see Hall (1987), and Capon, Farley and Heonig (1990). Management skill is an imperative indicator for SMEs business success. It is difficult to gain a qualitative insight into it. One way to analyse management's effectiveness across either an industry or peer group is to assess the revenue and net income per employee. These numeric Efficiency ratios provide quick representations of the effectiveness of management (DeThomas and Fredenberger 1985). Both quantitative figures are derived as either the total revenue for the period or the total net income per period divided by the employees figure.

The Employees Efficiency ratios measure the level of sales, profit, personal expense and capital employed generated per employee. Average Number of Employees is used as the number of employees can change during the year according to business needs. The numeric efficiency ratios are quick representations of the effectiveness of management from a strictly qualitative viewpoint. Given the importance of management efficiency for SMEs, it is suggested that it can be measured in terms of: 1). Employee Turnover (i.e. Operating Revenue / Number of Employees), 2) Revenue per Employee (i.e. Profit before Tax / Number of Employees), 3) Average Cost of Employees (i.e. cost of Employees / Number of Employees), 4) Capital Employed per Employees (i.e. Shareholders Funds plus Total Long Term Liabilities / Number of Employees), and 5) Cost of Employees to Operating Revenue.

5.4.4 Financial Scale

It is generally known that a company's financial scale i.e. operating revenue, asset and operating cash flow which indicate the scale of business have a marked effect on business performance. Small and medium sized enterprises (SMEs) may not have a long-term business or product development strategy as a result of their less formal organisational structure. Furthermore, due to their inherent flexibility, small firms are more likely to undertake innovation rather than make incremental improvements with their products. The scale of business may be considered as an important indicator of SMEs success. For example, higher total assets, operating revenue of business may have more market share power, more innovation ability, and strong supplier chains for benefit in business operation. Consequently, these financial scale ratios need to be analysed in the context of SMEs.

The size distribution of firms reflects the distribution of market power as well as segmentation and distortions in input and output markets that determine cost differentials between large and small firms. Some of these give an advantage to larger scale firms: for example, the fixed costs and transaction costs associated with regulations. Others can give SMEs an advantage: for example, it is often alleged that small firms pay lower labour costs than large firms, because they are exempt from protective labour standards and unionisation. In line with theses reasons, the following Financial Scale Ratios are considered in this thesis: 1) Operating Revenue (turnover), 2) Total Assets, 3) Total Capital Employed, 4) Operating Cash Flow, 5) Enterprise Value, and 6) Market Capital which are measured in thousand Euros.

5.5 Predictor Variables Selection

It is obvious that an important aspect of credit scoring models is the selection of the appropriate financial ratios and accounting based measures that will be used as predictor variables. From previous discussion of nine financial categories, there were 70 financial variables selected for analysis based on previous studies of company bankruptcy (Altman and Narayanan 1997; Charitou, Neophytou and Charalambous 2004; Keasey and Watson 1987; Lennox 1999; Ohlson 1980; Peel, Peel and Pope 1986). Also, some ratios are based on a number of studies on indicators in relation toward SMEs business failure or success which have been described above.

Table 5.5.1 gives the list of variables broken down into 9 financial categories based on the main risk factors of financial performance with description of the derivation formula. Besides discussing the variables to be used it is necessary also to explore the potential problems that might arise with the analysis and the their solution. In addition to a discussion of the suggested 70 variables the issue of potential problems in developing rating models is raised and possible solutions are reviewed. To deal with selection of effective variables for default prediction models, the first stage is to consider a wide range of financial ratios for potential model so that the best ratios can be identified to optimise the performance of the model. On the other hand, there is a concern of over-fitting, which occurs when the model functions only on the sample data but fails to engage with real-world data and therefore fails to produce accurate predictions when applied to a dataset different form the one it was developed on.

Table 5.5.1 70 financial ratios broken down into 9 categories

No of Variable	Financial Variables	Financial Resources Formula
Profitability Ratios		
V1	**Profit Margin (%)**	P/L before tax/Operation Revenue (Turnover)*100
V2	**Return on Shareholders Funds (%)**	P/L before tax/Shareholders funds*100
V3	**Return on Total Assets (%)**	(P/L before tax/Total Assets)*100
V4	**Return on Capital Employed (%)**	(P/L before tax/Interest Expense)/(Shareholders Funds +Non-Current Liabilities)*100
V5	**Gross Margin (%)**	(Gross profit/Operating Revenue)*100
V6	**EBIT Margin (%)**	(EBIT/Operating Revenue)*100
V7	**EBITDA Margin (%)**	(EBITDA/Operating Revenue)*100
V8	**ROE (%)**	(P/L for period/Shareholder funds)*100
V9	**ROA (%)**	(P/L for period/Total Assets)*100
V10	**ROCE (%)**	[(P/L for period-Interest Expense)/(Shareholders Funds +Non-Current Liabilities)]*100
V11	**Enterprise Value / EBITDA**	Enterprise Value/EBITDA
Liquidity Ratios		
V12	**Cash Ratio**	Cash & Cash Equivalent/Current Liabilities
V13	**Current Ratio**	Current Asset/Current Liabilities
V14	**Liquidity Ratio**	(Current Asset-Stock)/Current Liabilities
V15	**Interest Cover**	(Operating P/L/Interest Expense)*-1
V16	**EBITDA/Interest Expense**	EBITDA/Interest Expense
Assets Utilization Ratios		
V17	**Shareholders Funds per Employee (th)**	Shareholders Funds/ Number of Employees
V18	**Working Cap. per Employee (th)**	Working Capital/Number of Employees
V19	**Total Assets per Employee (th)**	Total Asset/Number of Employees
V20	**Fixed Assets per Employee (th)**	Fixed Asset/Number of Employees
V21	**Market Capital/Net Assets**	Market Capital/Net Assets
V22	**Working Capital/Total Assets**	Working Capital/Total Assets
V23	**Net Current Assets/Total Assets**	Net Current Assets/Total Assets
Structure Ratios (Leverage)		
V24	**Total Liabilities/Total Assets**	Total Liabilities/Total Assets
V25	**Shareholders Liquidity Ratio**	Shareholders Funds/Non-current Liabilities
V26	**Solvency Ratio (%)**	(Shareholders Funds/Total Assets)*100
V27	**Gearing (%)**	(Non-current Liabilities +Loans)/Shareholders Funds *100
V28	**Total Liabilities/Shareholders Funds**	Total Liabilities/Shareholders Funds
V29	**Debt/EBITDA**	Debt/EBITDA
V30	**Fixed Asset/ Shareholder Funds**	Fixed Asset/ Shareholder Funds
Growth Rate		
V31	**Change in ROA**	(ROAt-ROAt-1)/(|ROAt|+|ROAt-1|)
V32	**Change in Net Income**	(Nt-Nt-1)/(|Nt|+|Nt-1|)
V33	**Sale Growth**	(Sale t /Sale t-1)-1
V34	**EBIT Growth**	(EBITt/EBITt-1)-1
V35	**EBITDA Growth**	(EBITDAt/EBITDAt-1)-1

V36	**Net Profit Growth**	(NetPLt/NetPLt-1)-1
V37	**Capital Growth**	(Capitalt/Capitalt-1)-1
V38	**Enterprise Value Growth**	(Evt/Evt-1)-1
V39	**Market Cap. Growth**	(Market Cap. /Market Cap.t-1)-1
Cash Flow Related Ratios		
V40	**Market Cap/Cash Flow from Operations**	Market Cap/Cash Flow from operations
V41	**Cash Flow/Oper. Revenue**	(Cash flow/Operation Revenue)
V42	**Cash Flow/Current Liabilities**	Cash flow/Current Liabilities
V43	**Cash Flow/Interest Expense**	Cash flow/Interest Expense
V44	**Debtors/Cash Flow**	Debtors/Cash Flow
V45	**Cash Flow from Operation to Total Assets**	Cash flow from operation / Total Assets
V46	**Cash Flow from Operation to Current Liabilities**	Cash flow from operation / Current liabilities
V47	**Cash Flow from Operation to Sales**	Cash flow from operation / Sales
V48	**Cash Flow from Operation to Shareholders Funds**	Cash flow from operation/ Shareholders Funds
V49	**Cash Flow from Operation to Total Liabilities**	Cash flow from operation/ Total Liabilities
Activity (Efficiency)		
V50	**Stock Turnover**	Operating Revenue/Stocks
V51	**Net Assets Turnover**	Operating Revenue/(Shareholders Funds + Non-current Liabilities)
V52	**Assets Turnover**	Operating Revenue/Total Assets
V53	**Fixed Assets Turnover**	Operating Revenue/Fixed Assets
V54	**Working Capital/Sales**	**Working Capital/Sales**
V55	**Creditors/Debtors**	**Creditors/Debtors**
V56	**Cost of Empl./Gross Profit**	**Cost of Empl./Gross profit**
V57	**Collection Period (days)**	(Debtors/Operating Revenue)*360
V58	**Credit Period (days)**	(Creditors/Operating Revenue)*360
V59	**COGS to Sales (%)**	COGS/(Operating Revenue) *100
Employees Efficiency Ratio		
V60	**Operat. Rev. per Employee (th)**	Operating Revenue/Number of Employees
V61	**Aver. Cost of Employee/Year (th)**	(-Cost of Employees/Number of Employees)
V62	**Profit per Employee (th)**	PL before tax/Number of Employees
V63	**Capital Employed per Employees(th)**	(Shareholders Funds + Total Long Term Liabilities)/Number of Employees
V64	**Cost of Empl./Op. Revenue (%)**	(-Cost of Employees/Operating Revenue)*100
Financial Scale		
V65	**Operating Revenue (Turnover) (th)**	
V66	**Total Assets (th)**	
V67	**Total Capital Employed (th)**	(Shareholders Funds Total Long Term Liabilities)
V68	**Operation Cash Flow (th)**	
V69	**Enterprise Value (th)**	
V70	**Market Capital (th)**	

5.6 Data Analysis

5.6.1 Treatment of Missing Values

It is desirable that all credit factors included in model-building are available for the sample cases, but there are some credit factors that have a high predictive power, but are seldom reported by companies. In addition, even for the most widely available credit factors, there may exist a limited number of missing values. Missing values are inherent to datasets of financial figures. Dixon (1979) introduces the K-nearest neighbours imputation (KNNI) technique for dealing with missing values in supervised classification. A lot of methods were developed for dealing with missing data in sample surveys (Kalton and Kasprzyk 1986), but they have some drawbacks when they are applied to classification tasks.

The interest in dealing with missing values has continued with the statistical applications to new areas such as Data Mining, see Grzymala-Busse and Hu (2000). These applications include supervised classification as well as unsupervised classification (clustering). Bello (1995) compares several imputation techniques in regression analysis, a related area to classification. The presence of missing values in a dataset can affect the performance of a classifier constructed using that dataset as a training sample. Several methods have been proposed to treat missing data such as case deletion, mean imputation, median imputation and K-nearest neighbours imputation (KNNI), and the one used more frequently is deleting instances containing at least one missing value of a feature, see Acuña and Rodriguez (2004). Based on statistical analysis of different options, one could substitute these missing values with the mean of the value for the relevant samples/population.

The other way to deal with missing value problem is to use listwise or pairwise cases deletion. Listwise deletion (sometimes is labelled casewise) omits cases which do not have data on all variables in the variables list of the current analysis. Pairwise deletion omits cases which do not have data on a variable used in the current calculation only. This effect is undesirable, but pairwise deletion may be necessary when overall sample size is small or the number of cases with missing is large. Listwise deletion is preferred over pairwise deletion when sample size is large in relation to the number of cases which have missing data. However, even listwise deletion is considered an inefficient method which leads to bias, more detail see Little and Rubin (1987) and Allison (2001). Both listwise and pairwise methods assume missing values are missing completely at random (MCAR).

Among the variables defined in this research 9 variables were found to have high volumes of missing values, such as financial ratios that were based on Enterprise Value and Market Capital. Enterprise Value Growth and Market Capital Growth presented the largest amount of missing cases which is 150 out of total 445 (33.71%) in SME sample. One should also mention Shareholders Liquidity ratio (Shareholder Funds / Non-current Liabilities) where the lack of Non-current Liabilities value and Stock Turnover (Operating Revenue /Stocks) have lead to stocks items missing for 140 cases (31.46%) of SME businesses. It was concluded that for these variables with large numbers of missing values substituting with mean value or using pairwise case method will lead to bias in data analysis. As the result, these 9 variables are excluded and the remaining 61 financial variables were used in data analysis. Table 5.6.1 shows the number of cases with missing values and percentage of missing values for these variables.

Table 5.6.1 Financial ratios with large numbers of missing values

Financial Variables	**Cases of missing**	**Percentage of missing**
V11: Enterprise Value/EBITDA	84	18.89%
V21: Market Capital/Net Assets	81	18.20%
V25: Shareholders Liquidity ratio	70	15.73%
V38: Enterprise Value Growth	150	33.71%
V39: Market Cap. Growth	150	33.71%
V40: Market Cap/ Cash Flow from Operations	84	18.88%
V50: Stock Turnover	140	31.46%
V69: Enterprise Value	82	18.43%
V70: Market Capital	81	18.20%

5.6.2 Treatment of Outliers

While much of the analysis based on financial ratios employ methodology that relies on either univariate or multivariate normality assumptions and parametric test procedures, surprising little is known about the distributional properties of financial ratios, with some evidence summarised by Foster (1978). Often, departures from normality occur when the population contains some extreme observations that can dominate parameter estimates when they are presented. Cochran (1963) notes that such outliers have especially serious effect of increasing the sample variance and decreasing precision and suggests that this removal of extremes from the main body of the population may reduce the skewness and improve the normal approximation. Perhaps the most complete study related to the distribution properties of ratios is the study by Deakin (1976), which examines standard techniques to identify outliers for large samples of manufacturing firms. It is then shown that the presence of outliers has a tremendous influence on the parameter estimates for the distributions. After deleting outliers, normality or approximate normality was achieved for most of the distributions. Similar results were achieved for industry analyses. Deakin (1976) concludes that the normality assumption is generally not tenable except for the Debt/Total Asset ratio. Whilst square root and logarithmic transformations sometimes lead to normality, no guidelines were offered in financial literature concerning which transformation was appropriate in a given circumstance. Obviously the suggestion from Box and Cox (1964) could be used.

Data processing often involves detecting and isolating outliers that do not comply with the general behaviour of the data and are regarded as noise. In general, the outlier detection is based on statistical analysis, which considers different definitions of outlying values and their corresponding impact on the predictive power of the underlying data. Once the outlying values have been identified, the way to treat outliers could be to replace them with ‘boundary values’, which are calculated as the mean of the observed value for the population, plus or minus two standard deviations. In turn, the other way is to directly remove these values, this adjustment translates into a significant improvement in the overall performance of the model, while maintaining the original characteristics of the data. Also, it is known that the K-means cluster analysis can be applied to remove outlier impact. Cluster analysis serves to group objects based on the characteristics they possess (Hair, Anderson, Tatham and Black 1998) that is, according to their similarity (Fielding and Gilbert 2000). The basic rules for grouping are: to minimise the variability within clusters and maximise the variability between clusters (Su and Chou 2001). Based on the criterion of similarity, it is expected that most objects will be grouped in one cluster and the rest of the objects will be grouped to other clusters. Objects that cannot be grouped due to the lack of similarity may be viewed as outliers. Given the importance of K-means cluster methods for detecting outliers, the algorithm of K-means analysis is introduced in the following section.

5.7 Algorithm of K-means Cluster

K-means MacQueen (1967) is one of the simplest unsupervised learning algorithms that solve the clustering problem. To reiterate, the classic *k*-Means algorithm was popularised and refined by Hartigan (1975), (also see Hanigan and Wong (1979)). The basic operation of that algorithm is relatively simple: given a fixed number of (desired or hypothesised) *k* clusters, assign observations to those clusters so that the means across clusters (for all variables) are as different from each other as possible.

The objective in K-means clustering is to find a partition of the observations into a preset number of groups, *k*, that minimises the variation within each group. Each variable may have a different variation, of course. The variation of the j^{th} variable in the g^{th} group is measured by the within sum-of-squares,

$$s^2_{j(g)} = \frac{\sum_{i=1}^{n_g}(x_{ij(g)} - \bar{x}_{j(g)})^2}{n_g - 1} \qquad (5.7.1)$$

where n_g is the number of observations in the g^{th} group, and $\bar{x}_{j(g)}$ is the mean of the j^{th} variable in the g^{th} group. There are *m* such quantities. The variation of the observations within the g^{th} group is chosen as a linear combination of the sums-of-squares for all of the *m* variables. The coefficients in the linear combination determine the relative effects that the individual variables have on the clustering. The coefficients are usually chosen to be equal. The relative effects that the individual variables have on the clustering also depend on their scales. Now, to state more precisely the objective in *k*-means clustering, it is to find a partition of the observations into a preset number of groups *k* that minimises, over all groups, the total of the linear combinations of the within sum-of-squares for all variables. For linear combinations with unit coefficients, this quantity is

$$w = \sum_{g=1}^{k} \sum_{j=1}^{m} \sum_{i=1}^{n_g} (x_{ij(g)} - \bar{x}_{j(g)})^2 \qquad (5.7.2)$$

Determining the partitioning to minimise this quantity is a computationally intensive task. In practice, one seeks a local minimum that is a solution such that there is no single switch of an observation from one group to another group that will decrease the objective. Even the procedure used to achieve the local minimum is rather complicated. Hartigan and Wong (1978) give an algorithm for performing the clustering. Their algorithm forms a set of initial trial clusters and then transfers observations from one cluster to another while seeking to decrease the quantity in equation (5.7.2).

In either method for performing K-means clustering, it is necessary to choose initial points and then trial points to move around. In most algorithms these points are chosen arbitrarily. Faber (1994) has suggested that the points be chosen uniformly randomly. This choice gives preference to points in dense regions, which is consistent with an underlying concept of K-means clustering.

Milligan and Cooper (1985) perform a Monte Carlo study comparing 30 different procedures. The one they found that worked the best was the Calinski and Harabasz (1974) criterion which is formed as:

$$\frac{b/(k-1)}{w/(n-k)}$$, where b is the between-groups sum-of-squares,

$$b = \sum_{g=1}^{k}\sum_{j=1}^{m}(\bar{x}_{j(g)} - \bar{x}_j)^2$$, and w is the pooled within-groups sum-of-square.

5.7.1 Standardised Scale of Variables before K-means Analysis

The clustering depends on the variability of the variables. It may be necessary to scale the variables in order for the clustering to be sensible because the larger a variable's variance, the more impact it will have on the clustering. It is obvious to employ standardised scale for variables due to nature of the variables such as ratio or currency scale of variables. For example, Financial Scale variables, such as Operating Revenue, Total Assets, Total Capital Employed and Operating Cash Flow which are based on thousand Euros may impact clustering sensibility. For dealing with these large scale variables, the value of variables / square root of variance are used to standardise the scale of variables before k-means clustering analysis.

Two choices have to be made with nearest-neighbour methods: the value of k (the number of nearest neighbours) and the metric through which 'near' is defined. The choice of k depends on the compromise one wishes to make between bias and variance: smaller k means less bias in the estimates of the probabilities, but at the cost of larger variance, and the converse holds for larger k (Hand and Henley 1997). In the credit scoring context, when very large data sets are often available, large k can typically be used with impunity.

The procedure of deciding on k number can be composed of the following steps, see Hanigan and Wong (1979):

"1. Place ***K*** points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.

3. When all objects have been assigned, recalculate the positions of the ***K*** centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimised can be calculated."

Isolating outliers from the input data can be achieved using clustering. Given a standardised variables, a select K = 12 to remove outliers. Assuming even distribution then under 10% would fall in most extreme group and hence could be eliminated as outliers. In the sample the elimination rate is 5.92% that is 28 out of 473 cases which resulted in 445 SMEs classified in four groups as described previously in Table 5.3.1.

5.8 Factors Classification

The main applications of factor analytic techniques are: (1) to reduce the number of variables and (2) to detect structure in the relationships between variables, that is to classify variables. Therefore, factor analysis is applied as a data reduction or structure detection method (the term factor analysis was first introduced by Thurstone (1931).

A common problem, known as multicollinearity arises with many models, such as multi-factor models and models based on regression analysis. Multicollinearity problem is that explanatory variables can have a high degree of correlation between themselves and it may not be possible to determine their individual effects. Principle Components Analysis (PCA) may be used to overcome this problem with data.

The principal components method of extraction begins by finding a linear combination of variables (a component) that accounts for as much variation in the original variables as possible. It then finds another component that accounts for as much of the remaining variation as possible and is uncorrelated with the previous component, continuing in this way until there are as many components as original variables. Usually, a few components will account for most of the variation, and these components can be used to replace the original variables. This method is most often used to reduce the number of variables in the data file.

5.8.1 Algorithm of Principal Component Analysis (PCA)

PCA is based on an eigenvalue and eigenvector analysis of $V = X^{'}X/T$, the k × k symmetric matrix of correlations between the variables in *X*. Alexander (2001) interprets that each principle component is a linear combination of these columns, where the weights are chosen in such way that:

”1. the first principal component explains the greatest amount of the total variation in *X*, the second component explains the greatest amount of the remaining variation, and so on;
2. the principal components are uncorrelated with each other.”

