THE FINANCIAL CRISIS AND BANKING SECTOR STABILITY: THE CASE OF USA AND THE EURO ZONE

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DEDICATION

This dissertation is dedicated to my mother Yvette Mitchell and my son Dimitri Elijah Ryan. Their love and support gave me the strength needed to complete this dissertation and it is with pride and honour that I dedicate this work to them.

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Abstract

The recent financial crisis continues to draw attention in the literature given its deep impact. This dissertation investigates three main areas associated with the crisis. Firstly it focuses on bank default prediction models asking whether structural or accounting models can better predict default. In the second instance we investigate the credit rating agencies culpability in the financial crisis by attempting to trace the transmission from sovereign debt ratings to bank credit ratings, an area that is sparse in the literature. Finally we investigate the classification of bank ratings using four statistical techniques altering the independent variables with financial variables and principal components to assess which statistical method and technique is better able to classify ratings.

In the first instance the analysis compares accounting and structural default prediction models using a logit analysis to predict default. The paper uses panel data on US banks from the Federal Deposit Insurance Corporation database between 1993-2015 and the analysis is developed on 536 defaulted bank years and 25,614 non-defaulted bank years.

The dissertation goes on to evaluate the impact of sovereign credit ratings on the ratings assigned to banks. Using data on Euro zone countries by credit rating agencies Moody's, Standard and Poor's and Fitch between 2003-2013, I find that multiple notch sovereign downgrades do influence bank downgrades particularly in the crisis period. The study suggests that while a bank's financial fundamentals do play an important role in rating assignments the rating change of the sovereign provides stimulus for the amount of notches the bank is downgraded by. In the final chapter the empirical results suggest that the multiple discriminant analysis statistical model is the better classifier of bank credit ratings for all three rating agencies.

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LIST OF ABBREVIATIONS

0.1 Paper I- BANK DEFAULT

- IMF- International Monetary Fund
- BIS- Bank for International Settlement
- CRA- Credit rating agency
- ROC- Receiver operating characteristic
- EBITDA- Earnings before interest and taxes
- CAMEL- Capital, asset quality, management, earnings and liquidity
- FDIC- Federal Deposit Insurance Corporation
- PCA- Principal component analysis
- FSI- Financial soundess indicators
- lta- Log total assets
- cash- Cash and due from depository institutions
- secure- Securities
- good- Goodwill
- tbe- Total bank equity
- er- Efficiency ratio
- noncurrentll- Non-current loans and leases
- noncurrentlas- Non-current loans to assets
- niea- Non-interest expense to assets
- roa- Return on assets
- lancl- Loss allowance to non current loans
- ncaoreta- Non-current assets plus other real estate to assets

- ncll- Non-current loans to loans
- nlltcd- Net loans and leases to core deposits
- tier1rbc- Tier1 risk based capital
- cclr- Core capital leverage ratio
- gdp- Gross domestic product
- tbills- 3 month t-bill rate
- llta- Lagged log total assets
- ltbe- Lagged total bank equity
- lnoncurrentll- Lagged non-current loans and leases
- lniea- Lagged non-interest expense to assets
- ler- Lagged efficiency ratio
- llancl- Lagged loss allowance to non current loans
- lncaoreta- Lagged non-current assets plus other real estate to assets
- lnlltcd- Lagged net loans and leases to core deposits
- ltier1rbc- Lagged tier1 risk based capital
- lncll- Lagged non-current loans to loans
- lgdp- Lagged gross domestic product
- ltbills- Lagged 3 month t-bill rate
- totalassetsv- Total asset values
- d2d- Distance to distress
- ltotalassetsv- Lagged total asset values
- ld2d- Lagged distance to distress
- logtbe- Log total bank equity
- lognoncurrentll- Log non-current loans and leases
- logniea- Log non-interest expense to assets
- loger- Log efficiency ratio

- loglancl- Log loss allowance to non current loans
- logncaoreta- Log non-current assets plus other real estate to assets
- lognlltcd- Log net loans and leases to core deposits
- logtier1rbc- Log tier1 risk based capital
- logncll- Log non-current loans to loans
- bnoncurrentll- Box Cox transformed non-current loans and leases
- bniea- Box Cox transformed non-interest expense to assets
- blancl- Box Cox transformed loss allowance to non current loans
- bncaoreta- Box Cox transformed non-current assets plus other real estate to assets

0.2 Paper II- DO SOVEREIGN CREDIT RATINGS INFLUENCE BANK CREDIT RATINGS?

- S&P- Standard and Poor's
- PIGS- Portugal, Italy, Greece, Spain
- CDS- Credit default swap
- CDO- Collaterallized debt obligation
- roa- Return on assets
- nim- Net interest margin
- t1rbc- Tier1 risk based capital
- trbc- Total risk based capital
- plltl- Provisions for loan losses to total loans
- npltl- Non-performing loans to total loans
- tltd- Total loans to total deposits
- Sov $\uparrow_1$- Sovereign upgrade by 1 notch
- Sov $\uparrow_2$- Sovereign upgrade by 2 or more notches
- Sov $\downarrow_1$- Sovereign downgrade by 1 notch
- Sov $\downarrow_2$- Sovereign downgrade by 2 or more notches

0.3 Paper III- BANK CREDIT RATINGS MODELS

- Srat- Sovereign Rating
- ROA- Return on assets
- ROE- Return on common equity
- NIM- Net interest margin
- ER- Efficiency ratio
- T1RBC- Tier 1 risk-based capital ratio
- TRBC- Total risk-based capital ratio
- PLLTL- Provisional loan losses/total loans
- RLLTL- Reserve for loan losses/total loans
- NPLTL- Non-performing loans/total loans
- TLTD- Total loans/total deposits
- TLTA- Total loans/total assets
- DA- Deposits/assets
- DF- Deposits/funding
- TA- Total assets
- EA- Earning assets
- logassets- Log assets

1. GENERAL INTRODUCTION

1.1 Background of Study

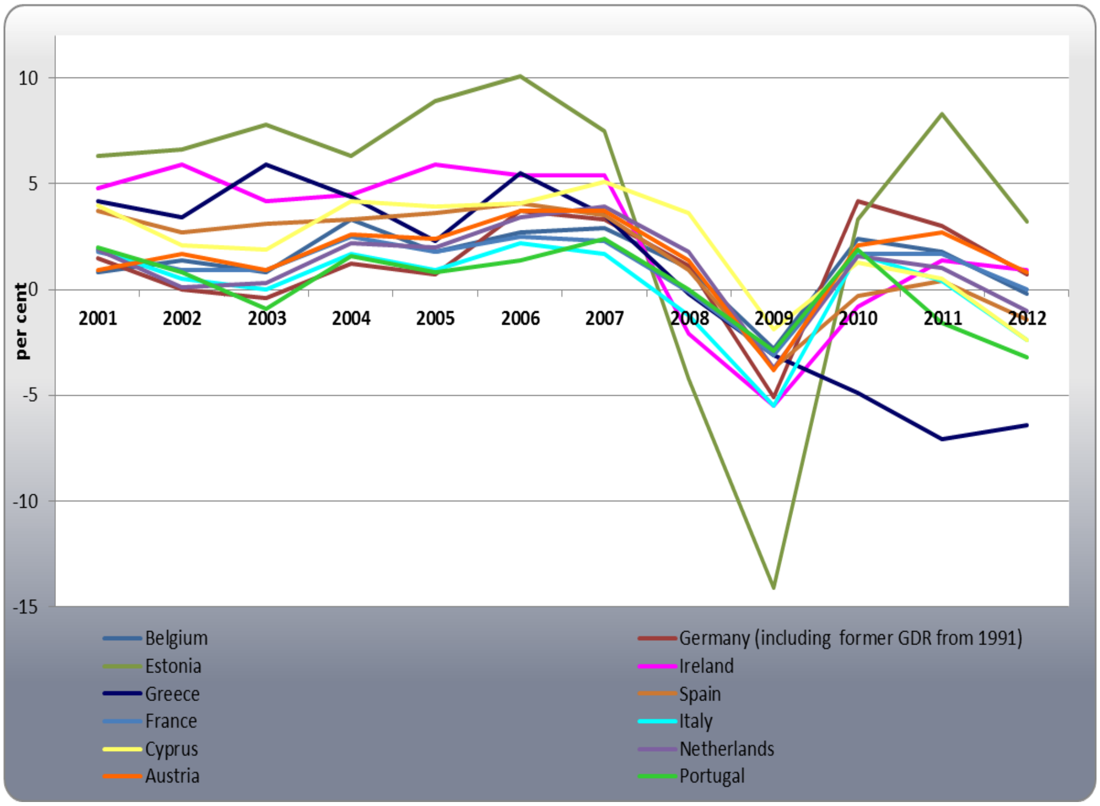
The 2008 financial crisis has taken its place in history as the most severe financial catastrophe since the Great Depression in the 1930's. The recent crisis brought many economies to the brink of financial turmoil, despite originating in the US other jurisdictions suffered immensely in the wake of this event. The tail end effects of the US catastrophe were felt by both developed and emerging markets and the world stood at the mercy of a haemorrhaging US financial system.