It is shown that this can be achieved by choosing the weights from the set of eigenvectors of the correlation matrix. Denote by W the k × k matrix of eigenvectors of V. Thus VW = WΛ, where Λ is the k × k diagonal matrix of eigenvalues of V. Order the columns of W according to size of corresponding eigenvalue.

Thus if W = (w_{ij}) for *i, j* = 1,…,*k*, then the m^{th} column of W, denoted $w_m = (w_{1m},......,w_{km})^{'}$, is the k × 1 eigenvector corresponding to the eigenvalue λ_m and the column labelling has been chosen so that $\lambda_1 > \lambda_2 > ...... > \lambda_k$. Define the m^{th} principal component of the system by

$$P_m = w_{1m}X_1 + w_{2m}X_2 + ... + w_{km}X_k, \qquad (5.8.1)$$

where X_i denotes the i^{th} column of *X*, that is, the standardised historical input data on the *i*th variable in the system. In matrix notation the above definition becomes: $P_m = Xw_m$, which has P_m as its m^{th} column, may be written *P* = *XW*. Since the variance of each principal component is determined by its corresponding eigenvalue, the proportion of the total variation in *X* that is explained by the m^{th} principal component is λ_m / (sum of eigenvalues). However, the sum of the eigenvalues is k, the number of variables in the system. Therefore the proportion of variation explained by the first n principal components together is $\sum_{i=1}^{n} \lambda_t / k$. Because of the choice of column labelling in W the principal components have been ordered so that P_1 belongs to the first and largest eigenvalue λ_1, P_2 belongs to the second largest eigenvalue λ_2, and so on. In a highly correlated system the first eigenvalue will be much large than the others, so that the first principal component alone will explain a large part of the variation.

Since $W' = W^{-1}$, equation $P = XW$ is equivalent to $X = PW'$, that is

$$X_i = w_{i1} P_1 + w_{i2} P_2 + ... + w_{ikP} P_k \qquad (5.8.2)$$

Thus each vector of input data may be written as a linear combination of the principal components. This is principal components representation of the original variables that lies at the core of PCA models.

PCA first finds the linear combination of variables as pointed out by Stevens (1992) which accounts for the maximum of variance, to be the first principal component (P_1). It is rewritten as

$$P_1 = w_{11} x_1 + w_{12} x_2 + w_{13} x_3 . + ... + w_{1n} x_n \qquad (5.8.3)$$

Often only the first few principal components are used to represent each of the input variables, because they are sufficient to explain most of the variation in the system. However, even without this dimension reduction, calculations of covariance for the original variables are greatly facilitated by the presentation of these variables by (5.8.2); the principal components are orthogonal so their unconditional covariance matrix is diagonal.

The next procedure is to find the second principal component (P_2) by accounting for the second largest amount of variance (which has removed the variances from P_1) and to ensure that the correlation between P_1 and P_2 is zero.

Since every principal component is independent to each other (Taffler 1983), it implies that the multicollinearity problem will not occur in PCA. The functional relationship is then fed into the principal component analysis procedure to transfer a set of responses into a set of uncorrelated principal components.

Comrey and Lee (1992) argue that if a variable's eigenvector absolute value is above 0.71 (it means that it accounts for 50% of the variance), the variable is excellent to explain the principal component.

5.8.2 Results in PCA Analysis

As a result of principal components analysis (PCA) in Table 5.8.1 presents that there are15 *PC* that have an eigenvalue greater than 1 and variables contain within the components are shown.

Table 5.8.1 Total variance explained in components.

	Initial Eigenvalues			**Variables in Component**
PC	**Total**	**% of Variance**	**Cumulative %**	
1	11.798	19.342	19.342	V01, V06, V07, V41, V47, V54, V57, V58, V64
2	7.971	13.068	32.410	V03, V09, V22, V23, V24, V26, V45, V52, V53
3	6.058	9.931	42.341	V17, V19, V20, V60, V61, V62, V63
4	5.135	8.418	50.759	V33, V42, V46, V49
5	**3.407**	**5.585**	**56.344**	V02, V04, V08, V10, V48
6	2.687	4.405	60.749	V15, V16, V43
7	2.526	4.142	64.891	V12, V13, V14
8	2.244	3.678	68.569	V27, V28, V30
9	1.986	3.256	71.826	V65, V66, V67
10	1.738	2.850	74.675	V34, V35, V36
11	1.611	2.642	77.317	V05, V59
12	1.408	2.308	79.624	V31, V32
13	1.242	2.036	81.660	V18, V51
14	1.166	1.912	83.573	V29, V44
15	**1.101**	**1.805**	**85.377**	V55, V56
16	.997	1.634	87.012	

If the first five principal components (PC_1 to PC_5) were selected for final models development, the results show that they would explain 56.344% of the variability in the original 61 variables, so it can considerably reduce the complexity of the data set by using these components, but with 43.656 % loss of information. However, if 15

PC are chosen i.e. their eigenvalue > 1, the efficiency of variable reduction is insignificant (i.e. 59 variables included in 15 *PC*, only 2 out of original 61 variables), although they explain nearly 85.377%. In this research, it is suggested that principal components analysis for variables reduction may obtain good solution if first five components (i.e. correlation between PC_1 to PC_5 are zero) are chosen. The first 5 PCA are explored using scatterplot analysis. This type of view is useful for selecting variables in PCA models and look at explained variables in terms of their ability to classify four groups of SMEs. The relationship of PCA scatterplot matrices showing the classification of 4 groups of SMEs are posted in Figure 5.8.1.

The purpose of scatterplot analysis is to view whether first five components could classify into 4 groups of SMEs well. The first plot in the first row shows the first component on the vertical axis versus the second component on the horizontal axis (the correlation between PC_1 and PC_2 is zero), and the order of the remaining plots follows the same logic. There appears to be a relationship between the first and second components, the scatterplot matrix shows a skewed distribution of dataset and most samples concentrate on the upper right corner with some scattered points around. The presented first component versus the second components matrix does not result in good classification for 4 groups of SMEs which may be caused by the fact that most cases are in group 4 (225 healthy SMEs). The first versus the third and fifth component matrices show the similar appearance. Only the first versus the fourth provide overlapping points focusing on the upper left corner but also could not classify well between each group of SMEs. Similar features appear in the other scatterplot matrices, their results show the cluster around one area and only a few points scattered around.

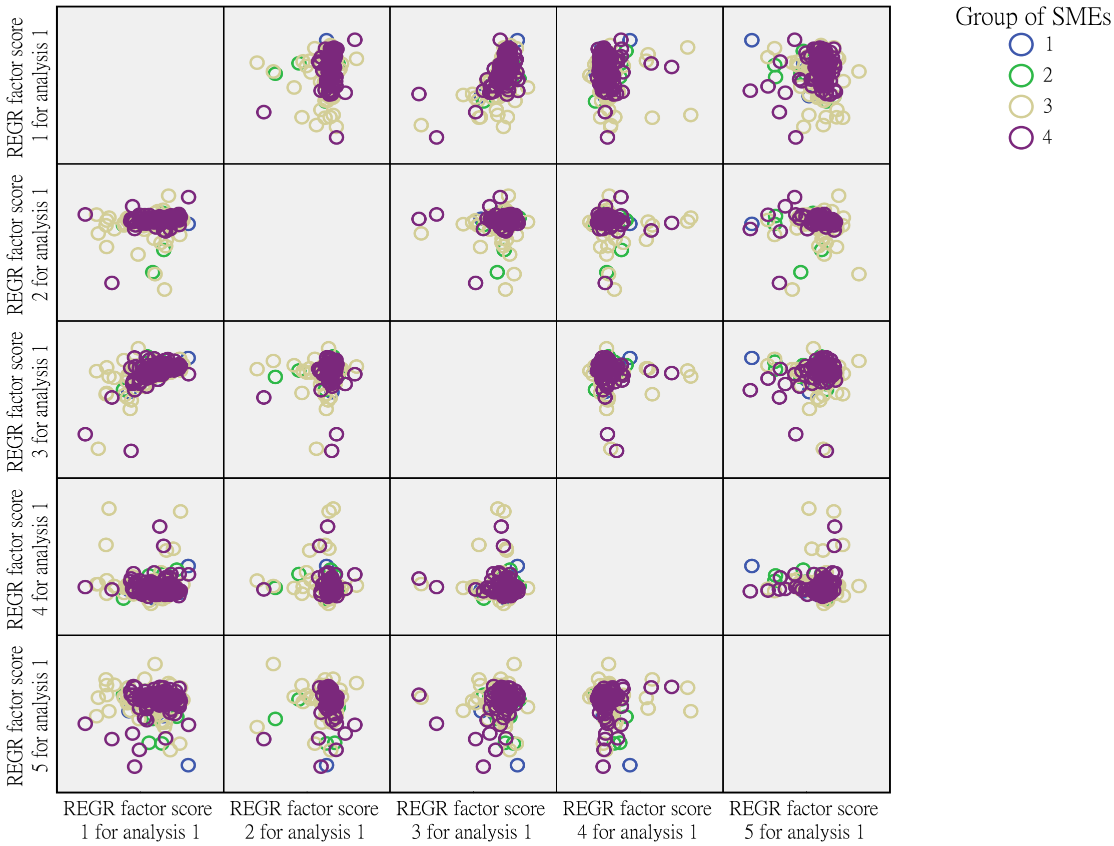

Figure 5.8.1 Scatterplot matrices of the component scores

The problem may be in great differences between the numbers in each group of SMEs, that is only 28 insolvent SMEs cases in Group 1, and 32 cases in Group 2 (flow-based and stock based distress). The most of cases are in Group 3 (flow-based distress) and Group 4 (healthy), 160 and 225 respectively. So the sample has greater proportions in these categories compared to Group 2 and Group1. It may lead to dataset having skewed distribution and so the failure to provide for effective classification. Although Principal Components Analysis (PCA) is most commonly used in variable reduction and for overcoming multicollinearity problem within correlated variables in data set, unfortunately, for this dataset the appearance in each of scatterplot matrix presented a skewed distribution and most cases overlap the groups focusing on one location with only a few cases scattered around this main cluster, even with removal of outliers.

It is notable that PCA is useful for eliminating redundancies and noise from data, but PCA may not be suitable in this research which particularly looks into SMEs with 4 groups of different default definition for credit risk models-building. Therefore, possible approaches for improving SMEs credit risk modelling are considered in later Chapters of this thesis.

5.9 Conclusion

This chapter provided a detailed description of the data that can serve a source of the potential predictor variables in relation to SMEs default prediction. The definition of default has been addressed including different insolvency terms under UK Insolvency Act of 1986 and Basel II reference definition of a default event. A common problem of default prediction consists in a small number of bankruptcies or real defaults available for model-building. As a consequence, it is necessary that not only default firms are included but also the different levels of financial distress have been considered in SMEs credit risk modelling.

There are different ratios traditionally used to determine how a large corporation is performing, company's financially prosperity or distress. There are additionally financial ratios useful in relation to SMEs performance such as Asset Utilisation ratios, Cash Flow Related Ratios, Employees Efficiency Ratios and Financial Scale. A large set of 70 financial variables classified into nine categories have been included as potential predictor variables for SMEs credit risk model development.

It is desirable that all credit factors included in model-building are available for the sample cases, but for some variables there may exist a large some number of missing values. Therefore, it is essential to check for missing values and outliers in dataset before entering variables into model-building. Among the variables defined in this research, 9 variables were found to have high volumes of missing values, e.g. financial ratios based on Enterprise Value and Market Capital. As the results, these 9 variables were excluded and the remaining 61 variables were used in data analysis. Regarding the treatment of outliers, K-means cluster analysis was applied to remove outlier impact. Outliers elimination resulted in 445 SMEs classified in four groups for analysis.

It is notable that the multi-factor models and models based on regression analysis may suffer from multicollinearity problem that is explanatory variables can have a high degree of correlation between themselves and it may not be possible to determine their individual effects. PCA may be used to overcome this problem with data. Therefore, Principle Components Analysis (PCA) was applied to detect structure in the relationships between variables. As a result of PCA, the first five components (PC_1 to PC_5) explained 56.344% of the variability in the original 61 variables. PC_1 to PC_5 explained variable are independent between components (i.e. correlation between PC_1 to PC_5 are zero).

The purpose of this analysis was to see whether components could classify into 4 groups of SMEs well. Unfortunately, from scatterplot matrices analysis of the PC_1 to PC_5 components, it was found that dataset has skewed distribution and it fails to provide for effective classification into 4 groups of SMEs i.e. the most cases are in Group 3 (flow-based distress) and Group 4 (healthy), 160 and 225 respectively. As a consequence, Chapter Six will explore further possible approaches for SMEs credit risk models.

CHAPTER SIX

Modelling SME Default over Different Definitions of Financial Distress

6.1 Introduction

Statistical credit risk models try to predict the probability that a loan applicant or existing borrower will default over a given time-horizon, usually of one year. According to the Basel Committee on Banking Supervision (BCBS 2006) banks are required to measure the one year default probability for the calculation of the equity exposure of loans. The aim of this thesis on SMEs credit risk modelling is to predict the likelihood that a company will fail to meet its financial obligations or default, and to provide a reliable indication of default probability. Since SMEs rests between corporate and retail exposures, possible modelling approaches for SMEs that have been considered are credit scoring models, which are widely used in retail consumer banking, and market-based Merton type models which are mostly applied in corporate credit risk. Credit scoring methods for SMEs are discussed in this Chapter, and Merton type models and comparison with credit scoring models will be addressed later in Chapter Seven.

This Chapter introduces a number of risk-rating models for the U.K. SMEs using an accounting-based approach, which utilises financial variables to distinguish between defaulting, financially distressed and non-defaulting firms and to predict corporate bankruptcy. An enhancement to these models is considered through features typical to credit scoring modelling. First, different definitions of default are explored. A common problem of default prediction consists in a small number of bankruptcies or real defaults available for model-building. The Chapter considers adopting different definitions of default and investigates their impact on the choice of predictor variables and model's predictive accuracy. Second, it examines whether the predictor variable transformation, which is routinely conducted in consumer credit scoring models, is necessary for SMEs credit scoring, and whether this enhances the predictive accuracy of the model. The analysis demonstrates that each default definition/ transformation considered leads to a different model and these are compared in terms of their composition and their predictive accuracy.

6.2 Modelling Approach

One possible approach to modelling Financial Distress would be to use a multinomial/ordinal models for all 4 levels of response. It should be mentioned that there is an additional complication for the use of such a models as the number of predictor variables increases, the number of observations (companies) falling into each cell (i.e. a combination of a particular level of the response variable) will be decreasing, leading to cells with 0 counts. This can lead to difficulties for estimation algorithms since they do not converge. Although multinomial/ordinal models have not be explored at this stage, it would be a possible approach for modelling different levels default of SMEs if there were sufficient firms available in the sample, covering all possible combinations.

Classification method explored here requires two categories with a default history: a ‘good’ credit group who have not defaulted and a ‘bad’ credit who have defaulted. Generally, two essential linear statistical tools, discriminant analysis and logistic regression, are the most commonly applied to construct credit scoring models. Linear discriminant analysis (LDA) has often been criticised because of its assumption of normality and that the good and bad credit classes are based on equal sample size, see Reichert, Cho and Wagner (1983). As far as UK research in corporate insolvency prediction is concerned, evidence shows that such research was undertaken mainly in the 1980s and early 1990s (El Hennaway and Morris 1983; Keasey and Watson 1986; Taffler 1984) based on Multiple Discriminant Analysis (MDA). It can thus be argued that the models developed in those studies may not be currently applicable, given that various economic changes have occurred in the UK since then.

Logistic regression is an alternative method for credit scoring. Basically, the logistic regression model emerged as the technique for predicting dichotomous outcomes. As a matter of fact, Harrell and Lee (1985) find that logistic regression is as efficient as the LDA approach. For predicting dichotomous outcomes, logistic regression is one the most appropriate techniques (Lee, Jo and Han 1997). A number of explorations of logistic regression model for credit scoring applications have been reported in literature. However, from practical experience, Caouette, Altman and Narayanan (1998), point out the market assessment of credit models varies with the size of the borrowers, and that credit scoring models has spread to large corporate, middle market, small business and retail credit consumers as shown in Table 6.2.1. It is implied that credit scoring models are likely to increasingly be used in lending decision. This use is likely to vary depending on the size of borrower and potential information disclosure capabilities.

Table 6.2.1 Range of possible application of quantitative credit risk models

Sized of borrower	**Possible application of credit risk models**
Large corporate credit	· Publicly traded information and extensive disclosure for many institutional investors with research capabilities. · Low monitoring (annual cycle). · Potential for higher use of credit models due to better data.
Middle market borrowers	· Publicly traded with moderate disclosure but little or no publicly traded debt. · Moderate use of credit scoring models and greater emphasis on management.
Middle market and private borrowers	· Most stock not publicly traded and no public debt. Reliance on financial statements. · Close monitoring. Reliance on collateral and covenants. · Limited use of credit scoring models.
Small business	· No stock traded even financial statements are unaudited information problems. · Reliance on individuals. Close monitoring. Reliance on collateral and covenants. · Moderate use of credit scoring models.
Consumer	· No financial statements. Fewer information problems because of credit bureaus. · Reliance on demographic variables. Collateral only consumer durables. No covenants. · Heavy use of credit scoring models.

Source: Caouette, Altman and Narayanan (1998)

6.3 Logistic Model

Logistic regression model is one of the most popular methods used in credit scoring models and does not necessarily require the assumptions of LDA. Harrell and Lee (1985) find that logistic regression is as efficient and accurate as LDA even though the assumptions of LDA are satisfied. In addition, the normal discrimination or classification problem is usually formulated by assuming that the two populations are multivariate normal with equal covariance matrices. Press and Wilson (1978) show that in many circumstances logistic discrimination is preferable to the usual linear discrimination based on either normal population with equal covariance matrices. They point out that logistic regression with maximum likelihood estimators (MLE) is preferable for solving both the classification problem and the problem of relating qualitative to explanatory variable i.e. nonnormality. As previously discussed, these shortcomings of LDA have led to the use of the logistic regression model which does not assume multinormality and also gives an estimate for the probability of failure (Keasey, McGuinness and Short 1990).

The logit model derives the coefficients of the independent variables to predict default probability of occurrence of a dichotomous dependent variable (Dielman 1996). In the context of failure prediction, the technique weighs the financial ratios and creates a score for each company in order to be classified as either failed or healthy. The function in logit analysis is called the logistic function and can be written as follows:

$$SC_i = \log\left[\frac{p_i}{1-p_i}\right] = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} = x_i \beta$$

$$p_i = \frac{\exp(x_i \beta)}{1+\exp(x_i \beta)}$$

$$p_i = \frac{1}{1+\exp-(x_i \beta)}$$

where p_i is the probability of experiencing distress (according to a selected definition) for i company and k predictor variables.

So this Chapter focuses on using the standard credit scoring modelling tool, i.e. binary logistic regression. Obviously, this requires a binary response variable, which can be formed in a number of different ways that will be discussed in section 6.5.

6.4 Predictor Variable Transformation

It is not unusual to perform predictor variable transformation before modelling the event of interest. It is normally done to satisfy the assumptions of the technique that will be used in later model-building stage, e.g. linear regression requires normally distributed predictor variables. Although logistic regression is not sensitive to deviations from normality, it is a custom to perform initial transformation of predictor variables that received the name of coarse-classification. The main reason for doing it is the fact that a lot of predictor variables used in retail banking are categorical, often consisting of many categories with few observations in each (e.g. Occupation). This would lead to a non-robust model, so the solution consists in grouping small categories together, which either belong logically to each other or exhibit similar relationship with the response variable. In order to develop a robust credit risk model for SMEs, the standard credit scoring approach will be used i.e. coarse classification, see Thomas, Edelman & Crook (2002)

6.4.1 Coarse Classification

Coarse classifying improves the robustness of the credit scoring models or the scorecard being developed, since it increases the size of the group with a particular regression coefficient. More importantly for continuous variables, it allows for non-monotonicity of the relationship between characteristics and outcome to be built into the model.

The first step would be to calculate the proportion of Bads in total number of observations that fall into each category, or Bad to Good Odds. Then categories with close values would be banded together into coarse-classes. Similar procedure is performed for continuous variables. In this case coarse-classification allows to eliminate outliers and to preserve non-monotonic patterns that maybe present in the data. In credit scoring coarse-classification is applied not only to traditional problems. More information on coarse-classification is given in Thomas, Edelman and Crook (2002).

Jung and Thomas (2004) investigate how to estimate the likelihood of a customer accepting a loan offer as a function of the offer parameters and how to choose the optimal set of parameters for the offer to the applicant in real time. The coarse classification is used to deal with characteristics, the bands and groups of variables and improves the robustness of building a credit scorecard. The logistic model is then built on the application and offer characteristics using the cases of training sample.