According to the 2011 Financial Crisis Inquiry Commission report the US financial crisis affected the lives of millions of American citizens and could have been avoided if the regulatory agents had adequately monitored and managed the financial environment. At the time of the report 26 million individuals were unemployed with about 4 million homes being lost and the same amount entering the foreclosure process. It is an event that stands as testimony to the fickle nature of a system that was improperly monitored and regulated.

The 2011 report states emphatically that the financial crisis was avoidable and was the result of a failure of regulation. The commission trace the events of the crisis to a number of significant events, in the first case they expound that the sub prime market lending, systematic rise in house prices and unsustainable lending practices coupled with a rise in derivatives and spin off products saw the collapse of the US financial system. At the helm of the financial crisis was the banks which were allowed to manipulate regulators and consumers and credit rating agencies who were later accused of rating products they themselves could not understand.

While the crisis originated in the US other jurisdictions such as the EU soon got swept into the tidal wave that was the financial crisis. EU banks which held many of the mortgage backed securities (MBS), collateralised debt obligations (CDO's) and credit default swaps (CDS) issued by the US soon found themselves in the depths of a calamity. The metamorphosis of the financial crisis into an economic crisis became evident. The GDP of Euro zone countries fell significantly in 2009, the immediate impacts ranged with declines between 14.1 per cent (Estonia) and 1.9 per cent (Cyprus)(Figure 1.1). However the effects were not contained to lower GDP as government deficits ballooned and rescue packages began to build to the tune of approximately 500 billion Euro painting a very bleak picture for the developed world.

Fig. 1.1: GDP at Market Prices for Selected Euro zone Countries (year on year per cent change)



Source: Eurostat

As Reinhart and Rogoff (2009) indicate in their analysis of historical crisis, a financial crisis as severe as the 2008 crisis tends to have lasting impacts; the run on effects of the housing market declines are evident from analysis of historical incidents. Output and employment fall dramatically in the wake of banking crisis and government debt tends to rise to astronomical proportions approximately 86 per cent in historical cases. The severity of the impacts of such a deep crisis has led the charge to evaluate and understand the events in the hope of improving monitoring systems. Organisations have led the way in investigating the crisis in order to prevent a recurrence of this catastrophic event, as George Santayana said "Those who cannot remember the past are doomed to repeat it".

The conclusions drawn from the 2011 Financial Crisis Inquiry Commission report are evaluated in this dissertation. In particular the report concludes that the crisis could have been avoided had the custodians of the financial sector manned their posts and used their monitoring tools appropriately. Rajan et al (2010), Wieland et al (2011), Taylor and Wieland (2009) all criticise the use of macroeconomic models and default prediction models and suggest that these models need to be in some way altered. On the other hand the commission argues that the crisis emerged due mainly to human error rather than the inability of models to predict bank failure. If the models are used incorrectly there is no doubt that they will result in a false sense of security.

The ECB president Jean Claude Trichet explained that "We need macroeconomic and financial models to discipline and structure our judgmental analysis. How should such models evolve? The key lesson I would draw from our experience is the danger of relying on a single tool, methodology or paradigm. Policy makers need to have input from various theoretical perspectives and from a range of empirical approaches. Open debate and a diversity of views must be cultivated – admittedly not always an easy task in an institution such as a central bank. We do not need to throw out our DSGE and asset-pricing models: rather we need to develop complementary tools to improve the robustness of our overall framework" (Opening speech at European Central Bank's annual conference on 18 November 2010.)

The inability of the default prediction models to warn of the impending crisis has been the subject of many financial stability discussions. While there is contention that the models did not indicate the impending default of major banking institutions the argument that the models were used in the incorrect way is one that resonates with regulatory agents. Finding ways to improve the prediction models and ensuring that supervisors are equipped with the appropriate knowledge to rigorously test these prediction models has presented new opportunities to use old models in new ways.

Illustrious models such as the Merton structural default prediction model and the Altman Z score models have stood the test of time. The recent crisis has presented new opportunities for these models to be tried, tested and improved. Shumway (2001), Hillegeist et al (2004), Reisz and Perlich (2004), Argawal and Taffler (2008), Miller

(2009), Trujillo-Ponce et al (2012) all investigate the ability of structural or accounting models to determine the default of an institution. The development of continuous improvement in the use of these models can present some unique benefits as much of the literature has assessed.

Another conclusion drawn from the 2011 Financial Crisis Inquiry Commission report speaks to the culpability of the credit rating agencies in the events leading up to the financial crisis. The Commission explains that the credit rating agents' "ratings helped the market soar and their downgrades through 2007 and 2008 wreaked havoc across markets and firms". The havoc wreaked by the credit rating agents also transcended borders as their severe downgrades of the European sovereigns and banks fueled the crisis in Europe.

Credit rating agencies (CRA's) have been profusely scrutinized in the wake of the financial crisis. Being that credit ratings are at the heart of investment decisions and are thought to represent the ability of an entity (be it a corporation, bank or government) to fulfil its obligations to investors. While the debt ridden countries of the Euro zone lit the fire of financial instability, the CRA's have been accused of fanning the flames. Engulfed in the financial fracas countries like Greece, Italy, Portugal, Ireland and Spain found their sovereign bonds downgraded to mere junk. Thomas L. Friedman wrote in 1996 that: "There are two superpowers in the world today in my opinion. There's the United States and there's Moody's Bond Rating Service. The United States can destroy you by dropping bombs, and Moody's can destroy you by downgrading your bonds. And believe me, it's not clear sometimes who's more powerful."

Credit ratings are highly visible to the market and transmit information which is deemed important to investors. The investment grade ratings many sovereigns received pre crisis put these developed economies in good financial standing. However the severe downgrades that came at the height of the financial crisis commenced a downward spiral that was thought to be initiated by CRA's. Research has shown that negative news elicit more volatility than positive news as regards credit ratings (Brooks et al (2004), Alsakka and ap Gwilym (2010), Afonso et al (2012)). The cost of debt is shown to be severely impacted by sovereign rating downgrades. At higher interest rates investment is dampened as investors are less inclined to borrow and economies that are ailing are pushed further into economic decline.

The transmission from banks to sovereigns have been analysed by (Reinhart and Rogoff (2009), Correa and Sapriza (2014)). Tracing these impacts reveals that as the banking sector encounters financial strain they approach the authorities for assistance, being that many sovereigns want to ensure the stability of the banking industry these bail outs usually transcend into financial burdens on the sovereigns. The fiscal pressure that emerges from rescue packages results in the sovereign themselves suffering debilitating downgrades (Correa and Sapriza (2014)). While the transmission from sovereigns to the market and from banks to sovereigns has been well evaluated in the literature there has been limited analysis of the transmission from sovereign ratings to bank credit ratings.

The spill over effects from sovereign downgrades had severe impacts on Euro zone countries. The potential exit of Greece from the EU based on its inability to recover from the detrimental impact of the severe sovereign downgrades received at the height of the European debt crisis stands as a testimony to the lasting effects of credit rating downgrades. In response to the crisis the European Securities and Markets Authority (ESMA) who have been charged with regulating the credit rating agencies encourage market participants to rely less on ratings which they explain “can amplify procyclicality and cause systemic disruption.” This disruption does not only transmit from sovereign rating changes to the market but can also occur from banks to sovereigns.

A wide range of studies surrounding credit ratings exists in the literature. From how credit ratings affect the market, to the determinants of sovereign credit ratings to the determinants of institution credit ratings. While all these studies add to the wealth of knowledge surrounding credit ratings, their development and overall impacts, the niche of analysing the link between sovereign and bank credit ratings is quite minimal. With the recent crisis it has become imperative to understand this transmission mechanism as we see links from banks to the sovereign and vice versa. The crisis originated in the banking sector as banks held useless US securities, as the sovereigns tried to aid these banks they found themselves at the helm of a catastrophe. In the EU the ballooning debt and fiscal perils meant that sovereigns were soon at the mercy of the unyielding credit rating agents and the impact that this had on the ratings Euro zone banks received is carefully evaluated in this dissertation.