The novelty of the approach adopted in this research consists in coarse-classification being conducted for 4 levels of Financial Distress as described in Chapter Five (section 5.3). Each predictor variable (given in Chapter Five as Table 5.5.1) was first split into quintiles (5 equal-sized groups of ordered data), for each quintile the proportions of Groups 1 to 4 were calculated and plotted for visual inspection. Figure 6.4.1 shows an example variable Cash Ratio.

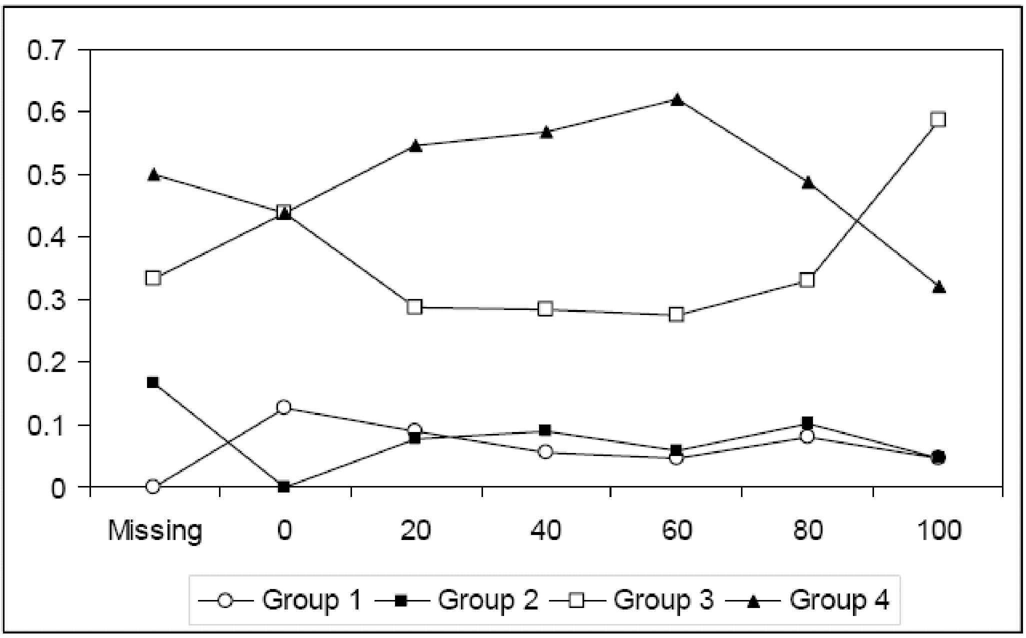

Figure 6.4.1 Example of coarse-classification (Cash Ratio).

The graph shows a largely non-linear trend, which was observed for a majority of predictor variables explored. Proportion of healthy companies (Group 4) starts to increase as the value of Cash Ratio increases, but then for the highest value of Cash Ratio, the proportion of healthy companies is decreasing. Group 3 (Interest Coverage < 1, line with dots) shows the opposite trend, with almost no change in the middle part of the data. There is little separation between Group 2 (Interest Coverage <1 and Insolvency Ratio <0) and Group 1 (Insolvent companies) and no general trend. This can be attributed to low numbers falling into these two groups.

The coarse-classification technique is helpful in revealing relationship patterns between the response variables and predictor variables taken separately. It also can be used for initial screening of predictor variables in order to reduce the number of potential predictors that will be explored at later stages.

6.4.2 Weight of Evidence (WOE)

Weight of evidence is related to the logarithm of the likelihood ratios of goods to bads at each category. Early scorecard developers recognised the importance of information odds and used them to produce raw scorecards. Probabilities of one outcome and another are multiplicative.

Let g_i be the number of goods who have attribute i of the variables and b_i be the number of bads who have that attribute. If $g = \sum_i g_i$ and $b = \sum_i b_i$, then let attribute i have a value which can be g_i / b_i, $(g_i / g_i + b_i)$, $g_i b / b_i g$, $\log(g_i /(g_i + b_i)$ or $\log(g_i b / b_i g)$. This approach gives the attribute values of the characteristics an ordering related to the odds of goods to bads among the sample of past applicants who have that attribute. The reason why this is the approach that is used in general is because it is appropriate for the continuous variables as well as the categorical variables.

Characteristics were categorised or coarse-classed on the basis of the weights of evidence (WOE):

$w_{ij} = \log(g_{ij}B_j / b_{ij}G_j)$, where $g_{ij}(b_{ij})$ are the corresponding numbers of goods and bads within the attribute *i* of characteristic *j*, $G_j(B_j)$ are total numbers of good/bad in the sample.

From initially considered 70 financial ratios, 9 ratios were removed from the analysis due to large proportion of missing values (described in Chapter Five section 5.5 and 5.6), after coarse-classification additional 5 ratios (Sale Growth, EBIT Growth, EBITDA Growth, Net profit Growth and Capital Growth) were discarded since they did not show notable separation between SME classes.

The remaining 56 variables were entered into the logistic regression using two different approaches to variable coding: dummy binary variables and weights of evidence. The former converts all *n* coarse-classes or bands of the variable into *n*-1 dummy binary variables.

The following section compares the composition and predictive accuracy of the models under different definitions of default, and using two coding approaches.

6.5 Different Definitions of Default

The point of observation of the default was chosen to be end of year 2004, the financial data available at this point was used to classify companies into different groups of financial health, as described below. The financial statements from 2001 were taken to derive ratios that could be used as early signs or predictors of financial distress. The time period of 3 years between the point of prediction and the default allows account to be taken for slow reporting of some companies and also looks into the measures that can be used as default signals at an early stage.

This section explores different definitions of default, starting from the strictest one - Insolvent Companies only (Group 1), and gradually loosening the definition by including Group 2, then Group 3.

In traditional credit scoring it is not uncommon to classify the performance of accounts into 3 groups: Good, Bad and Indeterminate, the latter are normally the borderline cases that are difficult to attribute to either Good or Bad category. Indeterminates are then excluded from modelling, since there is a general belief that this improves the discrimination between Good and Bad. However, there is a different view that excluding Indeterminates leads to a non-representative sample and creates the risk that the model will not rank these accounts appropriately (e.g. see Hand & Henley,1997).

In the current sample of SMEs, Group 1 can be viewed as 'Bad" in its strictest sense, and Group 4 as 'Good' in its strictest sense, whereas Group 2 and Group 3 can be classified as Indeterminate. There are several strategies of dealing with Indeterminate groups that will be explored:

1) Indeterminate groups are removed from modelling, Group 1 is modelled as 'Bad' versus Group 4-'Good'. This should give better separation between the insolvent and healthy companies, but on the other hand, it reduces the sample size;
2) Leaving all 4 groups in the analysis, with Group 4 defined as 'Good', and all other categories considered as 'Bad';
3) Taking Group 1 and 2 as 'Bad' and modelling it against Group 4 as 'Good', Group 3 is removed from the analysis, thus forming a half-way solution between the two approaches listed above;
4) Finally, opposing Group 3 (Bad) to Group 4 (Good) with the first two groups removed from the analysis, with the purpose of identifying whether a 'weak' definition of default which captures only one side of financial distress, can provide a robust modelling and acceptable level of predictive quality.

The subsequent analysis demonstrate that each of the 4 approaches considered leads to a different model. The logistic regression in SPSS was used with forward (conditional) selection mechanism to identify statistically significant predictors. The selection procedure adds variables to the model one at each step if those variables meet the specified level of significance and at the same time removes variables from the model if they fail to meet the specified level for staying in model. The level of significance for entry into the model was set to 0.5 for the score statistic, and removal level was fixed at 0.1 for the probability of a likelihood-ratio statistic based on conditional parameter estimates.

6.6 Composition of Models with Different Definitions of Default

As Table 6.6.1 shows the predictors in the model vary depending on the definition. It is notable that variables from all nine categories enter, although within a single model not all groups are represented. The most frequent group is Cash Flow Related variables, and in other groups cash based variables are often the leaders – Cash Ratio is the most heavily used variable in the Liquidity group, and Operating Cash Flow leads the Financial Scale group of variables. This shows the importance of cash-related predictors as early signs of financial distress, which is supported by previous research demonstrating that small business cannot survive without generating cash from their normal everyday operating activities. For example, DeThomas & Fredenberger (1985) argue that small-sized companies with poor cash flow planning are more vulnerable to financial distress than large firms.

Other frequent groups include Growth and Employees Efficiency Ratios, and again it is not surprising. For a small and medium sized business to be successful, a persistent growth in profitability, annual sales and operating revenue is required. Not all SMEs are capable of achieving a breakthrough growth in practice, therefore, Growth Ratios are thought to be significant indicators related to SME's success. These ratios measure the stability of the firm's performance.

It should be mentioned that coarse-classification has a notable effect on the composition of models, especially for 'Group 1 vs. Group 4' definition, and so does the removal of variables with missing values, this is mostly evident for 'Group 1, 2 vs. 4' definition. It means that there are non-monotonic patterns within the data that are utilized by coarse-classification and that missing values contain important information about the company's financial health.

Table 6.6.1. Composition of models with different definitions of default

Model	**Default Definition**			
	Group 1 vs Group 4	Groups 1,2,3 vs Group 4	Groups 1,2 vs Group 4	Group 3 vs Group 4
(A) Full list of original untransformed ratios	• Assets Turnover • Operating Cash Flow	• Cash Ratio • Liquidity Ratio • Debtors/Cash Flow • Profit per Employee	• Liquidity Ratio • Operating Cash Flow/ Sales • Cost of Employees/ Operating Revenue • Operating Cash Flow	• Cash Ratio • Total Liabilities/ Shareholders Funds • Debtors/Cash Flow • Profit per Employee
(B) Original untransformed ratios, those with missing values removed	• Operating Cash Flow	• Cash Ratio • Liquidity Ratio • Debtors/Cash Flow • Operating Cash Flow/ Shareholders Funds • Profit per Employee	• Operating Cash Flow/ Sales • Cost of Employees/ Operating Revenue • Operating Cash Flow	• Cash Ratio • Debtors/Cash Flow • Operating Cash Flow/ Shareholders Funds • Credit Period (days)
(C) Full list of coarse-classified ratios	• EBIT Growth • Net Profit Growth • Cash Flow/ Current Liabilities • Working Capital/ Sales • Credit Period (days) • Operating Revenue per Employee • Operating Revenue	• EBITDA Margin • Change in Net Income • Operating Cash Flow	• Profit Margin • Cash Ratio • EBIT Growth • Net Profit Growth	• EBITDA Margin • ROCE • Change in Net Income • Operating Cash Flow • Profit per Employee
(D) Coarse-classified ratios, those with missing values removed	• Total Assets per Employee • Cash Flow/ Current Liabilities • Total Assets	• EBITDA Margin • Debt/ EBITDA • Change in Net Income • Creditors/ Debtors	• Profit per Employee	• EBITDA Margin • Cash Ratio • Debt / EBITDA • Change in Net Income • Creditors/ Debtors

6.7 Predictive Accuracy of Models with Different Default Definitions

In the following material the aim is to compare various models and not to consider their predictive capability. In light of this the approach was to consider all the appropriate data and not use a training and a hold out samples or bootstrap methodology. The results presented do allow a fair comparison to be made. Obviously if one wished to explore the prediction capability then one would have to gain more data and then fit the models using a training set of data and make comparison of prediction on a hold out sample.

The predictive accuracy differs too, as presented in Table 6.7.1. To measure the predictive accuracy a random sample of 231 SMEs was selected from the original 445 SMEs companies and was scored by all 28 models that were developed. The companies were then ranked by the score and 116 companies (the number of healthy companies in the sample) with best ranking were selected (as if accepted for credit). Within accepted cases (approximately 50% of the sample) the frequencies of observed groups of financial distress were calculated, and these are reported in Table 6.7.1 for different default definitions. To aid the understanding of the results, the percentages accepted for each group of financial distress are also reported. The numbers in brackets in the second column give the total number of companies observed within a particular group of distress in the sample.

The quality of the model was judged by the number/percentage of healthy (Group 4) companies accepted, and therefore, correctly classified, and by the number/percentage of insolvent (Group 1) companies accepted, and therefore, incorrectly classified. Obviously, it is desirable to have as many healthy companies and as few bankrupt companies as possible among the accepted cases.

It can be seen from Table 6.7.1 that all models perform well, better than a random model that would accept roughly 50% of all distress levels. The exception are models with that use untransformed ratios (Model A and B) for ‘Group 1,2,3 vs Group 4’ definition which actually accept more than 50% of bankrupt companies, although they perform reasonably well on Group 4 by accepting 66.38% of them. The situation is remedied by coarse-classification (Model C), which increases the percentage of healthy companies accepted to 71.55%, and reduces the percentage of insolvent companies accepted to 31.25%.

Coarse-classification notably improves prediction across all definitions. Although it should be mentioned that for 'Group 1 vs. 4' it reduced the percentage of healthy companies accepted, however, this is counter-balanced by a dramatic decrease in accepted bankruptcies (only 1 company). Removal of missing values variables also has a positive effect on prediction, in general, although this effect is less pronounced as compared to coarse-classification.

Overall, the leaders in terms of accepting healthy companies are coarse-classified models with missing values included for 'Groups 1,2,3 vs. Group 4' and for 'Groups 3 vs. 4' definitions. However, the latter performs worse on Groups 1 and 2, which is to be expected since these groups were excluded from the model development. In terms of rejecting insolvent companies, the leader is the coarse-classified model with missing values included for 'Group 1 vs. Group 4' definition, although it should be mentioned that it only accepts 59.84% of healthy companies, and the performance on Groups 2 and 3 is quite close to a random model. Thus, whilst the removal of 'indeterminate' groups increased the ability of the model discriminate the insolvent companies, it had an adverse effect on the ability to rank other groups.

6.8 The Impact of Different Coding of Predictor Variables

Finally, the project explored the effect of different coding on the model composition and predictive accuracy. Table 6.8.1 and Table 6.8.2 compare models with coarse-classified financial ratios that were entered as categorical variables into the logistic regression model with binary (dummy variable) coding and weights of evidence coding. The advantage of binary coding comes from the fact that the resulting coefficient estimates are free from any relationship apart from the one that come from the estimation algorithm, but this approach leads to a large number of variables. The weights of evidence (WOE) approach reduce the number of variables in the model by giving the attributes an ordering related to the odds of Goods to Bads in the development sample, but WOE give a value to each attribute which depends only on that characteristic; they fail to account for relations between characteristics.

Table 6.7.1 Predictive accuracy of models built with different default definitions.

Model	Observed Level of Financial Distress	Default Definition							
		Group 1 vs Group 4		Groups 1,2,3 vs Group 4		Groups 1,2 vs Group 4		Group 3 vs Group 4	
		Number Accepted	% Accepted	Number Accepted	% Accepted	Number Accepted	% Accepted	Number Accepted	% Accepted
(A)	1 (16)	6	37.50%	10	62.50%	3	18.75%	9	56.25%
	2 (19)	6	31.58%	5	26.32%	7	36.84%	7	36.84%
	3 (80)	32	40.00%	24	30.00%	40	50.00%	24	30.00%
	4 (116)	72	62.07%	77	66.38%	66	56.90%	76	65.52%
(B)	1 (16)	6	37.50%	11	68.75%	3	18.75%	10	62.50%
	2 (19)	6	31.58%	6	31.58%	6	31.58%	7	36.84%
	3 (80)	25	31.25%	22	27.50%	33	41.25%	25	31.25%
	4 (116)	79	68.10%	77	66.38%	74	63.79%	74	63.79%
(C)	1 (16)	1	6.25%	5	31.25%	5	31.25%	7	43.75%
	2 (19)	8	42.11%	7	36.84%	4	21.05%	6	31.58%
	3 (80)	38	47.50%	21	26.25%	27	33.75%	20	25.00%
	4 (116)	69	59.48%	83	71.55%	80	68.97%	83	71.55%
(D)	1 (16)	4	25.00%	7	43.75%	7	43.75%	7	43.75%
	2 (19)	8	42.11%	6	31.58%	5	26.32%	7	36.84%
	3 (80)	29	36.25%	27	33.75%	22	27.50%	21	26.25%
	4 (116)	75	64.66%	76	65.52%	82	70.69%	81	69.83%

Table 6.8.1 Composition of models with different coding

Model	Default Definition			
	Group 1 vs Group 4	Groups 1,2,3 vs Group 4	Groups 1,2 vs Group 4	Group 3 vs Group 4
(E) Benchmark coarse-classified model	• EBIT Growth • Credit Period (days) • Operating Revenue per Employee	• EBITDA Margin • Debt/ EBITDA • Change in Net Income • Creditors/ Debtors	• Profit Margin • Cash Ratio • EBIT Growth • Net Profit Growth	• EBITDA Margin • Debt/ EBITDA • Change in Net Income • Creditors/ Debtors • Profit per Employee
(F) WOE coding	• EBIT Growth • Credit Period (days) • Operating Revenue per Employee • Total Assets	• EBITDA Margin • Debt/ EBITDA • Creditors/ Debtors	• Profit Margin • EBIT Growth	• EBITDA Margin • Debt/ EBITDA • Creditors/ Debtors
(G) Dummy variables	• EBIT Growth • Cash Flow/Current Liabilities • Credit Period (days) • Operating Revenue per Employee	• EBITDA Margin • Change in Net Income • Creditors/ Debtors	• Cash Ratio • EBIT Growth • Profit per Employee	• EBITDA Margin • Cash Ratio • Debt/ EBITDA • Creditors/ Debtors

Table 6.8.2 Predictive accuracy of models with different coding.

Model	Observed Level of Financial Distress	Default Definition							
		Group 1 vs Group 4		Groups 1,2,3 vs Group 4		Groups 1,2 vs Group 4		Group 3 vs Group 4	
		Number Accepted	% Accepted	Number Accepted	% Accepted	Number Accepted	% Accepted	Number Accepted	% Accepted
(E)	1 (16)	1	6.25%	7	43.75%	5	31.25%	6	37.50%
	2 (19)	7	36.84%	5	26.32%	4	21.05%	5	26.32%
	3 (80)	33	41.25%	21	26.25%	27	33.75%	20	25.00%
	4 (116)	75	64.66%	83	71.55%	80	68.97%	85	73.28%
(F)	1 (16)	3	18.75%	8	50.00%	8	50.00%	8	50.00%
	2 (19)	5	26.32%	4	21.05%	5	26.32%	4	21.05%
	3 (80)	34	42.50%	21	26.25%	23	28.75%	21	26.25%
	4 (116)	74	63.79%	83	71.55%	80	68.97%	83	71.55%
(G)	1 (16)	0	0.00%	8	50.00%	4	25.00%	8	50.00%
	2 (19)	7	36.84%	6	31.58%	4	21.05%	5	26.32%
	3 (80)	29	36.25%	26	32.50%	32	40.00%	22	27.50%
	4 (116)	80	68.97%	76	65.52%	76	65.52%	81	69.83%

To compare the effect of two coding schemes, a benchmark model (Model E in Tables 6.8.1 and 6.8.2) was developed by including only the predictors selected into Models C and D and applying the stepwise logistic regression that treated coarse-classified predictors as categorical variables. Then the same set of ratios that was used for Model E was transformed by means of WOE and by means of dummy variables. The stepwise logistic regression was applied again, producing Models F (WOE coding) and G (Dummy coding).

It can be seen from Table 6.8.1 that the choice of coding has a minimal effect on the composition of the models. As for predictive accuracy, as shown in Table 6.8.2, the picture is more varied. Across all default definitions WOE coding makes predictive accuracy slightly worse, which is particular evident for 'Groups 1,2,3 vs. Group 4', 'Group 1,2 vs. Group 4' and for 'Group 3 vs. 4', where the ability to distinguish insolvent companies drops to the level of random acceptance. Dummy coding does not improve prediction either for these definitions. However, for 'Group 1 vs. Group 4' definition dummy coding produces a desirable uplift in increasing the number of healthy companies accepted (from 64.66% in benchmark model to 68.97%) and reducing the number of bankruptcies accepted (from 6.25% to 0).

6.9 Conclusions

The study investigated the accounting-based approach that was originally developed for predicting the corporate failure, in application to small and medium business. Different definitions of default based on varying levels of financial distress were proposed, and their effect on predictor variables entering the model and effect on model's predictive accuracy was studied. In addition, there was an exploration of the potential value of predictor variable transformation and different coding schemes.

It was found that default definition had a notable effect on the composition of the models. Whilst the range of predictors selected into models under different definitions covered all categories of variables, it could be concluded that most frequent and therefore, most useful ones in distinguishing between insolvent and healthy companies were Cash Flow related variables, Growth and Employees Efficiency ratios.

All default definitions considered produced prediction better than a random selection. The choice of a particular definition would depend on the risk appetite of a particular lender and the prioritisation of objectives that are put forward when developing a model. If the priority is given to accepting more healthy companies, then the definition 'Group 1, 2, 3 vs. Group 4' should be considered, since it produces higher acceptance rates for healthy companies. If on the contrary, the focus is on rejecting as many potentially insolvent companies as possible, the definition 'Group 1 vs. Group 4' should be adopted, as it performs best on this particular aspect.