While it is expected that sovereign downgrades will in some way be considered when ratings are given to institutions in that jurisdiction we rarely expect it to manifest into rating changes for banks and other financial entities unless the banks themselves warrant a rating change. The magnitude and speed of rating downgrades meted out to banks in the wake of their sovereigns being downgraded raised many questions. At first glance the situation speaks to banks being downgraded due to their location, as the sovereign is weakened the banks suffer destabilising downgrades. Studies that evaluate the link between sovereign rating changes and bank rating changes are limited in the literature. Williams et al (2013), Alsakka et al (2014), Huang and Shen (2014) are a few who have pioneered research into this area.

In keeping with the theme of the contribution the credit rating agencies made to the financial crisis, the report explains the vast number of mortgage securities agencies like Moody’s rated, putting the figure over 600 a month. These securities received triple A ratings deeming them investment worthy. As governments, institutions and regulators put faith in the credit rating agencies and the ratings they were issuing a house of cards was built. As the house began to tumble a whooping 83 per cent of mortgage securities were ultimately downgraded. A lack of understanding of the methods used by the rating agencies and a lack of understanding of the products rated saw the burgeoning of the catastrophic crisis.

Works have addressed the determinants of credit ratings even pre-crisis and have attempted to use publicly available information to replicate ratings. Poon et al (1999,) discuss the determinants of credit ratings. Drawing on these works other papers have evaluated the ability of different statistical models to accurately classify ratings given some set of determinants. Dating as far back as 1966 Harrigan investigated the ability to classify ratings using an ordinary least squares model. Pinches and Mingo (1973), Pinches and Mingo (1975), Altman and Katz (1967) all use multiple discriminant analysis to attempt to classify credit ratings. Within recent there has been a surge in the use of ordered probit models and artificial neural networks (also known as computer learning) to replicate credit ratings.

The ability to classify credit ratings using publicly available information is a benefit to not only investors but also to the watch dogs charged with monitoring the financial system. Regulators can use these models to make the rating agents accountable for their actions and ensure that the rating process is in no way manipulated by high paying institutions interested in getting the best ratings for their products.

The numerous events that culminated in the financial crisis have set the tone for regulators and supervisors going forward. Stemming from these unfortunate events has come the push for financial stability and a focus by central banks and other institutions in both developed and developing nations to be the champions of change. The International Monetary Fund (IMF) has undertaken the mandate to encourage central banks to become more stability focused. BIS, the international banking regulator has tightened its grip on the banking fraternity implementing stricter capital requirements and eliminating some relaxing conditions which left banks wallowing in financial turmoil.

With the progress that has been made towards better identifying and understanding the fragile nature of the financial system the regulators have begun to clamp down on the financial sector. Despite claims that these measures stifle the growth of the sector it must be taken into account the devastation deregulation and self regulation caused and the lasting impacts the crisis will have. As we go forward the mandate for the supervisory bodies lies in ensuring that history is not repeated and that the major players in the financial arena are held accountable for their actions.

1.2 Objectives of Study

Given the vast amount of work that has been done in investigating and analysing the impacts of the financial crisis this research carves a niche in focusing the research in the area of the banking system as it relates to the catastrophic crisis events. The specific objectives of this dissertation are:

- To improve default model predictions and to compare the performance of the improved accounting/financial and structural models in default prediction. The paper critically investigates the non-normality of variables and the possible improvement to prediction models via transformation of non-normal variables.

- To determine the influence of sovereign debt ratings on bank ratings for the Euro zone countries. The analysis investigates whether banks were downgraded due to their jurisdiction or if the critical events at the time played a role in their severe downgrades.The paper also contributes to the literature in its assessment of the bank viability rating, a standalone rating issued to assess bank stability excluding external influences.

- An investigation into the ability of four statistical approaches, namely, ordered probit, multiple discriminant analysis, ordinary least squares and artificial neural networks, to accurately classify credit ratings of Euro zone banks using two sets of explanatory variables; financial data versus principal components.

1.3 Motivation

The inextricable links between the financial sector and macro economy have become illuminated by the crisis and continues to haunt many economies. The age old debate of default prediction models and their expediency has been surpassed by arguments about the mere usefulness of these models. As the crisis heightened and the movement towards better monitoring and mitigation tools intensified, the banking system has come to the forefront as an important component in the push for financial stability. As such one focus of this dissertation is the ability to predict default in the banking system.

At the helm of the crisis was the 2008 sub prime mortgage market scandal which ballooned out of control, propelled mainly by poor lending practices, fancy derivative products and the pure greed of lenders and investment bankers. This event was subsequently made worse as large US banks were forced to close their tills and the notion of government rescue that assured most citizens failed to materialise. Hence came the notion of systemic risk and burgeoning from that the notion of cross border systemic risk. The full on effect of the crisis was not contained to the US but sprung roots in other jurisdictions. Following which the wider EU community took a hit with international eyes glaring at Greece and more recently Cyprus.

As these events materialised the credit rating agencies also came to the focus as they among with supervisory bodies were charged with the responsibility of ensuring the financial ship sailed smoothly. As the vessel hit rough waters the rating agents were accused of rating products that "could be structured by cows" as one agent put it. With more scrutiny about their practices and methodologies the credit rating agents responded quickly and with brute force severely downgrading some sovereigns in the

Euro zone thereby sparking the events of the European debt crisis. This thesis evaluates their response to the ratings of banks following the sovereign downgrades and investigates whether the downgraded of the Euro zone sovereigns played an instrumental role in the downgrades meted out to Euro zone banks.

1.4 Contribution

This study attempts to add to the wealth of knowledge that exists surrounding the impact of the financial crisis on the banking sector. The area of default prediction models have been well documented in the literature. This thesis explores the area of default prediction as regards banks and applies tests the ability of structural versus accounting models to adequately predict default. We further the investigation by examining the non-normality of the explanatory variables and transforming them in a bid to improve the default detection rates.

The dissertation goes on to make a literary contribution. There have been limited studies which explore the link between the ratings of a sovereign and how that transmits to the credit rating of a bank. This study investigates and tests this transmission. We also include the accounting information for the banks involved in the study. It is assumed that exclusion of bank financials suggests that banks ratings are based solely on their jurisdiction. In an attempt to deepen other studies we included the financials of banks to investigate whether their rating downgrades were due solely to the sovereign change or because of the bank's financial fundamentals. In paper II we also address the bank viability rating posted by Fitch and compare and contrast it to the all in rating.

The research in paper III investigates both the statistical methods to best predict bank credit ratings and the best explanatory variables to be used in rating classification. Differing from the majority of studies which focus solely on the statistical approaches. This section of the dissertation looks at investigating 4 statistical approaches to bank credit rating classification, namely, ordered probit, multiple discriminant analysis, ordinary least squares and artificial neural networks. We add to the existing literature by testing both financial variables and principal components as explanatory variables for each statistical approach.

1.5 Outline

This dissertation focuses on the recent financial crisis and the banking sector, the main aim is to investigate existing models ability to grant regulators information about the weaknesses in the banks books and to further analyse the role rating agencies played in propelling the financial crisis. The dissertation has 3 proceeding papers; paper I analyses bank default prediction models. This paper takes an integral look at determining the default for US banks and constructs two models based on differing underlying fundamentals. The first model is an accounting model determined from the banks books and the second is a more structural type model.

In paper II the investigation of the impact of sovereign rating changes on bank rating changes is undertaken. This study looks at 82 banks across the Euro zone countries and assesses the influence sovereign ratings exert over bank ratings. This investigation answers the specific research question of the transmission from sovereign ratings to bank ratings. It also assesses whether banks in the Euro zone were downgraded solely due to their jurisdiction following severe rating downgrades of the Euro zone sovereigns.

In keeping with the impact on ratings during the financial crisis paper III evaluates 4 statistical models and their ability to accurately classify ratings based on either financial variables or principal components. The analysis is developed for three credit rating agencies; namely Moody's Standard and Poor's and Fitch. The dissertation concludes by giving a brief overview of the study and its findings and policy implications of the dissertation.

2. PAPER I- BANK DEFAULT PREDICTION

2.1 Introduction

The 2008 financial crisis heightened awareness of the management and regulation of the financial sector. The importance of prediction models has again come to the fore in the wake of the recent events of the crisis. There exists vast literature on the ability to predict financial distress in an institution and it focuses mainly on two types of models, (Altman (1968), Merton (1974), Shumway (2001), Hillegeist et al (2004), Reisz and Perlich (2004), Argawal and Taffler (2008), Trujillo-Ponce et al (2012)) all employ either accounting models, structural models or a combination of both to determine default in an institution. While most of the literature has found that structural models are better at detecting default in an institution, Shumway (2001) finds that the accounting model is in many cases weakened due to the multicollinearity problem. The idea behind an accounting model being used to assess the financial health of a firm is grounded in the notion that firm's books can give insight into the health of an institution. Altman (1968) implores academics to embrace the use of traditional financial ratios in an attempt to investigate institution failures. Since Altman's model, which was constructed on a multiple discriminant analysis (MDA) foundation, other accounting models (Ohlson (1980) and Zmijewski (1984)) using logit and probit analysis have also paved the way for the use of financial ratios in assessing firm health.

On the other hand structural model supporters like Hillegeist et al (2004) find the Merton framework to be more useful in forecasting default as compared to Altman's accounting framework, their findings have been supported by Reisz and Perlich (2004) who also find the Merton framework more useful but conclude that accounting models give more accurate predictions with a shorter time horizon.

Recent works have evaluated the combination of both the structural and accounting models. Such combination models are said to better predict default than any one model. Agarwal and Taffler (2008) echo these sentiments; they find that the structural and z score model, applicable to the UK, both possess similar predictive abilities but essentially measure varying aspects of bank distress. Like Agarwal and Taffler other authors Trujillo- Ponce et al (2012) sought to encourage the use of hybrid models that include both structural and accounting information as these are thought to possess even greater predictive abilities than any standalone model. Tinoco and Wilson (2013) go a step further and seek not only to combine the accounting and structural frameworks but also include macroeconomic variables in their prediction model.

This paper adds to the existing literature by (1) comparing the varying ability of a default model in and out of crisis period to ascertain which variables might be more suitable in differing cycles. We find that the capital variable tends to be important in all cycles and presents a way for regulators to closely monitor banking institutions. (2) The paper also addresses the problem of non-normality of financial data and attempts to normalise the variables to investigate the impact upon the model's classification strength.

Following the Introduction, section 2.2 looks at the relevant literature surrounding default prediction models, section 2.3 discusses the data used to develop the models, and gives an explanation of the methodology employed, section 2.4 explores the results and finally the chapter concludes in section 2.5.

2.2 Literature Review

The literature surrounding bank prediction models is wide and vast and has 2 main schools of thought, one focusing on the ability of accounting variables/ financial ratios to determine default and the other focusing on a structural framework. More recent studies have focused on the ability of a combination of both accounting and structural approaches in the determination of default. Great discourse has evolved in the literature assessing the ability of different statistical approaches in default determination, probit and logit along with hazard models have all been used and discussed in the literature regarding their ability to determine default of an institution.

The Merton default prediction model, popularised in 1974 is often referred to as the father of structural models. The main impetus behind the framework is the computation of default probabilities among other useful crisis indicators such as the distance to distress metric. As structural models do, the Merton Framework (1974) and Black and Scholes (1973) seeks to build in the information granted by the capital market into the default probabilities for an institution. Structural model supporters argue that one can gain insight into the default possibilities of an institution by analysing their market information.

According to Merton's model if the value of assets fall below the value of debt then the firm is facing default, in such a case the debt holders must be paid off first and the equity holders will get the residual, consider the two situations of no default and default in the table.

Tab. 2.1: Payoff Structure

	No Default	Default
Debt holders	D	A
Equity	A-D=E	0

In the event of NO DEFAULT, the asset values exceed the distress barrier (in the Merton model the distress barrier is the value of debt). $A > D$ In this instance the debt holders are paid D and the equity holders receive the residual A-D=E. Consider the alternate case of DEFAULT; this means that the firms asset values falls below the distress barrier, $A < D$ in this case the debt holders will receive A and the equity holders will receive 0.

Since equity can be viewed as a call option it can further be valued via the option pricing model. This aids the computation of a marked to market balance sheet which uses all available market information to compute a truer asset value for the firm. The first step is the computation of the implied asset value and the asset volatility, as assets and their volatility are not directly observable from the balance sheet. The option pricing model allows equity to be valued in the following way:

$$E = AN(d_1) - De^{-rT}N(d_2) \tag{2.1}$$

Where: d_1 is

$$\frac{ln(A/D) + (r + \sigma_A^2)T}{\sigma_A\sqrt{t}} \tag{2.2}$$

and d_2 is

$$d_1 - \sigma\sqrt{t} \tag{2.3}$$

Notably A is the implied asset value; D is the distress barrier or promised payments[1], σ is the volatility of asset return (σ_A) or of equity (σ_E), r the risk free interest rate, N(d) the cumulative probability under d and T the time component. It is important to note that the implied asset value and asset volatility are not given and must be solved via a simultaneous equation. Following which we employ Ito's lemma which is given by equation 2.4. Setting up a simultaneous system of equations 2.1 and 2.4 we use the Newton Raphson iteration method to solve the implied asset value and volatility. The methodology requires that the researcher start with a guess of A and $\sigma_A$and as the iterations converge the implied asset value and volatility is chosen.

$$E\sigma_E = A\sigma_A N(d_1) \tag{2.4}$$

In the event of minimal or no participation in the capital market, studies have been done where the book value of assets and volatility of those assets have been used (Souto (2008), Blavy and Souto (2009)). While this methodology loses the appeal of including market information in the financial stability indicators, it is shown to closely mirror the stability indicators that do include market information. After choosing the converged A and σ_A we substitute those values into d_2 which gives the distance to distress, that is how many standard deviations the asset value is from the default value. The risk

[1] In the Merton model this is the value of debt, more recent works compute this distress barrier as all short term liabilities plus half of long term liabilities.

adjusted probability of default is given by $N(-d_2)$ with N(d) being the cumulative probability of the standard normal density function under d.

Some works have placed more emphasis on the predictive powers of the compiled financial stability indicators to signal to regulators any impending crisis in the financial system. The thrust of the structural model work and the financial stability indicators is to give regulators and politicians an early warning system that allows them to appropriately identify credit risk and hopefully address it before it becomes catastrophic. In light of the main aim of the indicators it is important to critically evaluate the predictive power of such indicators to assess whether they do indeed signal credit risk. The paper by Gropp et al (2006) does exactly this, they use the distance to distress metric computed via the option pricing methodology and debt spreads to see if they do indeed alter before a downgrade in the EU banking system. The authors discover that the negative distance to distress metric can forecast a downgrade as much as 18 months prior, while the debt spread has a weaker predictive power. Their work has been supported by Curry et al (2007) where they showed that stock markets have predictive power of impending downgrades. They estimate that 2 years prior to downgrade stock prices tend to fall.

The Merton model also allows the computation of the probability of default for an institution and is given by $N(-d_2)$. According to Hull et al (2004) it is the probability that equity holders will not exercise their call option on the assets of the institution.

Despite its appeal the Merton framework has some limitations as identified by Benos and Papanastasopoulos (2007), Antunes and Silva (2010), the structural type model ignores many important aspects of a firms balance sheet for example liquidity measures, profitability and efficiency measures. While the model includes market information, the case of Northern Rock Bank is a clear indication of the problems with depending solely on market sentiment and failing to address the actual balance sheet measures that can be computed. The model is also blinded to the possibility of dividend payment. Additionally the assumption of a stagnant risk-free rate throughout the entire period seems somewhat unrealistic as the rate on government treasury bills alters on a more frequent basis, say monthly. Another limitation is the arbitrary way in which the distress barrier is chosen, for a financial institution in particular a bank, we take all short term liabilities plus half the long term liabilities and interest, but there is no standard explanation in choosing the long term liabilities. One may query why half and not one third etc.

Where the structural model is blinded the accounting model can shed some light. The idea behind an accounting model being used to assess the financial health of a firm is grounded in the notion that firm's books can give an in-depth insight into the health of an institution. Altman implores academics to embrace the use of traditional financial ratios in an attempt to investigate institution failures. Just as the Merton Structural model is considered the father of structural models, so too is Altman Z scoring model popularised by Altman (1968) considered the genesis of the accounting model framework. Since Altman's model which was constructed on a multiple discriminant analysis foundation, other accounting models, using logit and probit analysis, have also paved the way for the use of financial ratios in assessing firm health.

Notably the Altman Z-score model is used to analyse default of non-financial firms by assessing particular accounting ratios. Recent works have attempted to use similar accounting analysis to assess the default of financial institutions, in particular banks. Altman uses multiple discriminant analysis to identify 5 financial ratios that are said to determine the financial health of an institution (Table 2.3).