A noteworthy finding is that transformation (coarse-classification) of predictor variables improves predictive accuracy of the models, and so does the inclusion of variables with missing values into model-building. This implies the non-monotonic pattern of relationship between predictors and level of financial distress, and the value of missing information for discriminating between different levels of financial distress. The different coding schemes considered did not improve the predictive accuracy, apart from dummy variable approach for 'Group 1 vs. Group 4' definition.

Overall, the Chapter demonstrated that an accounting-based approach is a viable way for credit risk modelling for small business. It can be enhanced by certain lessons learned from modelling retail credit risk, thus leading to more accurate predictions and less capital reserves. Next Chapter will consider the comparison of accounting-based approach to options structural approach i.e. Merton-type models.

CHAPTER SEVEN

Evaluation of Merton Type and Credit Scoring Models

7.1 Introduction

Small and Medium Enterprises (SMEs) constitute a significant part of many western economies, see Acs and Audretsch (1993), OECD SMEs Outlook (2002) and Udell (2004). Whilst many of these enterprises raise money through family or other networks, a sizeable group will borrow from traditional suppliers of credit. (Within the UK it is often stated that 50% of SMEs do not borrow from traditional sources.) For those that do borrow from traditional sources the question arises of what measures should be used to assess applications for loans.

SMEs are defined within the EU as enterprises that are valued at less than 50 Million Euros (OECD SMEs Outlook 2002; BCBS 2005; BCBS 2006; Beresford and Saunders 2005). They encompass family run businesses, small consultancies, start up companies and companies employing 100 or so employees. Hence it is a diverse group of companies. The assessment of their likelihood of default is not immediately straightforward. The two approaches to assessment of default within companies is the Accounting based approach and the Merton based approach. This Chapter aims to compare empirically the two approaches as applied to SMEs.

In relation to credit risk assessment, credit scoring models has increasingly been used by financial institutions for consumer lending and more recently employed in small business exposures. Merton-type models can be considered as signalling an approach of corporate credit risk based on market information i.e. assets value and volatility derived from equity price. Both types of models may be seen as a possible approach assessing to SMEs credit risk. In Chapter Six, credit scoring models have been explored for SMEs by adopting different default definitions and investigating their impact on the choice of predictor variables and compared model predictive accuracy. In this chapter, Merton-type model will be developed and compared to credit scoring approach for SMEs credit risk assessment.

In the context of SMEs models-building, it is imperative to validate the methodology for assigning credit assessments which are involved in two main criterions: (1) the ability to predict defaults and (2) the accuracy of the default predictive measure.

The first criterion implies that a credit measure should be feasible and a timely signal of deteriorating credit quality or an impending credit event. The second criterion focuses on the accuracy of the credit assessment measure that is the credit assessment technology should have the ability to distinguish between default and non-default obligors so that it can be useful to banks and financial institutions as a robust system to validate the accuracy and consistency of internal rating processes systems, and the estimation of PDs (Probabilities of Default) to assist in capital allocation.

The research will apply different cutoff points on the different level of default definition using this to validate the models and examine the banks' different lending decisions i.e. different levels of acceptance.

To explore whether the models signal the default early a comparison is made of the predictive accuracy over a 3 year period before distress. The Merton type models are explored from 2001 to 2004 year horizon. Distance to Default (DD) and Expected Default Frequency (EDF) are calculated. Credit scoring models based on previous Chapter are used as benchmark models. Credit scores from benchmark credit scoring models are derived. Overall predicted correctly percentage as well as Type I and Type II error from various models are described. Merton models and credit scoring models are compared for their ability to predict accurately different groups of SMEs. A power curve is used for measuring models predictive accuracy with different financial distress across groups of SMEs. Receiver Operation

Characteristics (ROC) plots show the discrimination ability of different models. The test statistic, the Area Under ROC (AUROC), is used to measure model performance.

7.2 Merton Models Exploration

7.2.1 Algorithm of Equity Value and the Probability of Default

It is recognised that Merton (1974) and Black and Scholes (1973) proposed a simple model of the firm providing a way of relating credit risk to the capital structure of the firm, (i.e. so-call structural form model or market-based models). The algorithm of equity value in relation to probability of default is the key expression of Merton-type models. The equations of Merton model described in the following forms are applied in this research for calculating the distance to default (DD) and expected default frequency (EDF) for SMEs credit risk assessments.

Define E as the value of the firm's equity and A as the value of its assets. Let E_0 and A_0 be the values of E and A today and let E_T and A_T be their values at time T. X is defined as the book value of the debt of firm.

In the Merton framework the payment to the shareholders at time T, is given by

$$E_T = \max\left[A_T - X, 0\right] \qquad (7.1.1)$$

This shows that the equity is a call option on the assets of the firm with strike price equal to the promised debt payment. The current equity price is therefore

$$E_0 = A_0 N(d_1) - Xe^{-rT} N(d_2) \qquad (7.1.2)$$

where $$d_1 = \frac{\ln(A_0 e^{rT} / X)}{\sigma_A \sqrt{T}} + 0.5\sigma_A \sqrt{T} \qquad (7.1.3)$$

$d_2 = d_1 - \sigma_A \sqrt{T}$; σ_A is the volatility of the asset value, and r is the risk-free rate of interest, both of which are assumed to be constant. $N(.)$ is the accumulation density function of the standard normal distribution.

Define $X^* = Xe^{-rT}$ as the present value of the promised debt payment and let $L = X^* / A$ be a measure of leverage. Using these definitions the equity value is

$$E_0 = A_0\left[N(d_1) - LN(d_2)\right] \tag{7.1.4}$$

where $d_1 = \dfrac{-\ln(L)}{\sigma_A \sqrt{T}} + 0.5\sigma_A\sqrt{T}$; $d_2 = d_1 - \sigma_A\sqrt{T}$ (7.1.5)

As shown by Jones et al. (1984), because the equity value is a function of the asset value, one can use Ito's lemma to determine the instantaneous volatility of the equity from the asset volatility:

$$E_0\sigma_E = \frac{\partial E}{\partial A} A_0 \sigma_A \tag{7.1.6}$$

where σ_E is the instantaneous volatility of the company's equity at time zero. From equation (7.1.4), this leads to

$$\sigma_E = \frac{\sigma_A N(d_1)}{N(d_1) - LN(d_2)} \tag{7.1.7}$$

Equations (7.1.4) and (7.1.7) allow A_0 and σ_A to be obtained from E_0, σ_E, L and T. The risk-neutral probability, P that the company will default by time T is the probability that shareholders will not exercise their call option to buy the assets of the company for X at time T.

Probability of default is given by

$P = N(-d_2)$, where $d_2 = \dfrac{-\ln(L)}{\sigma_A\sqrt{T}} - 0.5\sigma_A\sqrt{T}$ (7.1.8)

This depends only on the leverage L, the asset volatility σ_A and the time to repayment T.

The implementation of Merton's model based on equations (7.1.4) and (7.1.7), has received considerable commercial attention in recent years. Moody's KMV uses it to estimate relative probability of default that is Expected Default Frequency (EDF). Credit Grades[51] uses it to estimate credit default swap spreads as well as carrying out similar empirical tests to those for the traditional Merton model.

A number of papers in the literature have recently critically assessed the Merton type models, examining the model's predictive power and comparing it with other credit risk approaches such as accounting-based or hybrid models. Thus, the comparison of the two major accounting-based and market-based models becomes a great challenge in credit risk measurement. A recent empirical studies, such as Kealhofer, Kwok and Weng (1998), Delianedis and Geske (1999), Delianedis and Geske (2001), Leland (2002), and Vassalou and Xing (2001) document that the theoretical probability measures estimated from structural default risk models have good predictive power over credit ratings and rating transitions.

Researchers have examined the contribution of the Merton model. Crosbie and Bohn (2003) examine the model employed by Moody's, known as Merton-KMV default probability model. Stein (2002), Arora, Bohn and Korablev (2005) address the accuracy of the KMV Merton model for capturing the information in traditional agency ratings and well known accounting variables.

Hillegeist, Keating, Cram and Lundstedt (2004), however, address that traditional models (updated versions of Altman's Z-Score and Ohlson's O-Score) can provide significant, incremental information and therefore, the theoretical probabilities estimated from structural models are not a sufficient statistic of the actual default probability. Campbell, Hilscher and Szilagyi (2005) estimate hazard models that incorporate both default probability of Merton-KMV and other variables for

[51] CreditGrades (a venture supported by RiskMetrics Group JP Morgan, Goldman Sachs, Deutsche Bank) - Industry-standard, company-specific risk measures that provide a robust and transparent source for default probabilities and credit spreads.

bankruptcy, finding that Merton-KMV seems to have relatively little forecasting power after conditioning on other variables.

There are several studies on Merton-type models in comparison with credit scoring approach such as accounting-based models or other type models that focus only on corporate default prediction. Research on SMEs credit risk modelling, however, as well as comparison of model performance is scarce. Therefore in this research, the object is to explore a Merton-type and credit scoring models for SME and to investigate their capability in default prediction.

7.3 Confusion Matrix

The most basic approach to understanding the performance of a default prediction model is to consider the number of predicted defaults (non-defaults) and compare this with the actual number of defaults (non-defaults) experienced. A common means of representing this is a simple contingency table or confusion matrix in Table 7.3.1 described as below.

Table 7.3.1 Confusion matrix

		Observed		
		default ='0'	non-default = '1'	
Predicted	Bad = '0'	a	b	a + b
	Good = '1'	c	d	c + d
		a + c	b + d	a + b + c + d

where '0' denoted as default sample unit; '1' denoted non-default sample unit

$a+b$ is predicted the total number of Bad (default) firms

$c+d$ is predicted the total number of Good (non-default) firms

Then four decision outcomes would be possible. If the rating score is below the cut-off value *C* and the debtor defaults subsequently, the decision was made correctly (cell = *a*). Otherwise the decision-maker wrongly classified a non-defaulter as a defaulter (cell = *c*). If the rating score is above the cut-off value and the debtor does not default, the classification was correct (cell = *d*). Otherwise, a defaulter was incorrectly assigned to the non-defaulters group (cell = b).

The overall predictive accuracy rate can be calculated as:

$$P_{AR} = (a + d)/(a + b + c + d) \quad (7.3.1)$$

It is important to explore the issues of different types of error. The overall accuracy rate is defined as the joint minimisation of Type I and Type II misclassification errors. Type I error is referred to as the error to classify a default firm as a non-default firm, whilst Type II error is defined as the error to predict a non-default firm as a default firm. From view on bank's lending decision, the Type I bankruptcy classification error is analogous to that of an accepted loan that defaults and the Type II error to a rejected loan that would have resulted in a successful payoff.

Type I error and Type II error can be defined in functions (7.3.2) and (7.3.3).

$$\text{Type I error} = b/(a + b) \quad (7.3.2)$$

$$\text{Type II error} = c/(c + d) \quad (7.3.3)$$

With regards to the importance between the Type I and Type II error, it depends on the users of the default prediction model. Therefore, the presentation of different types of error will provide valuable information to different stakeholders to rationalise the decision-making process.

7.4 Cost of Type I and Type II Error

It is notable that the cost of Type I error is the bank/ investor loss of principal and interest that was promised, or a loss in the market value the obligation. The case referred to as Type II error is that potential losses resulting from Type II error include the loss of return and origination fees when loans are either turned down or lost through non-competitive bidding. The correct prediction and cost scenarios are described schematically in Table 7.4.1.

Table 7.4.1 Types of Errors and Cost of Errors

Model	**Actual Defaulters (low credit quality)**	**Actual Non-defaulters (high credit quality)**
Predicted 'Bad'	Correct Prediction	Type I error: Lost principal through defaults. Recovery costs. Loss in market value.
Predicted 'Good'	Type II error: Opportunity costs and potential profits lost. Lost interest income and origination fees. Premature selling at disadvantageous prices e.g. when property or loan misclassify as credit deteriorate.	Correct prediction

It is usually the case that lending to defaulters is very much more costly than not lending to non-defaulters, and a bank's tolerance for the model's error rate might be different depending on the baseline default rate. In general, the costs of Type II error are typically far lower than that of a Type I error. Altman, Haldeman and Narayanan (1977) apply one of the first studies on this topic finding the cost of misclassification that is the ratio of the Type I: Type II cost was on the order of about 35:1.

Given this discussion, investors and financial institutions usually seek to keep models where the probability of making either type of error is as small as possible. Unfortunately, minimising one type of error usually comes at the expense of increasing the other type of error. That is, the probability of making a Type II error reduces as the probability of a Type I error increases.

When a financial institution decides on their lending strategies, cut-off points play an important role in relation to pricing and cost. However, it is difficult to determine the cut-off points resulting from the different types of errors that a classification may produce. It is notable that Ohlson (1980) logit model can be analogous to using logistic regression to compute a cutoff point related to probability such that all firms with individual probabilities higher (lower) than probability are classified as distress (non-distress). This information can in turn be used by a bank in the credit decision process. For example, if the cost of a Type I error is much larger than the cost of a Type II error, the cut-off probability should take on relatively low values because then more firms are classified as distress firms. The concrete empirical magnitudes of the costs of both errors are not known, but in the context of bankruptcy prediction models it is usually assumed that the costs of a Type I error are considerably greater than the costs of a Type II error (Begley, Ming and Watts 1996).

7.5 Model Validation Approach

One of the essential features of a good model is that it should differentiate bad (actual default) firms from good (actual non-default) firms apart from measures based on a confusion matrix that require specific cutoffs. There are two well-known approaches to testing a model for its power: one is Cumulative Accuracy Profile (CAP) with its output known as Accuracy Ratio (AR), and the other approach is Receiver Operating Characteristic (ROC) with its output known as Area Under ROC curve (AUROC).

7.5.1 Cumulative Accuracy Profiles (CAP)

Consider an arbitrary credit scoring model that produces a continuous rating score. The score under consideration could be a rating score such as Altman's Z-score (1968) or Ohlson's O-score (1980).

The default probability or credit score of debtors can be derived from building credit risk models. A high rating score is usually an indicator of a low default probability. Engelmann, Hayden and Tasche (2003) interpret that to obtain the CAP curve, all debtors are first ordered by their respective scores from safest to riskiest, that is, ranking from the debtor with the highest score to the debtor with the lowest score. For a cutoff point given a fraction X of the total number of debtors, the CAP curve is constructed by calculating the percentage $d(x)$ of the non-defaulters whose rating scores are equal to or higher than the maximum score of fraction *X*. This is done for *X* ranging from 0% to 100%. Figure 7.5.1 illustrates CAP curves.

A perfect rating model will assign the highest scores to the non-defaulters. In this case, the CAP is increasing linearly and then stays at one. For a random model without any discriminative power, the fraction *z* of all debtors with the highest rating scores will contain *X%* of all non-defaulters. Real rating systems will be somewhere in between these two extremely models. The quality of a rating system is measured by the accuracy ratio *AR*. It is defined as the ratio of the area a_R between the CAP of the rating model being validated and the CAP of the random model, and the area a_P between the CAP of the perfect rating model and the CAP of the random model, that is:

$$AR = \frac{a_R}{a_P} \quad (7.5.1)$$

Thus, the rating method is the better the closer AR is to one.

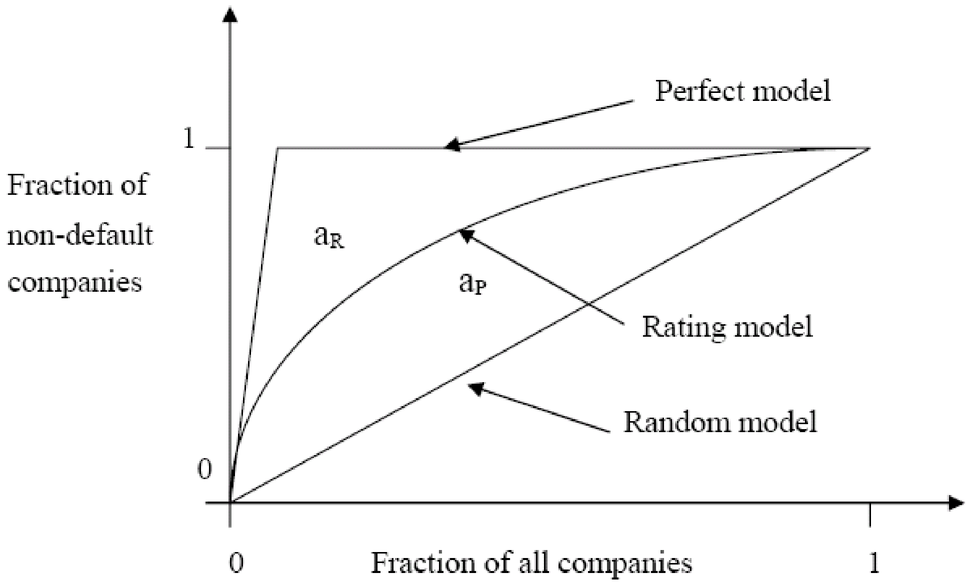

Figure 7.5.1 Cumulative accuracy profiles

Finally, after the completion of the default risk prediction modelling process and the exertion of goodness-of-fit tests, the estimated models are applied to the validation samples to produce out-of sample and out-of-time forecasts. Then the quality of the forecasts is evaluated with the concepts of Cumulative Accuracy Profiles (CAP) and Accuracy Ratios (AR) described above.

7.5.2 ROC Curve Analysis

Another approach to evaluate the utility of a default prediction model is the Areas Under ROC (AUROC) value. The meaning and use of the area under a receiver operating characteristics (ROC) curve and an overview of the variety of possible applications of ROC curves are given in Hanley and Mcneil (1982) and Swets (1988).

The Receiver Operating Characteristics Curve (ROC) is used to explore the relationship between the sensitivity and 1-specificity through a variety of different cutoff points (Thomas, Edelman and Crook 2002).

Sensitivity (*Sn*) is also called 'True Positive Rate' and is the probability of predicting a good company as healthy. Specificity (*Sp*), also called 'True Negative Rate', is the probability of a company to be predicted as a distressed company, when this company is truly distressed. The sensitivity and specificity can be calculated based on confusion matrix Table 7.3.1 as follows:

$$Sn = d/(b+d) \qquad (7.5.2)$$

$$Sp = a/(a+c) \qquad (7.5.3)$$

Where1-Specificity $(1-Sp)$ is the number of non-defaulters that were classified incorrectly as defaulters by using the cutoff value *C*. The total number of defaulter in the sample is denoted by $(a+c)$, and therefore:

$$1-Sp = 1-(a/(a+c)) = c/(a+c) \qquad (7.5.4)$$

The ROC curve is constructed in Figure 7.5.2 as follows. For all cutoff values *C* that are contained in the range of the rating scores the quantities (*Sn*) and (*1-Sp*) are calculated. The ROC curve is a plot of *Sn* versus *1-Sp*.

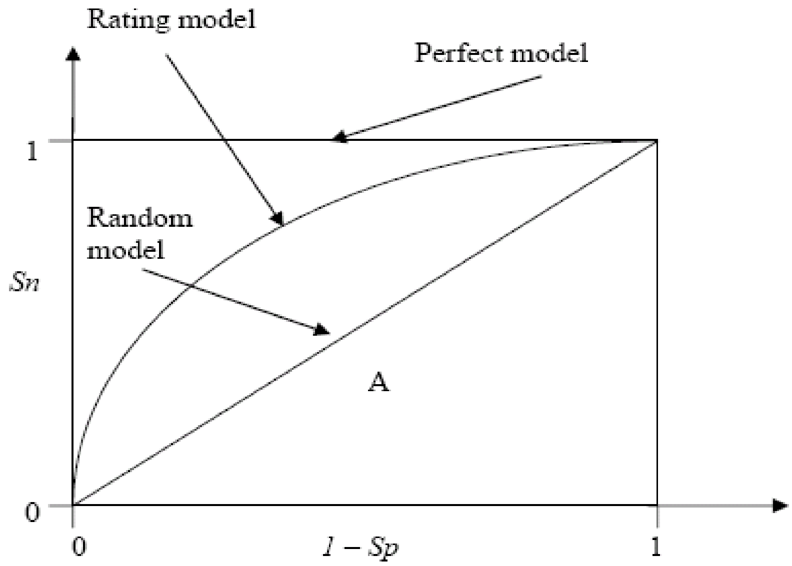

Figure 7.5.2 Receiver operating characteristic curves

A rating 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 (0, 1). Similarly, the larger the area under the ROC curve, the better the model. Denote this area by *A*. It can be calculated as:

$$A = \int_0^1 Sn(1 - Sp)d(1 - Sp) \qquad (7.5.5)$$

The area under the ROC curve (AUROC) is the area between the ROC curve and the diagonal line and hence the value of AUROC is between 0.5 and 1. The diagonal line (45 degree line) of ROC curve reflects the feature of a test with no discriminating power (Hand and Henley 1997). In fact, different cutoff points should reflect different sensitivity and specificity values, since the classification rule is different. Therefore, the further the ROC curve is from the diagonal line, the better the model performance (Thomas, Edelman and Crook 2002). In extreme cases, the area *A* is 0.5 for a random model without discriminative power and it is 1.0 for a perfect model. It is between 0.5 and 1.0 for any reasonable rating model in practice.

7.5.3 Connection between ROC and CAP

There is a relation between the Accuracy Ratio (AR) and the Area Under the ROC curve (AUROC) that can be to demonstrated that both measures are equivalent.

It is notable that the Accuracy Ratio is just a linear transformation of the area below the ROC curve. Hence, both concepts contain the same information and all properties of the area under the ROC curve are also applicable to the AR. For example, in extreme cases, a totally random model that bears no information on impending defaults has AR = 0, and AUROC = 0.5. For a perfect model, AR = AUROC = 1. The two approaches are equivalent with AR = 2AUROC-1. For more details and proof of this relationship see Engelmann et al (2003).

It can be proved by a simple calculation from the area $\boldsymbol{a_P}$ between the CAP of the perfect rating model and the CAP of the random model:

$$a_P = \frac{0.5 N_{ND}}{N_D + N_{ND}} \qquad (7.5.6)$$

Where N_{ND} is the number of non-defaulters

N_D is the number of defaulters.

Additional notation is introduced by Engelmann, Hayden and Tasche (2003) following random sample drawing assumption. "If a debtor is randomly drawn from the total sample of debtors, the resulting score is described by a random variable S_T. If the debtor is drawn randomly from the sample of defaulters only, the corresponding random variable is denoted by S_D and if the debtor is drawn from the sample of non-defaulters only, the random variable is denoted by S_{ND}."

The area a_R between the CAP of the rating model can be calculated and CAP of the random model is obtained as the cumulative distribution function $P(S_T < C)$, where S_T denotes as the distribution of the rating scores in the total population of all debtors. In terms of S_D *and* S_{ND}, *the* cumulative distribution function $P(S_T < C)$ can be expressed under Engelmann, Hayden and Tasche (2003) proof as:

$$“P(S_T < C) = \frac{N_{ND}P(S_{ND} < C) + N_D P(S_D < C)}{N_{ND} + N_D} \qquad (7.5.7)$$

It is assumed that the distributions of S_D and S_{ND} are continuous and for all possible scores C with $P(S_{ND} = C) = P(S_D = C) = 0$ is provided.
The area a_R is expressed as

$$a_R = \int_0^1 P(S_{ND} < C)dP(S_T < C) - 0.5$$

$$= \frac{N_{ND}\int_0^1 P(S_{ND} < C)dP(S_{ND} < C) + N_D\int_0^1 P(S_{ND} < C)dP(S_D < C)}{N_{ND} + N_D} - 0.5$$

$$= \frac{0.5N_{ND} + N_D A}{N_{ND} + N_D} - 0.5 = \frac{N_D(A - 0.5)}{N_{ND} + N_D}$$

With these expressions for a_P and a_R, the accuracy ratio can be calculated as:

$$AR = \frac{a_R}{a_P} = \frac{N_D(A - 0.5)}{0.5N_D} = 2(A - 0.5) \qquad (7.5.8)$$

This means that the accuracy ratio can be calculated directly from the area below the ROC curve and vice versa. Hence, both summary statistics contain the same information.”

The Receiver Operating Characteristic Curve (ROC) is based on a concept similar to the CAP curve and is widely used for diagnosing as well as for judging the discrimination ability of different statistical models. Sobehart, Keenan and Stein (2000) explain how to use this concept for validating internal rating models.

In this research, ROC is applied to the credit scoring models and Merton-type models and AUROC is employed for subsequent analysis.

7.6 Cutoff Point

In evaluating credit risk models, it is common to use measures such as confusion matrix with Type I and Type II errors and power curves and their associated statistics. Power curves such Cumulative Accuracy Profit (CAP) and Receiver Operating Characteristic (ROC) for validation models were addressed in previous section. Only using ROC curves, however, is not linked intuitively to common lending practices. Banks may find it helpful to define a lending cutoff or threshold as a guideline for either more junior credit officers or for pre-screening in loan underwriting. Such institutions require a simple rule for defining a cutoff above which credit will be granted and below which it will be denied. Other institutions desire a rational pricing scheme for lending. In fact, the cutoff point may be regarded as the bank's view on lending practices. In this research cutoff point will be associated with models performance.

Green and Swets (1966) show that for any ROC curve and cost function, there exists a point with minimal cost at which both the Type I and II errors are minimised within the constraints of the cost function. The optimal cutoff (i.e. the cutoff that minimises costs) can be determined through standard ROC analysis. Thomas et al. (2002) point out that it is important in practice to see how the scorecard performs at the chosen cuoff and suggest that one can use the ROC curve to identify suitable cutoff scores.

A study by Stein (2005) explores some quantitative insight into how such cutoffs can be developed. This framework accommodates real-world complications (e.g., relationship clients). In his study, he shows that the simple cutoff approach can be extended to a more complete pricing approach that is more flexible and more profitable. He also provides a simulation example to demonstrate that in general more powerful models i.e. with better performance in classification of defaults are more profitable than weaker ones that exclude fewer of the defaults.

Although in this research the focus is not on optimal cutoff point for cost-benefit lending decision, it would be of interest to explore that in further research, if the relevant data are available since identifying the drivers of these costs is usually institution specific.

7.7 Sample Selection and Input Variables of Merton Model

A sample of 246 SMEs with shareprice available from year 2001 to year 2004 is selected from the original 445 companies that were used to explore credit scoring approach in Chapter Six. The methodology used to calculate distance default (DD) and expected default frequency (EDF) is based on material presented in Chapter Four (section 4.9.1).

To evaluate the dynamic prediction of Merton model, the models are constructed over different horizons of distance to default (DD) from year 2001 to 2004. For example Merton DD 2001 indicates distance to default constructed in 2001. This will then be used to compare with the credit scoring approaches in their default predictive capability for SMEs.

The major input variables used in the Merton Model for calculating DD and EDF in 2004 are defined as:

Current Liability (*CL*) and Long-term Debt (*LD*) in thousand of sterling pounds (£th) are collected from company's financial statement based on Datastream. Equity (*E*) in million of sterling pounds(£M) is taken from Thomson ONE Banker database as the product of shareprice at the end of the month and the number of shares outstanding. The face value of debt (*X* in£M) computed as current liability (*CL*) plus 0.5* long-term debt (*LD*). Asset value (*A*) is the market value of firm assets (in£M). There are variables derived from algorithm of Equity Value for *DD* and *EDF* calculation:

$X^* = Xe^{-rT}$ as the present value of the promised debt payment and $L = X^* / A$ be a measure of leverage; σ_E is the equity volatility; σ_A is the asset volatility measure using $\sigma_A = \sigma_E E/ (E+X)$ and derived by this value of σ_A and equation (7.1.4) to infer the market value of each firm assets every day for the previous year and calculate a new estimate σ_A. T is the time period equal to 1. Free-interest rate is input based on the average one-year Repo (base) rate. *DD* and *EDF* are calculated from Merton equation (7.1.5) and (7.1.8).

7.8 Definition of Cutoff Point upon Groups of SMEs

SMEs were classified into 4 groups of financial distress, as previously described in Chapter Five on credit scoring models analysis. The numbers in each group of SMEs for the Merton sample were presented as follows:

For example in year 2004 of SMEs, only 18 insolvent companies were in Group 1, stock-based and flow-based distressed in Group 2 consisted of 18 companies, Group 3 included 83 companies with interest coverage less than one and 125 healthy SMEs were in Group 4. There are several possible decisions of how to deal with cutoff points for classifying predicted values. Taking an example of SMEs in 2004, the cutoff points are illustrated in Table 7.8.1:

1) First, a cutoff is considered where Group 4 is defined as 'Good' and all other categories considered as 'Bad'. That means that the bank would plan to accept only healthy companies or 125 SMEs with the best credit rating. From bank's lending strategy, this group is classified as safe and sound operational business that is characterised by lower probability of financial distress. Hence, it is very conservative lending decision that may turn down potential good borrowers.
2) Including Group 3 into the definition of 'Good' in addition to Group 4 against Group 2 and 1 combined as 'Bad' and therefore, 210 companies with best ranks will be accepted applicants.
3) Finally, only 18 insolvent companies are considered to be 'Bad', the rest of groups clustered as 'Good' comprising 228 businesses ranked above the cutoff point. It produces the highest acceptance rate.

Table 7.8.1 Cutoff selection with different definition of default in year 2004 of SMEs

Level of definition	Group 1: Insolvent	Group 2: Stock-based & Flow-based distress	Group 3: Flow-based distress	Group 4: Healthy
Observed no.	18	18	85	125
Groups 1,2,3 vs Group 4	'Bad' =121			Cut-off point 'Good' =125
Groups 1,2 vs Groups 3,4	'Bad' = 36		Cut-off point 'Good' = 210	
Group 1 vs Groups 2,3,4	'Bad' = 18	Cut-off point 'Good' = 228		

Of importance is the cutoff point determination. The cutoff points are applied in this research for total 246 SMEs sample from year 2001 to 2004 according to the definition summarised in Table 7.8.2 below. As each company in a sample will be attributed a credit score after modelling process, all companies can be ranked in terms of their credit scores or distance default (*DD*) for Merton-type models. The different cutoff points apply in this research depending on the observed number of 'Good' companies according to different definitions. For example, in year 2004 for definition 'Groups 1,2,3 vs. Group 4' 121 companies with the worst ranking are assigned as 'Bad' (i.e. distress), the cutoff point to distinguish between 'Good' (healthy) and 'Bad' (distress) firms can be determined by basing it upon the credit score value or distance to default (*DD*) of the 125th credit rank. Using the same logic cutoff points for Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4 indicate that companies with ranks above 210 and 228 respectively are considered to be 'Good'. Based on this approach, the predicted margins will be equal to the observed margins, that is, a + c = a + b or b + d = c + d (see confusion matrix in Table 7.3.1).

Table 7.8.2 Cutoff point summarised in various year of SMEs

Total SMEs = 246	Default Definition					
	Groups 1,2,3 v Group 4		Groups 1,2 v Groups 3,4		Group 1 v Groups 2,3,4	
	Observed No. of SMEs		Observed No. of SMEs		Observed No. of SMEs	
Year		Cutoff		Cutoff		Cutoff
	Bad	Good	Bad	Good	Bad	Good
2004	121	125	36	210	18	228
2003	90	156	22	224	7	239
2002	150	96	26	220	5	241

7.9 Statistics of Input Variables in Merton Models

Table 7.9.1 reports summary statistics for input variables used in the Merton model based on groups of SMEs in 2004. The average current liability (*CL*) presents higher amount in Group 1 insolvent (Mean *CL* = 10567.50) and Group 2 flow-based and stock-based distress (Mean *CL* = 9217.93) but lower value in Group 3 (Mean *CL* = 3980.51). Long-term debt (*LD*) in Group 4 signals that healthy companies may have improved access to finance in long-term credit commitment compared to other SMEs groups. As for the market price of equity (*E*), Group 1 (insolvent firms) has the market value (Mean *E* = 0.563074 in £M) less than Group 2 (Mean *E* = 9.289779 in £M). For flow-based distress companies in Group 3 and healthy SMEs in Group 4, the market value of equity is gradually increasing with Mean *E* = 17.59505 and Mean *E* = 29.76984 respectively.

The face value of debt (*X*) computed as current liability (*CL*) plus 0.5 * long-term debt (*LD*) is defined $X^* = Xe^{-rT}$ as the present value of the promised debt payment. Let $L = X^* / A$ be a measure of leverage which is an important parameter in Merton equation to evaluate distance to default (*DD*) and expected default frequency (*EDF*). Looking at leverage value (*L*), the results are very consistent with level of financial distress definition that is Group 1 shows highest leverage which may lead to higher default probability compared to the other of Groups of SMEs. For Group 2 and Group 3, the leverage value greatly decreases to 0.47905 and 0.19224 respectively. Group 4 has lowest leverage (0.15585) indicating that the healthy business retains a sound financial leverage structure and that may be a signal of association with lower default probability. Distance to default (*DD*) and expected default frequency (*EDF*) in each group of SMEs have been calculated from Merton models. Also, the results from *DD* and *EDF* look plausible with the highest default probability assigned to insolvent Group 1 (Mean *EDF* = 0.851592), then diminishing for Group 2 (Mean *EDF* = 0.393553) and further of Group 3 (Mean *EDF* = 0.160162) and Group 4 having the lowest one (Mean *EDF* = 0.136137). It is notable that the interpretation of statistics from input variables in Merton models showing their relationship with default probability is consistent with different default definitions.

Table 7.9.1 Summary statistics of input variable for Merton model with different definition of default

Inputs Var.	Group 1 SMEs (N=18)				Group 2 SMEs (N=18)				Group 3 SMEs (N=85)				Group 4 SMEs (N=125)			
	Mean	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
CL	10567.50	4304.996	714	12437	8399.88	9217.928	257	36717	3980.51	4291.721	77	29679	4800.26	4823.295	202	36582
LD	47.94	195.570	0	831	1115.67	2351.312	0	8900	791.43	1844.066	0	8771	1884.61	4755.483	0	36694
E	.563074	1.514643	.0641	6.3735	9.289799	17.09465	.0641	71.983	17.59505	24.89345	.0641	163.81	29.76984	124.4837	.0641	1361.7
X	10.59147	4.250784	.7140	12.437	8.957611	9.511932	.2600	36.759	4.376229	4.564030	.0770	29.869	5.742567	5.947715	.2080	40.155
A	10.77296	3.133730	2.3112	12.053	17.89809	21.99230	1.9304	93.855	21.78972	25.66634	1.2759	167.92	35.26995	125.0881	2.3125	1367.0
L	0.94106				0.47905				0.19224				0.15585			
$\boldsymbol{\sigma_E}$	.205788	.0318282	.1117	.2192	.311440	.1720438	.1248	.8505	.204487	.1408728	.0121	.8707	.173751	.3431784	.0129	3.8520
$\boldsymbol{\sigma_A}$	.016281	.0374458	.0012	.1225	.136708	.0882504	.0012	.3465	.147782	.1313222	.0012	.8220	.122754	.3413385	.0012	3.8472
DD	-25.5776	12.47777	-31.00	2.4059	-2.84810	10.34228	-30.99	3.0734	1.816658	7.300540	-29.00	23.256	3.065141	7.063315	-27.00	22.798
EDF	.851582	.3444476	.0081	1.0000	.393553	.3494781	.0011	1.0000	.160162	.2539532	.0000	1.0000	.136137	.2244299	.0000	1.0000

Notes: (1) Input the variables used in the KMV-Merton Model based groups of SMEs in year 2004.

(2) CL: Current Liability ((￡th) in thousand of sterling pounds); LD: Long-term Debt (￡th); E: Equity ((￡M) in million of sterling pounds) and is taken from Thomson ONE Banker database as the product of share price at the end of the month and the number of shares outstanding. ; X: is the face value of debt (￡M) computed as current liability(CL) plus 0.5* long-term debt (LD); A: is the market value of firm of firm assets (￡M); $X^* = Xe^{-rT}$ as the present value of the promised debt payment and $L = X^* / A$ be a measure of leverage; σ_E : equity volatility; σ_A : is the asset volatility measure using $\sigma_A = \sigma_E$ E/ (E+X) and we use this value of σ_A and equation (7.1.4) to infer the market value of each firm assets every day for the previous year and calculate a new estimate σ_A . The procedure is repeated until the new σ_A computed converges, so the absolute difference in less than 10 E-4 to the adjacent σ_A . DD: Distance Default; EDF: Expected Default Frequency.

(3) DD and EDF calculated from Merton equation (7.1.5) and (7.1.8);

(4) Free-interest rate input based on the average one-year Repo (base) rate r = 0.04375.

(5) T: the time period is equal to 1.

7.10 Statistics on Selected Credit Scoring Models

For comparing the performance of Merton model and credit scoring approach, the Models (A) to (G), correspond to Groups 1,2,3 versus Group 4, are selected to be a benchmark model from previous 28 models development addressed in Chapter Six. The reason for the selection of this benchmark is that the sample consists of all 4 levels of definitions of SMEs and includes most companies with shareprice available for Merton type models development. The composition of Model (A) to Model (G), include credit score estimates from predictors weighted by coefficients, are reported in Table 7.10.1 below.

Table7.10.1 Composition of benchmark credit scoring models

Model	Credit Score	Constant	Coefficient	Groups 1,2,3 vs Group 4
(A)	CS =	-0.064	-3.64	Cash Ratio
			2.529	Liquidity Ratio
			0.784	Debtors/Cash Flow
			0.557	Profit per Employee
(B)	CS =	0.041	-3.562	Cash Ratio
			2.283	Liquidity Ratio
			1.04	Debtors/Cash Flow
			0.948	Operating Cash Flow/ Shareholders Funds
			0.245	Profit per Employee
(C)	CS =	-2.581	0.736	EBITDA Margin
			-0.246	Change in Net Income
			0.319	Operating Cash Flow
(D)	CS =	-1.31	0.648	EBTDA Margin
			-0.283	Debt/ EBITDA
			0.344	Change in Net Income
			0.256	Creditors/ Debtors
(E)	CS =	-1.607	0.705	EBITDA Margin
			0.292	Debt/ EBITDA
			-0.277	Change in Net Income
			-0.209	Creditors/ Debtors
(F)	CS =	0.087	0.636	EBITDA Margin
			0.486	Debt/ EBITDA
			0.585	Creditors/ Debtors
(G)	CS =	1.358	-1.681	EBITDA Margin (dummy 1)
			-1.457	EBITDA Margin (dummy 2)
			-0.544	Change in Net Income (dummy 2)
			-0.927	Creditors/ Debtors (dummy 4)

Note: Model (A): Full list of original untransformed ratios
Model (B): Original untransformed ratio, those with missing values removed.
Model (C): Full list of coarse-classified ratios
Model (D): Coarse-classified ratios, those with missing values removed.
Model (E): Benchmark coarse-classified model
Model (F): WOE (weight of evidence) coding
Model (G): Dummy variables

It is notable that Liquidity Ratio shows superior weight on credit score in Model (A) and Model (B). EBITDA Margin gets an important weight on credit score in Model (C), (D), (E) and (F), only Model (G) with dummy coding transformation presents negative weights value on EBITDA Margin.

According to logistic function, credit score (*CS*) can be written as follows:

$$CS_i = \log\left[\frac{p_i}{1-p_i}\right] = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} = x_i\beta$$

and the probability (p_i) can be derived as $p_i = \dfrac{\exp(x_i\beta)}{1+\exp(x_i\beta)}$

Table 7.10.2 reports summary statistics for resulting probability from credit scoring models (A)-(G) across different groups of SMEs. Credit score (*CS*) is calculated from Table 7.10.1. For instance, *PR_A* indicates probability for Model A derived from *CS* = -0.064 + (-3.64) * Cash Ratio + 2.529 * Liquidity Ratio + 0.784 * Debtors/Cash Flow + 0.557 * Profit per employee. Therefore, probability of Model A can be could be calculated as $p_i = \dfrac{\exp(CS_i)}{1+\exp(CS_i)}$ which means higher (lower) value p_i indicated higher (lower) default probability.

It can be seen from Group 4 that healthy firms presenting lower probability across all credit scoring models (A)-(G). In Group 3 (Flow-based distress), only Model D presents lower mean probability (0.4834) compared to Group 2 (Flow-based and Stock-based distress) and Group 1 (insolvent firms) with mean probability equal to 0.4870 and 0.4973 respectively. In general Group 3 would be expected to have lower mean probability than Group 2 and Group 1, however, this is seen in the mean probabilities being irregularly between Group 3, Group 2 and Group 1. One possible interpretation of the mean probability being irregularly between groups is that only a small number insolvent and distress firms in Group 1 (*N* = 18) and Group 2 (*N* = 18) compared to Group 3 (*N* = 85). Another interpretation stems from the fact that the models were fitted to the definition of ‘Bad’ including Group 1,2,3, therefore, they cannot distinguish between them.

Table 7.10.2 Summary statistics of benchmark credit scoring models with different definition of default

Model Prob.	Group 1 SMEs (N=18)				Group 2 SMEs (N=18)				Group 3 SMEs (N=85)				Group 4 SMEs (N=125)			
	Mean	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
A	.5115090	.11679	.38274	.89433	.5701191	.14004	.37038	.93036	.5775010	.17336	.21585	.99704	.4603696	.14390	.00017	.95362
B	.4856258	.13563	.35820	.94917	.5326568	.14670	.34570	.97026	.5749007	.19291	.16861	.99990	.4419559	.15077	.00001	.94391
C	.5841102	.22673	.12390	.82171	.5915115	.23093	.15316	.85495	.6250778	.20271	.15316	.89944	.3760155	.20900	.07958	.88288
D	.4869974	.16569	.22882	.81169	.4972743	.22404	.14003	.77434	.4834067	.19663	.09204	.82303	.3665118	.19498	.07276	.84774
E	.5491573	.22488	.15303	.82807	.5942974	.22533	.11295	.85582	.6279453	.21810	.05255	.90105	.3580730	.20782	.08386	.91173
F	.5170537	.21329	.18433	.83541	.5888631	.22018	.12739	.83541	.5768714	.19758	.12739	.88903	.3402027	.20362	.12454	.83541
G	.5151234	.18344	.20457	.77730	.5841388	.20754	.20457	.85742	.5558338	.17322	.20457	.85742	.3635534	.18912	.20457	.82778

7.11 Comparison of Merton and Credit Scoring Approaches

In this research, the credit scoring analysis is based on financial predictors selected in year 2001 to give an early stage signal for default prediction based on the point of observation of the default in the end of 2004. Parallel, Merton models for four year time scale i.e. Merton DD 2001, 2002, 2003 and 2004 are constructed to validate their predictive accuracy in 2004. In this comparison, models predictive ability across time could be investigated. As a consequence, later section will compare their applicability through 3 years time scale.