The MDA methodology gives coefficient values for each of these ratios and the scoring model is then constructed as in (equation 2.5) below, where α is the coefficient value for the financial ratio determined by the multiple discriminant analysis and X is the explanatory variable or the ratio discussed above. Based on his analysis Altman devises generic coefficient values that can be applied to non-financial firms and a Z score can be computed. Where the $Z \geq 2.675$ the firm is categorised as non-bankrupt and where $Z < 2.675$ the firm is classified as bankrupt.

$$Z = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 \tag{2.5}$$

The multiple discriminant analysis methodology is subject to many shortcomings as pointed out by Ohlson (1980) and Eisenbeis (1977), Ohlson explained that the MDA requires specific criterion of the explanatory variables to be met, and in particular the variance covariance matrix of both groups (distressed and non-distressed firms) must be the same. Ohlson also argues that the score which results from using the MDA model is of little use intuitively as it is strictly a ranking mechanism. His final critique of the MDA lay in the matching requirements for the firms in both groups, Ohlson laments that the matching criteria is rather arbitrary in this type of model. Based on the critical shortcoming in the MDA, Ohlson suggests the use of a logit model with the ratios listed in table 2.3, as explanatory variables to predict default of a non-financial institution. The author tests three models based on the financial ratios, the first model assesses the ability to forecast bankruptcy over a 1 year horizon, the second model evaluates a 2 year horizon and the third model tests between 1-2 years. The resulting model shows that 96.12 per cent of institutions were correctly predicted as defaulting within a one year horizon, while 95.55 per cent were predicted to default within a two year time period and 92.84 per cent between 1-2 years.

Another model which lay the ground work for accounting prediction models is Zmijewski (1984) probit default prediction model. The author assesses the possible biases that may arise in sample selection for prediction models and seeks to construct a probit model that limits the identified bias of “oversampling” of distressed firms and sample selection bias. The main explanatory variables in the Zmijewski probit model are seen in table 2.3.

Since the development of the Merton and Altman frameworks there has been significant developments regarding models that attempt to identify default in institutions. One of these developments came from Shumway (2001) who proposes the use of a hazard model with a combination of accounting and market data to adequately forecast firm bankruptcy. He criticises the approach used by researchers in bankruptcy prediction and laments that single period static models fail to account for the varying nature of institutions over time. The paper explains that static models give inconsistent results which suffer from selection bias. Shumway also finds that models using accounting data often suffer from many variables being insignificant due in part to the multicollinearity problem. He proposes the use of a simple hazard model with both accounting and market variables and explains that these provide better out of sample forecasts.

Shumway advocates the use of a hazard model and purports that the hazard model determines the probability of bankruptcy of an institution based on the explanatory variables and a time component. The latter is sold as the improvement on the static model. While analysing a hazard model is out of the scope of this research I must argue that this approach appears to also introduce some bias in the model. Shumway argues that static models are biased because the researcher chooses when to evaluate the health of the firm (in the bankruptcy year and one year prior). He says in the hazard model is a time variant so a firms probability of bankruptcy changes over time. However, this also introduces some bias into the model as we must have some a priori expectation of older versus younger firms. That is to say we must have some idea about a higher or lower probability attached to older firms etc. In this chapter I argue that the main impetus behind any bankruptcy analysis should be a combination of the accounting information and the market information from the entity.

The paper uses data from 1962 to 1992, the firms that are common to three databases were used; Compustat Industrial file, the daily stock return file for NYSE and American Stock Exchange. The analysis finds that many of the accounting variables used by Altman and Zmijewski are found to be insignificant in determining bankruptcy. Using the hazard model with both accounting and market data, according to Shumway, provides better out of sample forecasts.

Hillegeist et al (2004) stands in support of the Black Scholes- Merton framework for bankruptcy prediction. They argue that the accounting models popularised by Altman (1968) and Ohlson (1980) suffer from severe shortcomings. According to Hillegeist accounting data is backward looking and gives little aid in forecasting future performance of an institution. Being that it is difficult to estimate future bankruptcy probabilities based on past data the author proposes the use of the Merton framework which he says gives more useful information than the accounting models. The author also argues that accounting data tends to be recorded conservatively. The latter leads to underestimation of asset values and can adversely impact leverage ratios.

Despite his arguments against accounting models, structural models also suffer some shortcomings which the author fails to recognise. While the market views on the firm are useful sometimes the market gets it wrong and in this case ignoring the accounting information can be detrimental. The case of Northern Rock is one example. The market placed great value on Northern Rock shares but the financials of the firm told a different story with the liquidity strain being evident. The eventual demise of Northern Rock came about due to its liquidity strain and could have been seen from examination of the accounting data and financial ratios. It is in this light that modern works have put forward arguments in support of combination models which blend both structural and accounting data into prediction models.

The paper by Hillgeist uses data from 1980 to 2000 and utilises 756 bankrupt firms' data a larger sample than most studies at that time. The paper applies a hazard rate model and finds that the Merton framework, referred to as the Black Scholes Merton model is better at predicting bankruptcy of firms. The latter model outperforms the accounting method popularised by Altman (1968) and Ohlson (1980).

Reisz and Perlich (2004) attempt to test both the structural and accounting framework's ability to accurately estimate probabilities of bankruptcy. They use data between 1988-2002 and quote a sample size of 5,784 industrial firms. While the paper focuses mainly on the structural method and ways to improve it they do not discount the usefulness of accounting models and conclude that such models give more accurate predictions with a shorter time horizon. The authors claim that the structural method is severely diminished by the inability to account for situations where managers take risks that may adversely affect firm value. They argue for an adjustment to the option picture by giving shareholders the ability to borrow to pay off the debt, the firm only goes into bankruptcy if shareholders are either unable to repay the loan at the agreed date or if the value of the firm falls below some distress barrier.

Reisz and Perlich go on to criticise many of the approaches popularised at the time (Hillgeist et al (2004)) arguing that the authors fail, like so many other papers that employ the structural model framework, to accurately account for this managerial risk that has been observed. By employing these new empirical adjustments the authors find that their model outperforms the Black Scholes Merton model. They also advocate that the accounting model outperforms the structural models under their approach at least within a 1 year time horizon.

Agarwal and Taffler (2008) echo sentiments regarding the importance of both accounting and structural models. They find that the structural and z score model, applicable to the UK, both possess similar predictive abilities but essentially measure distress in different ways. The importance of both methods is not lost on the authors and they argue that the ability to predict default is the same with both models. The authors criticise the approach employed by Hillgeist et al (2004) claiming that the paper fails to account for the misclassification that is synonymous with accounting data.

The performance of the distance to distress metric has been tried and tested in the literature, Miller 2009 and Bauer and Argawal 2014 explain the distance to distress metric tends to perform well at determining default probabilities. On the other hand Bauer and Argarwal 2014 also show that the hazard model structure outperforms both the Z score and contingent claim model.

As far as the predictive ability of structural versus accounting models go the results vary with regard to the performance of both models. The idea of developing hybrid models that combine both accounting and market based information appears to give more information in the way of default prediction. These ideas have been echoed by Kealhofer and Kurbat (2001), Loffler (2007), Mitchell and Roy (2008), Agarwal and Taffler (2008) and Li and Miu (2010) who all, with the exception of Kealhofer and Kurbat (2001), discuss the improvements in bankruptcy prediction that arise out of the use of a hybrid model. More recent studies such as Trujillo-Ponce (2012) and Tinoco and Wilson (2013) also investigate the improved prediction that comes about as a result of the use of models that combine both accounting and market based data. The authors sought to encourage the use of hybrid models as these are thought to possess even greater predictive abilities than any standalone model.

The paper by Agarwal and Bauer (2014) seeks to fill a void in the exiting literature by engaging a comparative analysis of hazard, accounting and structural models. The authors explain that the current literature examines each model on its own merit but fails to compare and contrast the performance of all models to detect failed firms.

The model by Agarwal and Bauer is fashioned on data from UK non-financial firms over the duration of 1979-2009. The data sample is made up of 28,804 firm years of which 274 are failed years (year in which the firm ceased operation). Accounting and market data is taken from the London Stock Exchange, Company Analysis, Exstat, DataStream, FAME and the London Business School Library.

The results show that all the default models adequately differentiated between failed and non-failed firms with the Z score and contingent claim models over estimating the probability of failed firms. The authors point out that this may signal miscalibration of the model and address the latter by using percentiles in the ROC analysis (receiver operating characteristic- a graphical plot that shows the performance of a binary classifier). Under the ROC analysis, which tests the accuracy of model classification, all models perform well with the area under the curve exceeding 80 per cent in all cases. Notwithstanding, the hazard models perform superior to the Z score and contingent claim model.

Finally the authors find that all the models contain important information relating to the distress of the firms. The do explain that the hazard models contain all distress related information but lament that the z score model appears to have more information than the contingent claims model regarding failures. In the end the paper concludes that the hazard models do appear to be superior in its ability to detect defaulted firm years compared to its rivals (z score and contingent models).

Campbell et al (2011) seek to develop a model that accurately determines financially distressed firms. They refer to their financial distress measure as the 'probability of failure' and expound upon its difference form other existing distress measures. The distress indicator is premised on data spanning January 1963 to December 2008 gathered from Kamakura Risk Information (KRIS). The model draws from works of Shumway 2001 and Chava and Jarrow 2004, the model uses both accounting and market data similar to the hazard model developed by Shumway.

In the prediction model the authors use a logit model and find that all variables are significant. They explain that the model with the better prediction ability includes all the variables. Further they find that firms with weaker profitability and lower liquidity coupled with rigorous volatility and higher average leverage are more susceptible to failure.

Regarding the model evaluation the authors explain that both the pseudo R^2 and the accuracy ratio indicate that the model is viable giving 31.6 per cent and 95.5 per cent respectively. A comparison of the financial distress model to Shumway's 2001 model shows that the Campbell et al (2011) model is better able to detect financial distress of a firm between 12 and 16 per cent. When compared to the distance to distress model used by KMV, the authors find that their model is between 49 and 94 per cent more accurate at predicting distress in a financial firm.

The next phase of the research investigates the performance on the stock market of distressed stocks. The authors find that there is a continued underperformance of distressed stock in the sample between 1981-2008. The continued underperformance of distress stocks continues across size and industry indicating that the possible lack of information and inability to short sell distressed stocks may in some way be responsible for their continued underperformance.

The paper by Altman (2014) seeks to assess the ability of the Z score model, developed and extended by Altman to accurately classify distressed firms. The authors explain that the since the inception of the Z score model there has been extensive work including extensions to the literary framework popularized by Altman. The paper seeks to develop an intensive look at the research done in the area and presents an analysis of the extensive literature using the Z score framework.

In addition to evaluating the published work the authors seek to extend the original scoring model. Firstly they look at extending the database of distressed firms. While the original accounting model focuses on US bankrupt firms this analysis includes both Chinese and European distressed firms.

The work by McLeay and Omar (2000) addresses ways to deal with two types of financial ratios identified by the authors (i) unbounded and (ii) bounded ratios. According to the authors bounded ratios only take positive values and can have extremes in the right tail end of their distribution while unbounded ratios can take on both positive and negative values and have both left and right tail extremities.

The research begs the question whether or not non-normal financial ratios influence the predictive ability of models. The impetus put forward by the authors is a transformation of non-normal financial ratios using a skewness and kurtosis approach. They then seek to compare the ability of the prediction model using the transformed financial ratios vs. the model which uses the non-normal ratios.

The construction of the model is based on data for failed and non-failed manufacturing firms, a total of 359 between the period 1980-1991. Based on existing literature 28 financial ratios are compiled drawing from the balance sheet and income statement of the firms in the sample. The methodological approach involves testing the 28 ratios for normality and categorizing them into 'most normal' and 'least normal' categories prior the transformation process.

The authors use both discriminant analysis and logit analysis to test the predictive ability of the models. The models are constructed using the 'most' and 'least' normal ratios and compared based on transformation or financial ratios vs. non-transformed financial ratios.

As regards the discriminant analysis it was found that the best classification occurred with the transformed data set giving a maximum improvement of 7.9 per cent, in particular the 'least normal' data showed vast improvement given the transformation. On the other hand the logit model showed no change between the transformed and non-transformed data for the 'most normal' data but did show vast improvement in the 'least normal' data. The author explains that the logit model tends to be more reactionary to non-normal data hence the improvements given the transformation.

Frecka and Hopwood (1983) along with Deakin (1976) all investigate the extreme skewness that is characteristic of financial data. The latter found that 10 out of 11 financial ratios investigated were subject to skewness which had implications for the estimations they were used in. Frecka and Hopwood argue that normailty approximations are necessary to improve the estimated models and seek to transform the non-normal financial ratios by eliminating the skew. The authors utilise a sample of manufacturing firms between the period 1950-1979 and show that the transformation of the financial ratios to near normality has a vast improvement on the estimation results.

Ezzamel and Mar-Molinero (1990) share similar sentiments as to the importance of a near normal distribution. They argue that non-normality can impact the estimates and a near normal distribution is quite frequent and many statistical tests use normality of variables as an underlying assumption, therefore normality of financial ratios should be closely investigated and non-normal variables be transformed in order to get estimates that are useful given the underlying assumptions.

In his 1977 piece Eisenbeis closely investigates the shortcomings of utilizing a discriminant analysis methodology in the application of finance and economic econometrics. He laments that statisticians rarely observe and account for the non-normality

Tab. 2.2: Financial ratios in Ciampi 2015

Profitability	Cash flow/turnover
Return on equity	Interest charges/bank loans
Return on investment	Turnover/net operative assets
Return on sales	Leverage
Value added/turnover	Bank loans/turnover
EBITDA/turnover	Net financial position/turnover
EBITDA/cash flow	Total debts/(total debts+equity)
Interest charges/turnover	Financial debts/equity
Interest charges/EBITDA	Total debts/EBITDA
Turnover/number of employees	Equity/long-term material assets
Value added/number of employees Liquidity	Liquidity
Long term assets/number of employees	Current ratio
Cash flow/total debts	Acid test ratio

which tends to be inherent in much econometric and finance data. The other limitations identified by Eisenbeis include the dispersion dynamics of the data, understanding the contribution of variables to the model, high dimension data and the impact, costs of misclassification and evaluating errors.

Davydenko and Franks (2008) address bankruptcies in three European countries namely UK, France and Germany and investigate how the banks handle creditors in light of the possibility of bankruptcy, for example the researchers found that creditors are made to put out more collateral in France in an attempt to minimize the pricey nature of bankruptcies.

Ciampi (2015) investigates the impact of corporate governance on the default of small enterprises. The research investigates 934 Italian small enterprises and develops a prediction model with financial ratios, comparing the default detection rates of this model to one developed with both financial ratios and corporate governance variables. The financial ratios that were selected for the model can be seen in the table 2.2 taken from Ciampi (2015). The second model also includes a range of governance variables some of which include; board size, CEO turnover, audit committee and outside directors. The research finds that the inclusion of the corporate governance variables improves the detection rate of default for small enterprises. The authors explain that small enterprises are significantly different from their medium and large counterparts with respect to the availability of data, profitability and the impact of external events on the business. As such the development of prediction models for small enterprises need to take account of differing institutional elements when devising prediction models.

In the paper by Mare (2015) the author explicitly investigates the importance of macroeconomic factors in the determination of default of small Italian banks over the period 1993-2011. The author also uses bank level financial ratios in the model as capturing the probability of bank default is heavily dependent on individual bank operation, ratios taken from the CAMEL framework are included. As a further extension in the inclusion of macroeconomic variables the author includes the interbank deposit rate (average 3 mth deposits), unemployment rate and the concentration of commercial banks (per cent of commercial bank outlets/ total commercial bank outlets in region).

Wheelcock and Wilson (2000) investigate the landscape of the financial sector, in particular banks, during the period 1984-1993. They explain that a mass of banks had either failed or been acquired from as early as 1985 following a relatively stable landscape in the banking sector. The paper seeks to assess the particular variables that may have contributed significantly to the upsurge in failures and acquisitions in the US banking sector. The authors find that the inefficiency played an imperative role in bank failure and also limited the bank's ability to be acquired. Various banking studies measure bank efficiency in a number of ways, one measure looks at the business of the bank in terms of the number of loans granted and the amount of accounts opened while other approaches look at the income generated by the bank. The authors found such efficiency measures to speak directly to the health of the bank.

In the paper by Antoniades (2015) the elements that propelled the 2007-2008 financial crisis are examined. It is argued that the major impact to large banks was the holding of non-household real estate, this is akin to financing by banks of large real estate projects and the like that went bust with the financial turmoil. Antoniades argues that the channels through which the banks were affected is threefold namely; the inability to monetize asset holdings put liquidity pressures on banks, off balance sheet activities and marketable securities were the three-ways by which banks were affected. The focus of large banks on big real estate projects were ultimately their downfall as argued by Antoniades (2015), while smaller banks held more exposures to household real estate and were ultimately subjected to the subprime shortcomings due in part to poor lending practices it was the "too big to fail" banks exposures that ultimately drove the crisis.

Tian et al (2015) pursue an investigation much like this paper, they assess the predictive ability of a range of models, from the accounting model to a structural model, but go on to include in their analysis a specific variable selection method known as LASSO (least absolute shrinkage and selection operator). The analysis focuses on 17,570 non-financial firms from the US and the authors find that accounting data holds important information about future default of firms. Where many studies tend to focus on market data they argue that market data and by extension the distance to default variable do not provide as much insight into possible default as do the accounting data.

The majority of prediction models are only able to determine default within a one year time horizon, many papers focus on and succeed in building models that perform well within this short time horizon. In direct contrast, the paper by du Jardin (2015) focuses on the longer tem predictive ability of bankruptcy models. du Jardin explains that assessing the firm health prior to default approximately 2-3 years helps to uncover the process by which firms operate in the “failure space”. The assessment of this operation aids the prediction ability of the models and ensures that the ability to predict failure over a 3 year period is strengthened.