Merton models and credit scoring models will be compared for their ability to discriminate between good and bad firms. Different definitions of default and cut-off points have been considered in this thesis and model performance will be compared across these definitions and cut-offs. Overall correctly predicted percentage as well as Type I and Type II error from various models are described. ROC plots show the discrimination ability of different models. The performance statistic is the Area Under Receiver Operation Characteristics (AUROC) Curve.

7.12 Overall Predicted Correct Percentage and Type I Type II Error

In previous Chapter Six, to measure the predictive accuracy a random sample of 231 SMEs was selected from the original 445 companies and was scored by all credit scoring models that were developed. In this Chapter, for comparison of Merton type models with benchmark credit scoring models, there are 246 SMEs with shareprice available selected from 445 companies for calculation DD and EDF for Merton type models development. That is why sample size differs between Chapter Six and Chapter Seven.

Table 7.12.1 reports the model performance including Type I and Type II error and overall percentage correctly predicted for different default definition of SMEs groups in 2004.

Table 7.12.1 Type I, Type II error and correctly predicted percentage of models in 2004

Model	Performance	Default Definition		
		Groups 123 v Group 4	Groups 12 v Groups 34	Group 1 v Groups 234
(A)	Type I error	32.2%	88.9%	94.4%
	Type II error	31.7%	15.2%	7.5%
	Overall	68.3%	74.0%	86.2%
(B)	Type I error	33.1%	88.9%	94.4%
	Type II error	32.0%	15.2%	7.5%
	Overall	67.5%	74.0%	86.2%
(C)	Type I error	27.3%	72.2%	100.0%
	Type II error	26.4%	12.8%	7.9%
	Overall	73.2%	78.9%	85.4%
(D)	Type I error	36.4%	75.0%	94.4%
	Type II error	35.2%	12.9%	7.5%
	Overall	64.2%	78.1%	86.2%
(E)	Type I error	26.4%	77.8%	94.4%
	Type II error	25.6%	13.2%	7.5%
	Overall	74.0%	77.2%	86.2%
(F)	Type I error	25.7%	75.0%	94.4%
	Type II error	24.7%	12.9%	7.5%
	Overall	74.8%	78.0%	86.2%
(G)	Type I error	28.1%	71.6%	100.0%
	Type II error	24.8%	13.8%	7.9%
	Overall	73.6%	76.4%	85.4%
Merton DD 2004	Type I error	45.5%	44.4%	22.2%
	Type II error	44.0%	7.6%	1.8%
	Overall	55.3%	87.0%	96.7%
Merton DD 2003	Type I error	48.8%	77.8%	88.9%
	Type II error	47.2%	13.3%	7.0%
	Overall	52.0%	77.2%	87.0%
Merton DD 2002	Type I error	41.3%	66.7%	61.0%
	Type II error	49.6%	11.4%	4.8%
	Overall	54.6%	80.5%	91.1%
Merton DD 2001	Type I error	56.2%	86.1%	88.9%
	Type II error	54.4%	14.8%	7.0%
	Overall	44.7%	74.8%	87.0%

In Groups 1,2,3 vs Group 4, it can be seen that all credit scoring models perform well, better than a random model that would accept roughly 50% of all distress levels. It is notable that the predictor variables transformation indicated by Model (C) (i.e. full list of coarse-classified ratios) and (E) (i.e. benchmark coarse-classified model) with predicted correct percentage are 73.2% and 74% respectively. Models (F) (i.e. with WOE coding) and Model (G) (i.e. with dummy coding) also improved the models’ predicted correct percentage 74.8% and 73.6% respectively. Chapter Six, it was shown that WOE coding and dummy coding do not improve models predictive accuracy for Groups 1,2,3 vs Group 4. It is found that the results may differ depending on the cutoff point selection (in this Chapter, cutoff point is with 125th healthy companies from 246 sample SMEs for default prediction) which is based on different sample consideration (previous study in Chapter Six, cutoff point is with 116th healthy companies from 231 sample SMEs for default prediction) and these differences will impact variability in the models performance.

It is notable that Merton DD models can be constructed from same year input parameters. For instance, Merton DD 2001 indicates distance to default constructed in 2001 and Merton DD 2002 distance to default calculated in 2002, and so on. In this section all forms of Merton DD 2001 to 2004 models are used to predict default observations in year 2004.

Among Merton DD models with different time horizons, the discrimination ability seems only slightly higher than a random model except for Merton DD 2001 predicting SMEs default in 2004 which presents worse performance, not even above 50% of random one. However, Merton DD 2004 model presents better performance for predicting default in 2004 compared to earlier year horizon of Merton models i.e. in year 2003, 2002 and 2001.

Both Merton type and credit scoring models increase their overall predicted percentage from Groups 1,2 vs Groups 3,4 to Group 1 vs Groups 2,3,4. It can be seen that Merton type and credit scoring models improved in correct prediction of ‘Good’ (i.e. defined as non-defaulters in group) but deteriorated in correct prediction of ‘Bad’ (i.e. defined as insolvent and distressed). Both types of error should be examined. Overall, credit scoring and Merton models present increasing Type I error and diminishing Type II error across the definition ‘Groups 1,2 vs Groups 3,4’ except for Merton 2003 DD and 2001 DD models. In general, if only a small number of default companied is available, a model will intend to classify most companies as ‘Good’ and give rise to overall ‘accuracy’ rate of ‘Good’ but also defaulters will be misclassified as 'Good', leading to a high rate of Type I error. Hence, the results of Type I and Type II error should be interpreted with care or the use of alternative validation methods should be considered, i.e. ROC and AUROC analysis.

In Groups 1,2,3 vs Group 4, overall credit scoring models in contrast with Merton models, present higher correctly predicted percentage, especially, Model F (WOE coding) performs the best with value of 74.8% and has also smaller Type I error of 25.7% and Type II error of 24.7%.

Overall, in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4, it is found that the Merton DD 2004 gives higher correctly predicted percentage of 87% and 96.7%, and also a lower Type I error (Type II error) of 44.4% (7.6%) and 22.2 % (1.8%) respectively. It is notable that credit scoring models in Group 1 vs Groups 2,3,4 produce large Type I error, even in Model C (full list of coarse-classified variables) and Model G (dummy coding) presenting Type I error equal to 100% indicating that none of default firms were classified correctly.

7.13 AUROC and ROC Analysis

Table 7.13.1 presents Area under ROC curve (AUROC) of models with different default definitions for 2004. It is useful in validating the models predictive accuracy which can be more clearly understood thorough the AUROC value. In general, AUROC value of credit scoring models and Merton models indicates their predictive power is better than random model (i.e. AUROC = 0.5) apart from Model B in Group 1 vs Groups 2,3,4 (AUROC = 0.492) and Merton DD 2001 in Groups 1,2,3 vs Group 4 (AUROC = 0.442) and Group 1 vs Groups 2,3,4 (AUROC = 0.497).

Looking at AUROC in credit scoring models, it presents higher predictive accuracy in Groups 1,2,3 vs Group 4 but decreases in Groups 1,2 vs Groups 3,4 and shows the worst predictive power in Group 1 vs Groups 2,3,4. In contrast, for Merton DD 2004 models AUROC value is lower in Groups 1,2,3 vs Group 4 then gradually increases through Groups 1,2 vs Groups 3,4 to Group 1 vs Groups 2,3,4.

Overall from AUROC analysis, credit scoring models outperform Merton models in Groups 1,2,3 vs Group 4. Obviously, Merton DD 2004 predicting SMEs default in 2004 shows the best performance in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4 compared to earlier years of Merton models. Merton DD 2001 appears to have the worse predictive accuracy for 2004. The distinctive feature of Merton model for credit assessment is that distance to default (DD) can be obtained from shareprice (i.e. market information) instantaneously from equity market, and therefore, models for default prediction and credit rating adjustment can be used in the same horizon year. Overall credit scoring models demonstrate better performance when there was a considerable number of 'Bad' or acceptance rate was relatively low. Merton models perform better with higher acceptance rates. Although this is of little practical value, same year predictions are considered here for the sake of consistency.

Table 7.13.1AUROC analysis in different default groups of SMEs in 2004

Model	Groups 1,2,3 vs Group 4	Groups 1,2 vs Groups 3,4	Group 1 vs Groups 2,3,4
	Area Under ROC	Area Under ROC	Area Under ROC
A	.709	.594	.520
B	.707	.554	**.492**
C	.782	.634	.619
D	.671	.613	.604
E	.793	.617	.582
F	.780	.635	.586
G	.756	.650	.590
Merton DD 2004	**.592**	**.831**	**.912**
Merton DD 2003	.561	.650	.714
Merton DD 2002	.511	.590	.644
Merton DD 2001	**.442**	.533	**.497**

7.14 ROC Curve and AUROC Profile of Models Comparison

The ROC (receiver operation characteristic) curve is a plot of the true positive rate (sensitivity) against the false positive rate (1-specifity) for the different possible cutoff points of a classifier. While ROC curves are a useful way to visualise the model's performance, it is often convenient to summarise the predictive accuracy into a summary statistic. The closer the ROC is to its perfect model (i.e. Area Under the ROC curve equal to 1), the better the model performs. In contrast, the closer the model's ROC is to the uninformative ROC (diagonal line), the worse the model performs. The more area there is below the model ROC and above the uninformative ROC, the better the model is doing overall (Hanley and McNeil, 1982). Figure 7.14.1 displays an example of ROC and AUROC profile for models performance comparison.

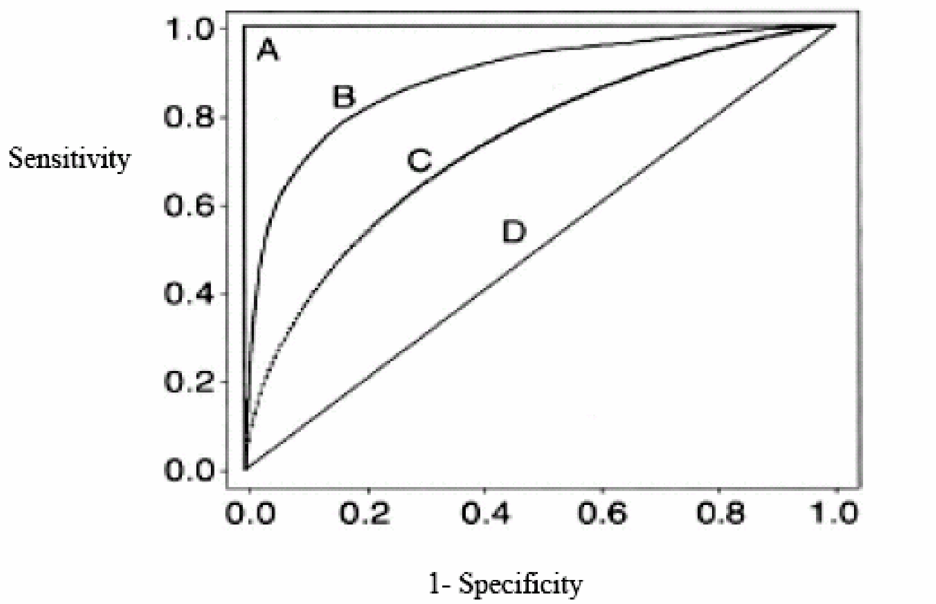

Figure 7.14.1 ROC and AUROC displays the models performance comparison.

Four ROC curves with different values of the Area Under ROC curve (AUROC). A perfect model (A) has an AUROC of 1. The diagonal line D (the 45 degree line segment from '0, 0' to '1, 1') has an AUROC of 0.5. ROC curve of model B and C lie between these two extremes. Model B with the higher AUROC has a better overall performance than model C.

In this section Merton-type models and credit scoring models are compared using ROC plots and AUROC.

The results in ROC plots present clearly models predictive power comparison. Credit scoring benchmark models are based on 2001 financial predictors for early signals default prediction in year 2004. In Merton type DD models, distance to default (DD) is calculated from 2001 to 2004 for default prediction in 2004. The comparison is useful to view the feature of models applicability over the time scale. Therefore, models predictive accuracy comparison should be based on same group of definition. An example of ROC curves plots can be viewed from within Merton type DD models performance, and therefore compared to benchmark credit scoring models. Area under ROC (AUROC) value is provided for validating models predictive accuracy.

Figure 7.14.2 presents ROC curves of Merton DD models within Groups 1,2,3 vs Group 4 in 2004. It is shown that Merton DD 2004 appears to have a better predictive power than the other year of Merton DD models, that are only slightly above reference line (i.e. random model) except for ROC curve of Merton DD 2001 (i.e. AUROC = 0.442) which is below reference line indicating predictive power is worse than random one.

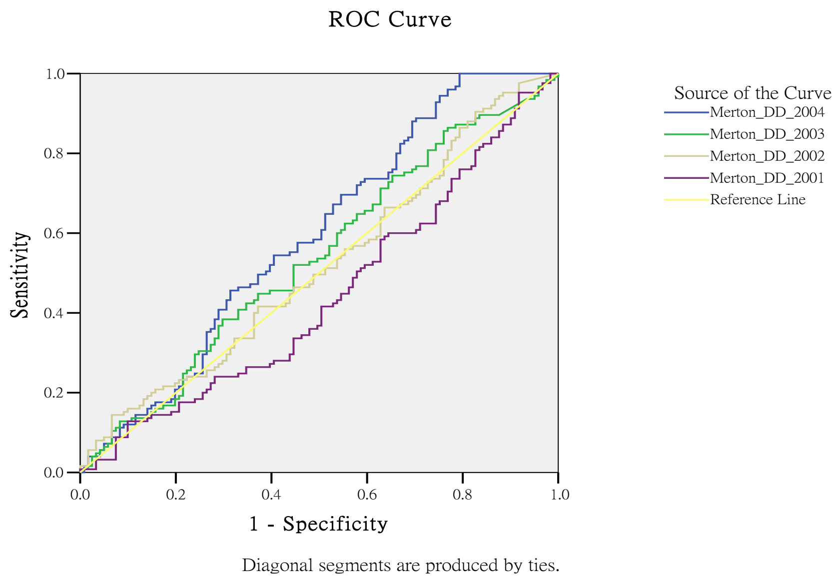

Figure 7.14.2 ROC of Merton DD models in Groups 1,2,3 vs Group 4

Figure 7.14.3 plots the ROC curves for credit scoring models and Merton DD 2004 model in Groups 1,2,3 vs Group 4. All credit scoring models appear to have better predictive power compared to Merton DD 2004 model in this group.

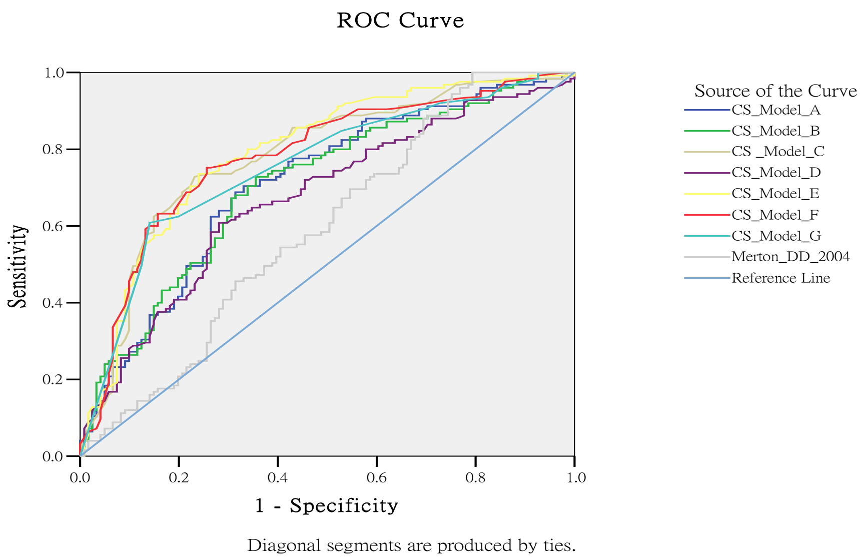

Figure 7.14.3 ROC comparing Credit Scoring models and Merton DD 2004 in Groups 1,2,3 vs Group 4

In Groups 1,2 vs Groups 3,4, ROC curve shows the predictive power of models illustrated below. ROC features for Merton DD models in Groups 1,2 vs Groups 3,4 is framed in Figure 7.14.4. It is shown that Merton DD 2004 presented the excellent performance (AUROC = 0.831) in comparison with the other Merton models. It can be seen from the ROC curve that the performance of Merton DD 2003 (AUROC = 0.650) and 2001(AUROC = 0.533) is almost no different from random models (i.e. AUROC = 0.5).

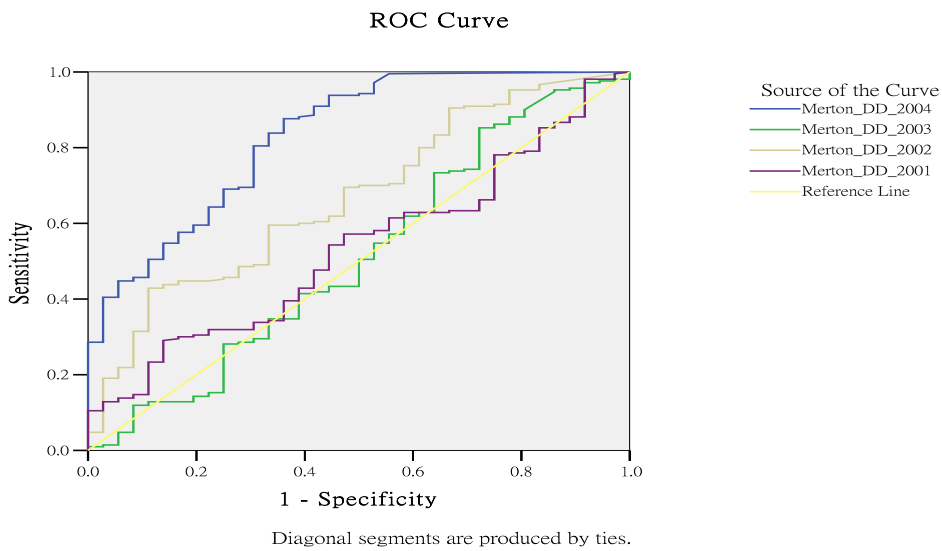

Figure 7.14.4 ROC of Merton DD Models comparison in Groups 1,2 vs Groups 3,4

Comparing credit scoring models and Merton DD 2004 models in Groups 1,2 vs Groups 3,4, Figure 7.14.5 shows that Merton DD 2004 outperforms all credit scoring models. However, all models in this group perform well i.e. their AUROC value greater than 0.5.

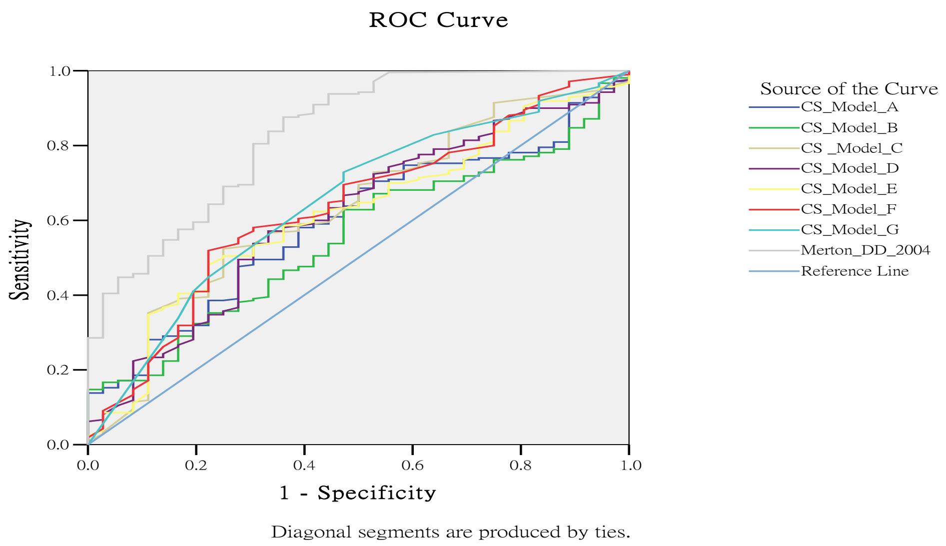

Figure 7.14.5 ROC comparing credit scoring models and Merton DD 2004 in Groups 1,2 vs Groups 3,4

Figure 7.14.6 presents ROC curve of Merton DD models in Group 1 vs Groups 2,3,4. ROC curve shows that Merton DD 2004 model (AUROC = 0.912) has the best predictive power compared to the other Merton models. Merton DD 2001 (AUROC = 0.497) appears to have the worst default prediction in this group.