Tab. 2.3: Accounting Models Explanatory Variables

Accounting Model	Explanatory Variables
Altman Z-Score	Net working capital/Total Assets
	Retained earnings/Total Assets
	EBIT/Total Assets
	Market Value of Equity/Book Value of Total Liabilities
	Sales/Total Assets
Ohlson	Size – log (Total Assets/GNP Price level index)
	TLTA – Total Liabilities / Total Assets
	WCTA – Working Capital / Total Assets
	CLCA – Current Liabilities / Current Assets
	ONENEG – 1 IF Total liabilities >Total Assets, 0 if otherwise
	NITA – Net Income / Total Assets
	FUTL – Funds provided by operations / Total Liabilities
	INTWO – 1 if net income was negative, 0 otherwise
	CHIN – $(NI_t - NI_{t-1})/(NI_t - NI_{t-1})$ where NI is Net Income
Zmijewski	NITL – Net Income / Total Liabilities
	TLTA – Total Liabilities/ Total Assets
	CACL – Current assets / Current Liabilities

2.2.1 Regulation of financial firms and the link between regulation and bank failure

Firms in the finance industry provide a broad spectrum of services for their clients. The services granted range from taking deposits and giving loans (in the case of banks, credit unions, trust companies etc), making investments (investment banks and brokerage firms) and pension and insurance management. The financial industry in many ways facilitates the flow of funds from those with little investment opportunity to those with greater investment opportunities. Banks and other financial intermediaries are the lifeline of many economies.

It is important that this life support granted by the financial industry is closely monitored and regulated since externalities exist and the externalities can have detrimental impacts on economic systems. Asymmetric information, social externalities and the principal agent problem are some externalities found in the financial industry.

Regulation with respect to the disclosure of information by financial firms can reduce the asymmetric information externality. Though found to be costly, the lack of financial disclosure has been seen to send a negative signal to the market as explained by Ross (1979), Grossman (1981) and Milgrom (1981). Disclosure for firm's must be associated with some cost as the converse would mean firms would willingly disclose all financial information Admati (2000). The costs involve hiring an accounting agency to prepare and verify the information, also dissemination may involve giving competitors first hand knowledge on the workings of the firm thereby minimising its competitive advantage. As Admati (2000) shows there are real costs associated with disclosure and this minimises a firms willingness to do so on its own. While one might deduce that this propels the call for regulation Fishman and Hagerty (2003) dispute the call for increased regulation and conclude that this does not necessarily improve the market as they find firms disclosure should meet the socially optimum level given the increased costs to firms in disclosure.

The breadth of regulation literature takes differing views on the regulation of firms one school of thought proposes increased regulation to minimise the externalities while others point to the costs associated with such. Merton (1995) foresaw the revolutionary changes that were occurring in the financial industry, he explains that improved technology and a change in the nature of financial products all changed the game leading to new thoughts in ways of regulating this new financial evolution. Similarly Harding and Ross (2009) evaluate the improvements needed to existing regulation of financial institutions in order to curb any pending crisis. They estimate that regulation must account for the "too big to fail" institutions and any forward looking regulation must include ways to handle these institutions, one such recommendation is the implementation of policies that minimise the risk financial institutions take particularly when choosing their capital structure, just as Merton (1978) and Marcus (1984) estimate the cost to banks increase when they have capital positions that are not robust, they lament that this encourages financial institutions to seek riskier positions by holding more leverage.

Meltzer (1967) delves into a useful discussion concerning the regulation of the banking sector. He explains that regulation will serve the public interest only if the benefit it provides outweighs its costs. Regulating the banking industry as he explains is premised on a few economic principles, the first being the costs of having a banking monopoly. The paper highlights that the economies of scale associated with the banking sector can perpetuate a monopoly particularly through acquisitions and mergers, hence regulation which makes entry onerous and puts restrictions on the type of products banks can acquire is important. On the other hand he explains that high levels of competition in the banking sector can also be problematic since it can lead bankers to take high risks in an attempt to make profits, much of which was seen with the 2008 financial crisis. As such both monopolies and high levels of competition in the banking sector can be problematic and therefore regulation must be introduced to minimise costs on both sides.

The discourse on bank regulation has deepened with the advent of the recent financial crisis, on the heels of the 2008 catastrophe has come a re-evaluation of capital standards and a push toward tighter supervision and regulation of an important sector (Basel III accord). After much relaxed regulation, financial innovation, off balance sheet activities and products that bankers used at their discretion to garner profits there has been increased attention paid to the assets banks hold and the quality of those assets, a lesson learned from the crisis. Despite the costs associated with increased regulation it is important that the risks in the banking sector are adequately monitored and managed. The systemic nature and run on effects of a bank failure can have detrimental impacts to an economy as was witnessed by the most recent crisis. The impact of one bank on the system must be closely studied by regulators, no longer is banks' own risk of failure limited to that particular institution, moreover Acharya (2009) shows that focusing on one bank's capital requirements fail to discourage risk shifting by banks, something that can seriously affect the health of the financial sector. Similarly Altunbas et al (2007) found that European banks holding higher levels of capital tended to be lower risk takers, a finding that stands in contrast to Blum (1999) who argues that stricter capital requirements on the banking sector contributes to increased risk taking by banks.

Despite the seemingly apparent link between regulation and bank failure where one might assume that higher levels of regulation minimise the risk of bank failure, Cagan (1965) argues the opposite. He found that there exists no link between recession severity and bank failure, some banks have failed in short downturns and there appears to be limited relation between bank failures and the depth of a recession.

The argument for or against stricter bank regulation is far and wide and has been investigated in the literature for quite some time. While increased regulation has its merits Friedman and Schwartz (1971) show that while the implementation of the FED did indeed minimise bank runs, they still occurred and as such regulation has not been successful at eliminating crisis in the financial sector. The recent crisis speaks to the impact of lax regulation and the detrimental and lasting effects which can trickle down to other sectors and the overall economy. In light of this, the importance of regulatory traffic lights for the financial sector is warranted to ease the possibility of devastation in the financial sector.

The case of Northern Rock as investigated by Brummer (2007) highlights the misgivings of the regulator and rests the blame squarely on the Financial Services Authorities shoulders along with the Bank of England. The regulatory vanguards were thought to allow the institution to operate in a manner that was detrimental, their reliance on as the author puts it "unreliable wholesale funding" and their ability to command a large share of the mortgage market in comparison to major players should have raised alarm bells with the regulatory bodies. The piece points to the need for proper regulation and not simply more or less regulation.

Tsuji (1999) addresses the link between bank failure and the capital ratio. Contrary to more recent findings the author argues that there may exist a positive relationship between higher levels of capital ratio and bank failure. Generally one would argue that this acts as a buffer for the bank in times of hardship the bank can rely on its capital to absorb any major losses. On the other hand Tsuji argues that higher levels of this ratio may lead to "diversification loss" as the bank may opt to lower its risk weighted assets by giving fewer loans and thereby ultimately affects the banks ability to turnover loans. Lending and investment is the corner stone of banking business and the inability to do this is seen to adversely affect bank health by the author.

Along the same trend of thought as Tsuji (1999), Blair and Heggestad (1978) propose the idea of over regulation that actually increases the probability of failure of a bank. The banks mandate is profit maximisation in the model developed and the regulatory agents seek to minimise the risky behaviour of the bank to minimise or eliminate negative externalities. However the authors explain that the banks profitability is based on its ability to engage in risk and heavy regulation to mitigate such risky behaviour adversely affects the bank's profitability.

Bernauer and Kobi (2002) argue that there exists a predicament regarding stricter versus more lenient banking regulation and that regulators must find the right balance. The paper explains that stricter bank regulatory policies can lead to a credit crunch but prevent bank failure and there in lies the dilemma regulators face. The analysis is based on approximately 100,000 bank years in the 1990's and focuses on banks that face challenges, that is, have high non-performing loan ratios and are poorly capitalized. The authors point to a behavioural pattern of weak banks which sees them increasing their capital asset ratios during times of economic downturn, versus stronger banks who lower this ratio.

2.2.2 Bank failure and the financial stability concept

Financial stability has generated much discourse given the financial crisis and previous crises which have served to destabilise markets. Though one general definition has not been settled there have been varying degrees of the description of financial stability. Crockett (1997), Mishkin (1999), Oosterloo and Haan (2003), Miskin and Herbertsson (2006) all define financial stability in terms of what it is not (financial instability). Financial instability as Mishkin and Herbertsson (2006) elucidate is founded in the imperfect information that plagues financial and many other markets, this gives rise to the moral hazard and adverse selection problems in the financial industry and hence can be defined as:

Financial instability occurs when there is a disruption to financial markets in which asymmetric information and hence adverse selection and moral hazard problems become much worse, so that financial markets are unable to channel funds efficiently to those with the most productive investment opportunities. Mishkin (1996)

The subprime market scandal however was initiated by lack of information on the intricacies of products spun by investment banks and the willful selection of individuals who were knowingly at the lower end of the lending spectrum. As the real estate market was hit by surging house prices coupled with variable rate mortgages tied to the value of the homes, such increases meant that low-income families were unable to afford their now excessively high mortgage payment. This in addition to the low credit quality of mortgage backed securities and collateralized debt obligations saw an exponential surge in mortgage defaults.