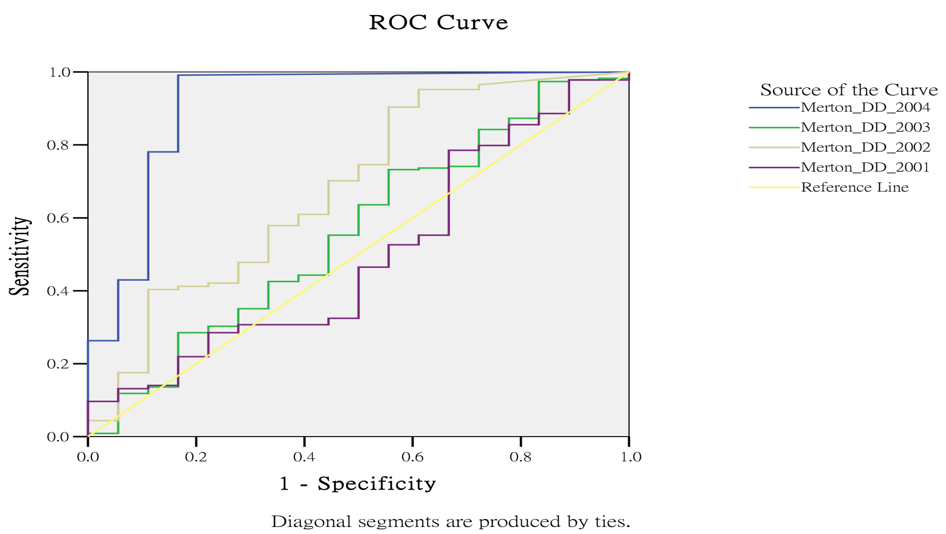

Figure 7.14.6 ROC of Merton DD models in Group 1 vs Groups 2,3,4

Credit scoring models in Group 1 v Groups 2,3,4 as well as Merton DD 2004 are shown in Figure 7.14.7. All credit scoring model have their predictive power around the reference line showing their AUROC greater than 0.5 except for Model B (AUROC = 0.492), however, the performance of Merton DD 2004 (AUROC = 0.912) is much better in comparison with credit scoring models in this groups.

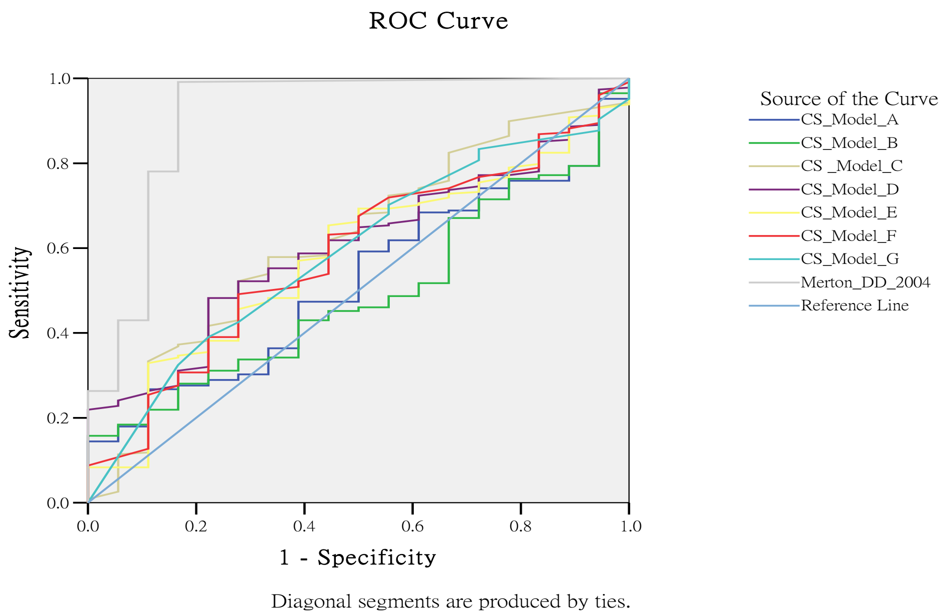

Figure 7.14.7 ROC comparing credit scoring models and Merton DD 2004 in Group 1 vs Groups 2,3,4

7.15 Type I and Type II Error of Models in 2003 and 2002

In this section, the predictive power of models over different time horizon will be investigated. It would be of interest to verify the applicability of models predictive power over varying time scale. Credit scoring models and Merton models will be explored for examining their predictive capability to the default year in 2002 and 2003.

Table 7.15.1 and 7.15.2 report overall predicted correct percentage and Type I and Type II of models in 2003 and 2002 respectively. As can be seen from Table 7.15.1, the results of Type I and Type II appear consistent with previous analysis in 2004. Type I error presents a higher rate in Groups 1,2 vs Groups 3,4 and then the error rises to the highest rate in Group 1 vs Groups 2,3,4. It is notable that credit scoring models present impractical classification that is up to 100% Type I error such as Model D and E in Groups 1,2 vs Groups 3,4 and all credit scoring models in Group 1 vs Groups 2,3,4 only excluding Model E.

Merton DD 2002 and Merton DD 2003 present lower Type I error in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4 indicating that more distressed firms are classified as default firms correctly compared to credit scoring models.

Table 7.15.1 Overall correctly predicted percentage and Type I, Type II error of models in 2003

Model	Performance	Default Definition		
		Groups 123 v Group 4	Groups 12 v Groups 34	Group 1 v Groups 234
(A)	Type I error	52.2%	95.5%	100.0%
	Type II error	30.1%	9.4%	2.9%
	Overall	61.8%	82.9%	94.3%
(B)	Type I error	58.9%	95.5%	100.0%
	Type II error	34.0%	9.4%	2.9%
	Overall	56.9%	82.9%	94.3%
(C)	Type I error	54.4%	86.4%	100.0%
	Type II error	31.4%	8.5%	2.9%
	Overall	60.2%	84.6%	94.3%
(D)	Type I error	57.8%	100.0%	100.0%
	Type II error	33.3%	9.8%	2.9%
	Overall	57.7%	90.2%	94.3%
(E)	Type I error	52.2%	100.0%	100.0%
	Type II error	30.1%	9.8%	2.9%
	Overall	61.8%	90.2%	94.3%
(F)	Type I error	55.6%	90.1%	85.7%
	Type II error	32.1%	8.9%	2.5%
	Overall	59.4%	83.7%	95.1%
(G)	Type I error	54.4%	90.1%	100.0%
	Type II error	31.4%	8.9%	2.9%
	Overall	60.1%	83.7%	94.3%
Merton DD 2003	Type I error	47.8%	72.7%	42.9%
	Type II error	27.6%	7.1%	1.3%
	Overall	65.0%	87.0%	97.6%
Merton DD 2002	Type I error	60.6%	69.2%	57.1%
	Type II error	34.6%	9.2%	1.7%
	Overall	43.9%	85.4%	96.3%
Merton DD 2001	Type I error	67.8%	84.6%	100.0%
	Type II error	39.1%	10.0%	2.9%
	Overall	50.4%	82.1%	94.3%

Table 7.15.2 presents similar results for SMEs models in 2002. Again, credit scoring models show large Type I error in Groups 1, 2 vs Groups 3,4 with the error reaching 100% in Group 1 vs Groups 2,3,4 indicating that none of distress firms can be predicted as default firms correctly. Merton DD 2002 presents the better classification ability indicating much more distress firms can be classified as default firms correctly i.e. lower Type I error against credit scoring models.

Table 7.15.2 Overall correctly predicted percentage and Type I, Type II error of models in 2002

Model	Performance	Default Definition		
		Groups 123 v Group 4	Groups 12 v Groups 34	Group 1 v Groups 234
(A)	Type I error	22.7%	92.3%	100%
	Type II error	35.4%	10.9%	2.1%
	Overall	72.4%	80.5%	95.9%
(B)	Type I error	36.0%	92.3%	100%
	Type II error	41.6%	10.9%	2.1%
	Overall	68.3%	80.5%	95.9%
(C)	Type I error	22.0%	76.9%	100%
	Type II error	34.4%	9.1%	2.1%
	Overall	73.2%	83.7%	95.9%
(D)	Type I error	26.0%	92.3%	100%
	Type II error	40.6%	10.9%	2.1%
	Overall	68.3%	80.5%	95.9%
(E)	Type I error	21.3%	80.8%	100%
	Type II error	33.3%	8.6%	2.1%
	Overall	74.0%	83.7%	95.9%
(F)	Type I error	20.0%	84.6%	100%
	Type II error	31.2%	10.0%	2.1%
	Overall	75.6%	82.1%	95.9%
(G)	Type I error	21.3%	84.6%	100%
	Type II error	33.3%	10.0%	2.1%
	Overall	74.0%	82.1%	95.9%
Merton DD 2002	Type I error	32.7%	57.7%	60.0%
	Type II error	51.0%	6.8%	1.2%
	Overall	60.2%	87.8%	97.6
Merton DD 2001	Type I error	43.3%	76.9%	100%
	Type II error	67.7%	9.1%	2.1%
	Overall	47.2%	83.7%	95.9%

Looking at Type I (Type II) error and the correctly predicted percentage, it can be concluded that overall credit scoring models demonstrated better performance in Groups 1,2,3 vs Group 4 but worse prediction in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4 compared to Merton type models. However, it is necessary to test by AUROC to validate models predictive accuracy as well as their applicability through 3-year horizon with different default definitions.

7.16 Analysis of Models Applicability in Different Year Horizon

Credit scoring models constructed in year 2001 were tested for predictive applicability through year 2002 to 2004. Merton type DD models developed from year 2001 to 2004 are compared through time scale of 2002 to 2004. AUROC analysis provides the validation of models performance through 3-year horizon. For analysis of the models applicability on a different time scale, their comparison should be based on the same default definitions. First, Table 7.16.1 reports models performance through 3-year time scale in Groups 1,2,3 vs Group 4.

Starting from Groups 1,2,3 vs Group 4, credit scoring models give the best prediction in 2002. It is observed that Model F (WOE coding) achieves the best predictive accuracy i.e. AUROC = 0.819, also Model E (benchmark coarse-classified) and Model (C) (full list of coarse-classified) perform well showing AUROC = 0.806 and 0.801 respectively. However, credit scoring models show decline in predictive accuracy for 2003, and thereafter models retain their good level of default prediction in 2004. It would be interesting to discover what possible factors affect models poor performance in 2003,[52] for example it could be economic shock in that year. It is known that changes in regulations that effect SMEs industries could dramatically impact industries propensity to fail. Under these circumstances, model users should consider possible model calibration and validation of model predictive ability during the significant economics events in the year. It is known that some events may have a lagged effect and bank in practice using credit scoring models may be monitoring on a monthly basis, so model deterioration will be picked up.

Looking at Merton DD models, the predictive power is good for predicting default in the same year. For example, Merton DD 2002 appears to better perform in 2002 with AUROC = 0.597 but looses its predicted accuracy in 2003 and 2004 with

[52] The Iraq war and its effect on oil prices created an economics risk uncertainty factor around the world in 2003.

AUROC = 0.531 and 0.511 respectively. The predictive capability shows the same feature in Merton DD 2003 (AUROC = 0.635), but predictive accuracy declines in 2004 (AUROC = 0.561). However, the earlier year horizon Merton DD 2002 and Merton DD 2001 perform worse when predicting default in 2003.

For the overall performance of models in Groups 1,2,3 vs Group 4, credit scoring models present the superior predictive accuracy in 2002 and 2004 compared to Merton DD models. However, Merton DD 2003 presents the better predictive power in 2003 compared to credit scoring models.

Overall in Groups 1,2,3 vs Group 4, it can be recommended that credit scoring models are appropriate models for SMEs in 2002 and 2004. It is suggested in general, credit scoring models can be used to predict default through 2002 to 2004 in this group. However, among Merton models only Merton DD 2003 gives slightly better predictive accuracy in 2003 in this group.

Table 7.16.1 AUROC analysis in 3-year horizon within Groups 1,2,3 vs Group 4

Model	Groups 1,2,3 vs Group 4		
	2004 SMEs (AUR)	2003 SMEs (AUR)	2002 SMEs (AUR)
A	.709	.576	.767
B	.707	.564	.750
C	.782	.595	.801
D	.671	.563	.730
E	.793	.583	.806
F	.780	.577	**.819**
G	.756	.555	.779
Merton DD 2004	**.592**		
Merton DD 2003	.561	**.635**	
Merton DD 2002	.511	.531	**.597**
Merton DD 2001	.442	.497	.452

Focusing on Groups 1,2 vs Groups 3,4 in Table 7.16.2 all credit scoring models appear to have predictive power above random model except Model A (AUROC = 0.446) and Model B (AUROC = 0.434), and these models, in general, present a tendency to decline in 2003 and slightly rise up in 2004.

Generally, Merton DD models present the feature of superior predictive power in the default year. Merton DD 2002 outperform scoring models in 2002 (AUROC = 0.749) but its predictive accuracy declines in 2003 and 2004. Merton DD 2003 (AUROC = 0.728) performs well in 2003 and predictive accuracy declines in 2004. Merton DD 2004 (AUROC = 0.831) shows the highest predictive accuracy in 2004 compared with credit scoring models. An early year horizon model i.e. Merton DD 2001 shows the less predictive accuracy in later default year e.g. 2002 (AUROC = 0.544) and decline in AUROC in 2003(AUROC = 0.536) and 2004 (AUROC = 0.533). Overall Merton models can be used for default prediction in the same time horizon in Groups 1,2 vs Groups 3,4 which is a moderate distress definition.

Table 7.16.2 AUROC analysis in 3-year horizon within Groups 1,2 vs Groups 3,4

Model	Groups 1,2 vs Groups 3,4		
	2004 SMEs (AUR)	2003 SMEs (AUR)	2002 SMEs (AUR)
A	.594	.455	.628
B	.554	.426	.523
C	.634	.521	.595
D	.613	.512	.613
E	.617	.497	.582
F	.635	.489	.632
G	.650	.483	.586
Merton DD 2004	**.831**		
Merton DD 2003	.650	**.728**	
Merton DD 2002	.590	.604	**.749**
Merton DD 2001	.533	.514	.544

Looking at Group 1vs Groups 2,3,4 in Table 7.16.3, where only Group 1 (insolvent firms) is defined as ‘Bad’ (defaulters) i.e. there are 18 insolvent firms in 2004; 7 and 5 insolvent firms in 2003 and 2002 respectively. As the result, the acceptance rate is higher, and there are a lot of firms clustered as ‘Good’ and only a small number of default firms included in analysis. The models performance in this group will show higher Type I error. Therefore, AUROC analysis can provide a better view on model predictive accuracy. It can be seen for credit scoring models that AUROC shows worse results in 2002 and slightly improved performance in 2003, 2004.

It is notable that Model C (full list of coarse-classified ratios), Model E (benchmark coarse-classified), Model F (WOE coding) and Model G (Dummy coding) present worse classification than a random model in 2002 but these model increase their predictive accuracy in 2003 and 2004.

It can be seen that Merton DD 2002 (AUROC = 0.841) shows excellent discrimination in 2002 compared with credit scoring model but its predictive accuracy declines in 2003 and 2004. Merton DD 2003 (AUROC = 0.758) shows good performance in 2003 but decreases its predictive accuracy in 2004. Merton DD 2004 (AUROC = 0.912) performs well in terms of discrimination accuracy in 2004 amongst all the models.

The results in Group 1 vs Groups 2,3,4 Merton models are consistent to results in Groups 1,2 vs Groups 3,4. As a consequence, one may take into consideration the timescale between point of prediction and default from the practical perspective. Distance default (DD) is usually translated to probability of default (known as PD) to give a quantitative measure as to how likely a company is going to default. Therefore, the knowledge that the company is going to decline in credit quality or rise in default probability in this year can be helpful in adjusting credit rating. When considering a loan to a company, a bank wants to know the likelihood default for a duration of loan. In this sense Merton models seem only useful for a relatively short loan terms.

Table 7.16.3 AUROC analysis in 3-year horizon within Group 1 vs Groups 2,3,4

Model	Group 1 vs Groups 2,3,4		
	2004 SMEs (AUR)	2003 SMEs (AUR)	2002 SMEs (AUR)
A	.520	.608	.542
B	.492	.475	.531
C	.619	.526	.382
D	.604	.614	.534
E	.582	.557	.406
F	.586	.591	.450
G	.590	.569	.436
Merton DD 2004	**.912**		
Merton DD 2003	.714	**.758**	
Merton DD 2002	.644	.724	**.841**
Merton DD 2001	.497	.459	.455

7.18 Conclusion

This research investigated the credit scoring approach and Merton type model for predicting SMEs failure. Different cutoff points based on varying levels of default definition were proposed, and their effect on model's predictive accuracy was studied with regard to Type I and Type II errors. ROC curve plots described the model performance and AUROC analysis was used for validating models predictive accuracy. In addition, the capability of models was examined to predict default through 4 year horizon on the basis of different default definition groups.

Based on confusion matrix that gives Type I, Type II error and overall correctly predicted percentage, for models based on the definition 'Groups 123 vs Group 4' in 2004, it was found that predictor variables transformation in Model C (full list of coarse-classified ratios), Model E (benchmark coarse-classified model), Model F (WOE coding) and Model G (dummy coding) improved the models' overall predicted correct percentage compared with original untransformed ratio models.

When models performance was based on default year in 2004, overall credit scoring models presented better correctly predicted percentage in 'Groups 1,2,3 vs Group 4' but Type I error increased rapidly in 'Groups 1,2 vs Groups 3,4' and 'Group 1 vs Groups 2,3,4'. It was indicated that with only a small number of default firms included in distress group the model performs less accurately, i.e. large Type I error is observed. The Merton DD 2004 shows higher predicted correctly percentage in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4 i.e. lower Type I error compared to credit scoring models.

Overall from AUROC analysis of model performance in 2004, credit scoring models outperform in Groups 1,2,3 vs Group 4 compared with Merton models. However, Merton DD 2004 model presents better predictive accuracy in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4 where only a small number of distressed firms are included in classification. Obviously, Merton DD 2004 predicts well SMEs default in 2004 showing the best performance than the other year Merton models.

Given this, it may be concluded that Merton model, which is based on distance default (DD) derived from shareprice (i.e. market information) instantaneously from equity market, can be applied to credit rating validation and default probability estimation in the same year of default prediction in contrast with accounting- based models that require financial statement at least one year before the default. This is due to need for the appropriate information to be available.

Furthermore, the predictive power of models over 3-year horizon was investigated in years from 2002 to 2004 based on different levels of default groups.

For the 'Groups 1,2,3 vs Group 4', overall credit scoring models present the superior predictive accuracy in 2002 and 2004 in comparison with Merton DD 2003 presenting the better predictive power in 2003. In 'Groups 1,2 vs Groups 3,4' and 'Group 1 vs Groups 2,3,4', it was found that Merton models constructed instantaneously in the same default year presented better predictive accuracy compared with credit scoring models.

Overall, credit scoring models demonstrated better performance when the sample group included a considerable number of 'Bad' firms or cutoff point was selected so that an acceptance rate was relatively low, otherwise model's predictive accuracy would decline. Merton model presented better predictive accuracy with higher acceptance rates.

Looking at model predictive accuracy across the time scale, in general Merton model performed better when it was used to predict default in the same year horizon, however, credit scoring models constructed in 2001 were able to give early signs of default year in 2004. In addition, one may take into consideration that if the company is going to decline in credit quality or raise in default probability this year, Merton type models can be helpful in adjusting credit rating. When considering a loan to a company, a bank wants to know the likelihood default for duration of loan. In this sense Merton models are only useful for a relatively short loan terms.

CHAPTER EIGHT

Conclusion and Discussion

8.1 Summary of Research Findings

Credit risk modelling plays increasingly important role in banks' risk management. Banks have devoted many resources to developing internal models to better quantify their financial risks, customer profitability analysis, risk-based pricing, active portfolio management and capital structure decision. These efforts have been recognised and encouraged by bank regulators. Recently, banks and financial institutions have extended these efforts into the field of credit risk modelling.

In this thesis credit risk modelling for SMEs has been explored. SMEs fall between the models developed for the corporate and retail sectors. However, research on credit risk modelling for SMEs sector is scarce, and this is surprising, given the important of this sector in any national economy, see Berger and Frame (2005). Yet small companies, have problems in obtaining credit, since the majority of them do not have publicly traded equity and certified audited financial statements.

The primary objective of the research has been to develop effective approach for SMEs credit risk measurement. This is a topic which not only academic researchers and financial practitioners but also regulators are paying increased attention to in the areas of credit risk assessment.

This research aims to investigate how accounting based models and Merton type models perform using the potential predictors over different time horizon. The recommendations can assist financial institutions in implementing internal rating system to evaluate performance of SMEs. In order to improve an institution's competitive advantage in the area of risk management, new methods and technologies must be developed capable of detecting potential credit failure. The research provides empirical findings which give insight into credit rating and provide discussions for further study.

The aims of this research are addressed as three sub-objectives:

1. Reviewing the framework of Basel Accord in relation to credit risk in banking and SMEs.
2. Developing possible approaches for SMEs credit risk modelling.
3. Validating models predictive accuracy.

8.2 Framework of Basel II in relation to Credit Risk Measurement

The Basel II Accord (2006) is the most major change in credit risk measurement in the legal and economic framework of bank financing. Given its importance, the framework of new Accord has been addressed in relation to credit risk components, risk exposures, internal rating based (IRB) approach, the potential impact on banking systems and practical implementation issues.

Basel II Capital Accord makes stronger attempt to link the risk associated with counterparty to the amount of regulatory capital that is required. In the new Accord, financial institutions will be allowed to select their risk management approach from either the 'standardised approach' or the 'Internal Rating Based' (IRB) approach. For financial institutions without the capability to measure credit risk on their own, the Accord proposes a 'standardised approach', whereby the financial institution can rely on ratings provided by external rating agencies. The responsibility is upon the regulator to map the agency ratings into capital requirements through setting average default probability. The IRB approach allows banks to apply their own internal ratings. Banks adopting the IRB approach will assign default probabilities to counterparties based on internal credit grades obtained.

The new Accord recognises three techniques for mapping the risk grade to a default probability:

1. Historical average default probabilities based on internal default experience;
2. Mapping internal grades to external rating agencies;
3. Statistical default models.

The emphasis on the risk grade is maintained even in those instances where the financial institution would be capable of assigning individual default probabilities for each borrower. In such cases, Accord requires that the default probability of the grade, computed as an average of the individual default probabilities, be applied in computing the risk-weighted assets.

For both the standardised and the IRB approaches, the default probability for a single firm is a function of its risk assessment, either externally or internally derived. This approach reflects the processes applied by most of banks in the OECD and by the leading non-OECD banks.

The related studies were discussed on the subject of banks implementation of the new Accord in relation to impact on SMEs sectors and how to improve SMEs access to finance. These issues would raise the possibility of a new shift in bank lending, as banks increase loans to large, investment grade corporates at the expense of smaller, unrated firms. It was suggested that credit risk capital requirements relating to SMEs are likely to decrease under Basel II and an increased use of internal ratings as a basis for pricing decisions should therefore not lead to an increase in the cost of finance.

8.3 Developing Possible Approach for SMEs Credit Risk Modelling

In studies of company default one can often use published data, available from a number of sources, unfortunately in the area of Small and Medium Sized business there is greater difficulty in obtaining data and this is particularly true at the lower end. At this stage of the research, alternative techniques were explored to create dataset for SMEs credit risk modelling. A credit scoring model using logistic regression and Merton type model have been considered for credit research of SMEs in UK.

The initial stage of the research was based on simulation methods. A set of data for non-defaulting but not including defaulting SMEs was constructed with 116 SMEs. This has been a major limitation to the current study i.e. lack of default frequency and pubic information. Under Basel II, SMEs are defined as companies with an annual turnover of less than €50M Euros (regardless of any other criteria).The SMEs companies were selected from database of UK businesses based on industry classification benchmark included basic materials, industrials, consumer goods, health care, consumer services, telecommunications and technology sectors, but excluding Oil & Gas, Utilities and Financial companies (banks, insurance, brokerage, REITs, ect.). 15 financial variables used in previous studies for SMEs default were considered as potential predictors.

The results in full simulation data produced theoretical independent normal variates for the financial ratios for each business, which is clearly not realistic. The coefficients as expected are generally close to the expected values which may be in part due to the size of sample considered. In the partial simulation, the results have shown to be more volatile compared to full simulation. This may be due to the decrease in sample size simulated and colinearity between the variables.

Merton type model was used to generate default probabilities for all 116 businesses in the sample by use of simulation method intended to relate these probabilities to the financial ratios using logistic regressions, as in credit scoring. This would have allowed comparison between the two methods. It was found that the businesses seem to be stable with probabilities of default close to zero. There are three issues arising from the findings which can be addressed in further analysis. First, for the SMEs selected there was a lack of volatility in the equity price in the period of observation and hence it lead to low probability of default. Second, the criterion for selection was biased to companies that had survived and hence default probabilities would be expected to be low. Finally, lack of volatility in equity price may be due to lack of trading in SME stock or just the length of period observed.

Moreover, the relationship between Distance to Default (DD) and Expected Default Frequency (EDF) (calculated from real dataset) of 116 SMEs to financial and accounting measures based on previous 15 financial variables was explored by linear regression to assess whether the two models are employing equivalent information. It is notable that overall the results show low R^2 value in these models even when outliers are excluded. This indicates there are only weak relationships between the information contained within the Merton type variables, DD and EDF, and the Accounting variables.

8.4 Evaluating Model Utility

Simulation methods were used to explore credit risk models for SMEs. Following the use of simulation method it was decided to explore further credit risk models for SMEs using Accounting models. A further set of variables was considered. Subsequently the data was used to investigate the Merton type model.

8.4.1 Extended Data Selection for SMEs Credit risk Modelling

The work described in Chapter Five was aimed at more robust models development. The data set collected contained both defaulting, financial distressed and healthy SMES. Sample selection of financially distressed SMEs used the criteria based on stock-based distress, if its insolvency ratio (Shareholders Funds / Total Assets) was negative, or flow-based distress, if its interest cover based on cash flow (EBITDA/ Interest Payable) was less than one. As a consequence, sample was composed of different default definitions: Insolvent in Group 1; Flow-Based and Stock-Based Distress in Group 2; only Flow-Based Distress in Group 3 and Healthy in Group 4.

A large set of potential predictor variables were included in nine financial categories. There were (1) Profitability (2) Liquidity (3) Leverage (Structure Ratios) (4) Growth Rate (5) Activity (Efficiency) (6) Asset Utilisation Ratios (7) Cash Flow Related Ratios (8) Employees Efficiency Ratios and (9) Financial Scale. K-means cluster analysis was applied to remove outlier impact. Finally, outliers elimination resulted in 455 SMEs classified in four groups for analysis.

Principle Component Analysis was used to detect structure in the relationship between variables which may provide the first stage to analysis of data for further models construction. As a result of PCA the first five components (PC_1 to PC_5) were chosen for explaining 56.34% of the variability in the original 61 variables. PC_1 to PC_5 explained variables are independent between components (i.e. correlation between PC_1 to PC_5 are zero). It was then investigated whether variables in PC_1 to PC_5 components, could be used to classify into 4 groups of SMEs. Unfortunately, from scatterplot matrices analysis of the PC_1 to PC_5 components, it was found that dataset had skewed distribution and failed to provide effective classification into 4 groups of SMEs i.e. the most cases are in Group 3 (flow-based distress) and Group 4 (healthy), 160 and 225 respectively. As a consequence, research reported in Chapter Six would consider further possible approaches for SMEs credit risk models.

8.4.2 Modelling SMEs Default and Predictive Accuracy

The aim of Chapter Six was to explore enhanced Accounting based modelling. This included standard credit scoring methods to enhance model predictive accuracy. Different definitions of default were explored to deal with data limitation since a problem of default prediction is that there are only a small number of bankruptcies in most samples. The different definitions of default included stock-based and cash flow-based distress. The models variable composition was also considered as well as models predictive accuracy.

To explore variable default predictors in relation to SMEs credit risk assessments, initially 61 variables were considered, but this was reduced to 56 after the removal of variables with high proportions of missing values. Two different variables coding were used: dummy binary variables and weights of evidence.

The approach was different from traditional discriminant analysis since it is uncommon to classify the performance of account into 4 groups: Group 1 as insolvent, Group 2 as stock-based and flow-based distress, Group 3 as flow-based distress only and Group 4 as healthy firms. Overall 28 models were developed and their predictive accuracy compared.

It was found that the predictors in the model vary depending on the default definition. Variables from all nine groups enter into the models, although within a single model not all groups are represented. The most frequent group is Cash Flow Related variables indicating the importance of cash-related predictors as early signs of financial distress. Next frequent group include Growth Ratios. These show whether SMEs are capable of achieving a breakthrough growth in practice and are important indicators to SMEs success performance, since for a small business to be successful, a persistent growth in profitability, annual sales and operating revenue is required. Another frequent group, Employees Efficiency Ratios, provided quick representations of the effectiveness of management. These predictors could be considered as SMEs risk indicators for model-building.

Another noteworthy finding is that transformation (coarse-classification) of predictor variable improved predictive accuracy of the models, but dummy and weights of evidence coding did not improve accuracy significantly. Overall this research demonstrated that an accounting-based approach is a viable way to credit modelling for SMEs. It can be enhanced by use of modelling retail credit risk, thus leading to more accurate predictions and less capital reserves.

8.4.3 Evaluation of Merton Type and Credit Scoring Models

To extend Chapter Six research on possible approaches for SMEs modelling, Chapter Seven presented a summary of work to validate benchmark credit scoring models and Merton type models. This framework specifically addresses issues of cutoff points with different default definitions in relation to predictive accuracy of models as well as early signals for company's failure prediction across the time scale.

Different cutoff points based on varying levels of default definition were proposed, and Type I and Type II error were examined. It was noted that SMEs were grouped in 3 levels of default definitions. First, Groups 1,2,3 vs Group 4 a cutoff is considered where Group 4 is defined as 'Good' and all other categories considered as 'Bad'. Hence, it is very conservative lending decision that may turn down potential good borrowers. The same logic of cutoff point was applied in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4 indicating increased higher accepted rate of 'Good' across all levels Receiver Operating Characteristic (ROC) plots graphically demonstrate models performance and AUROC (Area Under ROC curve) summarise model's predictive accuracy. In addition, the capability of models through 3-year horizon was examined.

Type I and Type II error vary across different definitions. With regards to the Types of Error analysis, credit scoring model show the better performance to deal with the Type II error and the worst ability to manage the Type I error when there are a small number of default firms. Overall, credit scoring models were shown to increase Type I error in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4. They showed lower Type II error compared to Merton models but Merton models showed lower Type I error. It was noted that Merton DD 2004 presented better performance than the credit scoring and other earlier years of Merton DD models in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4, with correctly predicted percentage of 87% and 96.7%, and also a lower Type I error (Type II error) of 44.4% (7.6%) and 22.2 % (1.8%) respectively.

Investors and financial institutions usually seek to keep models where the probability of making either Type I error is as small as possible. Unfortunately, minimising one type of error usually comes at the expense of increasing the other type of error. That is, the probability of making a Type II error reduced as the probability of a Type I error is increased. A bank's tolerance for the model's error rate, however, might be different depending on the baseline default rate since default firms perceived to be much more costly rejected non-default companies. Thus, Type I and Type II error of models should be interpreted with care and the use of alternative performance measures was considered i.e. ROC and AUROC analysis.

Cutoff point selection with varying default rate of whole exposures in different groups may impact the model performance. Overall, credit scoring models demonstrated better performance in Groups 1,2,3 vs Group 4. They showed worse predictive accuracy due to small number of defaulting firms included in Groups 1,2 vs Groups 3,4 and Group 1 vs Groups 2,3,4 in contrast with Merton model that presented better performance in these groups.

Overall, credit scoring models demonstrated better performance when the sample group included a considerable number of 'Bad' firms or cutoff point was selected so that an acceptance rate was relatively low, otherwise model's predictive accuracy would decline. Merton model presented better predictive accuracy with higher acceptance rates.

Looking at model predictive accuracy across the time scale, in general Merton model performed better when it was used to predict default in the same year horizon, however, credit scoring models constructed in 2001 were able to give early signs of default year in 2004. In addition, one may take into consideration that the company may decline in credit quality or rise default probability in this year and so Merton type models can be helpful in adjusting credit rating. When considering a loan to a company, a bank wants to know the likelihood default for duration of loan. In this sense Merton models is only useful for relatively short loan terms.

It was found that credit scoring models suffered a decline in their predictive accuracy in 2003. It was suggested that the model validation and predictor variables adjustment should be considered since models predictive accuracy may be affected by significant economics events. In addition, these events may impact SMEs with a higher risk, for example, one should examine the economic environment, e.g. impact from previous and the current surge of interest rate or other activities in credit risk issues. It also would be necessary to consider possible economic risk factors for SMEs credit risk modelling in the future research.

8.5 Discussion and Suggestion for Further Research

Credit risk management poses certain specific challenges for quantitative modelling, which were the limitation in this research, but can be considered for further research.

8.5.1 Lack of Public Information and Data Limitation

When exploring the credit quality of corporation it is typically the case that there is scarcity of publicly available information. This creates problems for SMEs lending, as the management of a firm is usually better informed about the true economic prospects of the firm and hence about default risk than are prospective lenders. This is the issue about information asymmetry. The lack of publicly available credit data is also a substantial obstacle to the use of statistical methods in credit risk, a problem that is compounded by the fact that in credit risk the risk management horizon is usually at least one year. It is fair to say that data problems are the main obstacle to the reliable calibration of credit models.

While reliable and timely financial data can usually be obtained for the larger corporate borrower, there are difficulties obtaining such information for smaller borrowers, and it is particularly difficult to obtain for companies in financial distress or default, which are the key to the construction of accurate credit risk models. The scarcity of reliable data required for building credit risk models stems from the highly infrequent nature of default events. In some cases where no historical data are available at all, both model development and validation must rely on heuristic methods and domain experts. When historical data are available, however, model validation can proceed in a more objective and rigorous context.

8.5.2 Non-Financial Predictors Consideration

A large number of financial ratios should be considered in building the model so that the best ratios can be selected in combination with other non-financial factors to optimise the performance of the models. There are a number of studies of the information content of qualitative, i.e. non-financial, ratio information. Lussier (1985) use non-financial variables such as management experience, record keeping and financial control, age of owner, parent owned a business ect. to construct a failure-forecasting model. Keasey and Watson (1987) employ variables such as management structure, accounting information system, auditing delays, and financial statements to construct a failure-forecasting model. Kuo, Wang, Sheu and Li (2003) evaluate financial ratios and non-financial variable such as number of correspondent banks, magnitude of short-term debt and open credit line. Their results show that financial ratios matched with non-financial variables can improve the model's ability to discriminate any difference between successful and failed firms. It seems that models containing the non-financial ratio information were more robust and significantly out-performed the model utilising financial ratios alone.

From previous studies, there are some crucial non-financial variables which could be considered in the further research:

- Management skill
- Company age
- Number of correspondent banks
- Magnitude of short-term debt
- Open credit line: total credit line minus the total loans.
- Capacity to repay debt
- Repayment track record
- The security or collateral support if needed
- Credit score of SME’s owner or manager.
- Personal credit records of owner or manager.
- Parent owned a business.

In general, non-financial variables consist of quantifiable attributes that help to differentiate companies in the dataset for modelling. Statistical analysis determines the relevance of these variables which are significantly related to the risk of the companies in the default prediction. Non-financial data may provide more confidence in prediction for small business. Thus these financial and non-financial predictor variables if available could be considered for SMEs credit risk modelling.

8.5.3 Economic Factors Consideration

Macroeconomic variables provide an additional analytical dimension to the statistical models. These variables provide an indication of the overall economic environment within one country and the dynamics of this environment over time. As such, the model learns that more firms default in harder economic times and that weak financials combined with a weak economy will more likely result in a default event than weak financials in a strong economy.

In practice, financial institutions are in the business of risk management, and their lending will seek to balance risk and credit quality to ensure profit generation. Bank's lending policy is highly confidential, as it reflects how they position themselves in the market; however it is likely to be influenced by such economic factors as:

- Interest rates;
- Exchange rates;
- Inflation;
- Unemployment rate
- Business cycles;
- Government industry policy; and
- GDP and GDP growth rates.

It is notable that the financial health of a firm varies with randomly fluctuating macroeconomic factors, such as changes in economic growth, since different firms are affected by common macroeconomic factors such as growth of GDP, interest rate sensitivity and sensitivity to exchange rate. Given their importance, economic factors combined with possible modelling approaches in SMEs credit risk measurement i.e. general industries or specific industries should be considered in further research.

8.5.4 Industry Risk Information

Well presented industry information which indicates an understanding of industry risk and risk management, reflects favourably on an applicants' (obligors) business competency, and gives confidence to the lender as well as improved SMEs assess to finance. Although some qualitative information is not easy to measure, some industries risk factors could be indicated by benchmark industries index or industrial performance analysis. The industry risk factors that especially impact SMEs business include:

- Industry competitiveness;
- Tariff protection;
- Industry regulations and pending regulations;
- Domestic and environmental risk;
- Environmental laws and regulations; and
- The growth stage of the businesses industry.

This information is important as the assessment of credit risk of an individual financial proposal is influenced by these factors and whether the firm is in a new, emerging, developing, mature or declining industry.

8.5.5 Model Validation

Financial institutions management and regulators have a fiduciary responsibility to shareholders and liability suppliers to fully validate or audit, all models used. This is one of the most important prescriptions of the New Basel Capital Accords. All credit models used should be subjected to critical analysis and review, either publicly or privately. Many of the most exciting developments in credit modelling will come in the area of model performance assessment. Therefore, models evaluation and validation in banking in relation to Basel II implementing are the area of most rapid advance in the practical use of credit models.

The growing importance of models in helping executives answer some of bank's most critical questions from compliance and capital adequacy to business performance and risk-adjusted compensation. Model validation is often thought of as a rather technical and mathematical exercise. Bank losses from model risk, however, are often caused by poor governance of the wider modelling process, or by a poor understanding of the assumptions and limitations surrounding the model results, rather than by errors in equations.

An ideal credit risk management system should utilise multiple credit models to help diversify this modelling risk. Such a system would allow the user full control of the model audit and performance testing process. Despite their inherent difficulties, credit models provide the key component to a successful credit risk management system. This is because they can be used to estimate true credit-adjusted valuations that correctly reflect the risk-adjusted value to the borrowers' promise to repay. The most sophisticated tests involve using historical periods with substantially different market conditions or tests in other countries with different market conditions

8.5.6 Cutoff Ratio with Cost-Benefit Lending Analysis

The issue of model error cost is a complex and important one. It is often the case, for example, that a particular model will outperform another under one set of cost assumptions, but will be disadvantaged under a different set of assumptions.

Since different institutions have different cost and pay-off structures, it is difficult to present a single cost function that is appropriate across all companies. In the case of default prediction, it describes the percentage of non-defaulting firms that must be inadvertently denied credit in order to avoid lending to a specific percentage of defaulting firms when using a specific default model. Since there are (usually large) costs associated with extending credit to defaulting firms and (usually smaller) costs associated with not granting credit (or granting credit with overly restrictive terms) to subsequently non-defaulting firms. ROC analysis produces a form of cost-benefit analysis (Stein 2005). For this reason, further research would be interested in developing models performance with optimal cutoff ratio selection in bank's cost-benefit lending analysis. It may be based on cutoff approaches extended to a more complete pricing approach that is more flexible and more profitable. The approach permits the relative value of two models to be quantified and can be extended to accommodate real-world conventions such as relationship lending.

8.5.7 Internal Rating System

Since banks often lend to firms not rated by rating agencies, they often have the need of supplementary credit assessments. A bank's individual exposures to such firms, however, are often relatively small i.e. SMEs business, it is typically uneconomical for borrowers to pay to obtain an agency rating or for banks to devote extensive internal resource to the analysis of particular borrower's credit quality. Therefore, in further research for SMEs risk assessment, model development would be considered as an internal rating model. Such models may explore more accurately prediction as well as default probability assigned to a grade for individual borrower. Furthermore, internal rating model in combination with economics and industries risk factors analysis will provide banks with a lending decision for SMEs credit pricing and risk assessment.

8.5.8 Private Firms Credit Risk Modelling

It is the most challenging for SMEs modelling since SMEs include a great proportion of private firms, in particular, attempts to develop fundamental models for private firms have been hampered by a lack of data. Private companies are generally not required to publish the same level of financial data as public companies. As such, inconsistency in the interpretation and accuracy across private company financial data is far greater than for public companies. This weakens the ability of a model to estimate volatility and market capitalisation from data and thus to estimate private company credit risk. It is considered that lack of private company credit risk measurement poses difficulties for institutions looking to manage or shift private firm credit exposures through structured products and the credit enhancement markets. In further research on private firm credit risk, it will be necessary to compile and analyse financial, company, industry and other information affecting or indicating a company's health and performance. They may also include a credit score or rating based on an information provider's subjective assessment. A more objective and quantified approach, however, would be desirable.

8.6 Conclusion

This thesis provided an empirical analysis for exploring possible approaches to modelling credit risk of SMEs, and proposed some directions for further research.

Two major approaches: Accounting-based and Merton type models were compared. Observations were made on suitability, advantages and disadvantages of both methods. The main limitation of this research was perceived to be due to scarcity of publicly available information on SMEs.

Despite of this limitation, the thesis provided a much needed analysis of credit risk presented by one of the most important economic sectors (SMEs) and filled-in the gap in literature. Possible extensions to the current research may develop along the following directions:

- inclusion of non-financial predictors into the models;
- inclusion of economic factors and industry specific information developing;
- approaches to model validation;
- performing cost-benefit analysis for the optimal cut-off selection;
- modelling credit risk of private firms.

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APPENDIX－Typical Spreadsheet for the Merton Type Model