In an attempt to mitigate the impacts of risk associated with the banking sector from hampering the financial sector the Basel Committee on Banking Supervision implemented strict capital requirement rules that banks must abide by to minimise their exposure to credit risk. Banks had to hold capital as a percentage of their risk weighted assets as assets were classified into different risk weighted categories. Low risk holdings, such as cash, were assigned 0 per cent risk weight while risky assets were assigned 100 per cent risk weighting with varying per cents in between.

The birth of Basel 1 in 1988 was the pilot program and focused mainly on achieving financial stability through minimising credit risk. Since the Basel I accord, Basel II and Basel III have been developed. The Basel III accord has come about due to the recent financial crisis and has been updated to ensure that individual banks pay particular attention to improving supervision, liquidity and funding. The aim of Basel III is to aid banks in cushioning economic shocks that may have detrimental impacts.

The report entitled Basel III: A global regulatory framework for more resilient banks and banking systems (2010) p.1 states that:

"One of the main reasons the economic and financial crisis, which began in 2007, became so severe was that the banking sectors of many countries had built up excessive on and off-balance sheet leverage. This was accompanied by a gradual erosion of the level and quality of the capital base. At the same time, many banks were holding insufficient liquidity buffers. The banking system therefore was not able to absorb the resulting systemic trading and credit losses nor could it cope with the reintermediation of large off-balance sheet exposures that had built up in the shadow banking system."

As a result the main impetus of the Basel III accord is to ensure that capital buffers are improved and liquidity measures are in place to shore up the banking sector and minimise the possible reoccurrence of the 2007 crisis. The tighter controls with regard to capital will come in the form of:

- Strengthen the capital base by

    1. Increase in capital requirements for common equity from 2 per cent to 4.5 per cent of risk weighted assets.
    2. Increase in tier 1 ratio from 4 per cent to 6 per cent.
    3. Excluding the use of tier 1 debt and tier 2 debt (closer to bonds) instruments which are hybrid as they include an element of debt and equity.
    4. Combining both tier 1 and tier 2 capital.
    5. Eliminating tier 3 capital.

6. Ensuring that all capital is disclosed.

- Capturing a wide range of risks

  1. Subject to 12 months of stress a new computation for value at risk will be devised and capital requirements will depend heavily on this computation of the risk of investments.
  2. Higher levels of capital are to be held for re-securitisation.
  3. The risk of counterparty exposure is to be met with the holding of larger capital buffers.

- Inclusion of a leverage ratio

  1. discouraging the accumulation of leverage and seeking to limit the ability of firms to engage in systematic and harmful deleveraging..
  2. ensuring that the computation of the leverage ratio is consistent to ensure comparisons can be made.

While the Basel III accord has been proposed to mitigate the impacts felt in the financial sector many argue that its implementation will stunt economic growth and dampen the extension of credit by the banking sector (Allen et al (2012)). Slovik and Cournede (2011) highlight the macroeconomic impacts resulting from the Basel III accord. They show that consumers will be subjected to higher interest rates on credit as banks will pass on higher funding costs to consumers. They estimate that a one percentage point increase in a bank's capital to risk weighted assets ratio will increase lending spreads by 15 basis points. The stricter capital requirements are also shown to feed a slow down in economic growth resulting from discouraged investment due to higher borrowing costs.

In direct contrast the paper "Fallacies, Irrelevant Facts, and Myths in the Discussion of Capital Regulation: Why Bank Equity is Not Expensive" by Admati et al (2011) put forward arguments in favour of higher capital holdings. They explain that there are no opportunity cost and inefficiencies associated with higher equity holdings as suggested by Hellman et al (2000),Slovik and Cournede (2011) and Allen (2012) and much of the banking literature. Admati et al (2011) conjecture that "bank equity is not expensive, regulators should use equity requirements as a powerful, effective, and flexible tool with which to maintain the health and stability of the financial system."

Despite the arguments in favour of and against higher capital holdings one conclusion is clear, the bank system has to be closely monitored and regulated to prevent a recurrence of the recent financial crisis. The impetus of ensuring and maintaining financial stability lies with the regulatory bodies. Lax regulation was the corner stone of the crisis and stemming from this experience comes the burgeoning of a new era of tighter controls and more prudent regulation. There is a direct link between regulatory action and financial stability and going forward regulatory bodies have a vested interest in ensuring they are at the helm of a stable financial ship.

2.2.3 The US financial system and its financial institutions

The Federal Reserve acts as the Central Bank in the United States of America. Being at the helm of the financial system means that the reserve holds supervisory and regulatory responsibilities for the institutions that make up the financial system in the US. According to the report entitled 'The Federal Reserve System: Purposes and Functions' *"there exists a clear but sometimes confused distinction between supervision and regulation as per the Reserve's responsibilities......Bank supervision involves the monitoring, inspecting, and examining of banking organizations to assess their condition and their compliance with relevant laws and regulations........Bank regulation entails issuing specific regulations and guidelines governing the operations, activities, and acquisitions of banking organizations."*

To fully comprehend the role the Federal Reserve currently plays in the upkeep of the financial system and how those roles and responsibilities have altered overtime one must first fully grasp the history of the institution. The fed came into being in 1913 following a particularly severe run on the banking industry due to flailing confidence which sparked panicked bank runs.

The inception of the Federal Reserve also saw the enactment of laws to aid it's functioning and the stability of the US financial system. The Great Depression resulted in a tumultuous financial system and the Emergency Banking Act and the Banking Act were implemented in 1933. The former grants the office of comptroller of currency the power to oversee any national bank threatened with failure while the latter saw the establishment of the Federal Deposit Insurance Corporation (FDIC) in an attempt to bring some stability to the financial system. With the FDIC it was noted that bank runs posed less of a threat to the financial system.

Apart from the Fed there are other regulators who ensure the smooth functioning of the US financial system, table 2.5 identifies some other regulatory agencies. The FDIC also shares joint supervisory responsibility with the FED for the US banking system. Under the purview of the FDIC falls approximately 4,500 state chartered banks and 400 state chartered thrifts. The institution also acts as the deposit insurer for banks and has an important role as a supervisory authority after the FED.

Another important institution in the artillery of regulators is the Office of the Comptroller of Currency (OCC), this institution was chartered in 1863 by the National Currency Act and is responsible for approximately 1,500 national banks and also oversees branches of foreign banks. Another body listed in the table is the Office of Thrift Supervision (OTS), established in 1989 OTS stands as a supervisor of savings and loan holding companies, federal and state thrifts.

Table 2.4 gives some players in the US financial system and their share of the system

Tab. 2.4: US Financial System Structure 2002-2014

	2002		2007		2008		2009		2010		2014 q3	
	% share	% GDP	% share	% GDP	% share	% GDP	% share	% GDP	% share	% GDP	% share	% GDP
Fed	**1.9**	**6.9**	**1.4**	**6.4**	**3.6**	**15.1**	**3.6**	**15.7**	**4.0**	**16.0**	**5.0**	**26.0**
Depository institutions	**24.0**	**88.3**	**22.1**	**97.8**	**25.9**	**109.0**	**25.9**	**112.6**	**25.0**	**113.6**	**26.0**	**120.0**
Commercial banking	19.1	70.0	18.0	79.5	22.1	92.8	22.5	97.8	19.0	86.0	19.0	89.0
U.S.-chartered commercial banks	*14.1*	*51.8*	*13.3*	*58.7*	*15.9*	*67.1*	*16.0*	*69.5*	*17.0*	*77.0*	*16.0*	*76.0*
Foreign banking offices in U.S. 2/	*2.1*	*7.7*	*1.6*	*7.1*	*2.6*	*10.9*	*2.0*	*8.8*	*2.1*	*8.9*	*3.0*	*13.0*
Banks in U.S.-affiliated areas	*0.2*	*0.7*	*0.2*	*0.8*	*0.2*	*0.7*	*0.2*	*0.7*	*0.0*	-	-	-
BHCs 3/	*2.7*	*9.8*	*2.9*	*12.9*	*3.4*	*14.2*	*4.3*	*18.8*	-	-	-	-
Savings associations 4/	3.5	12.9	2.9	12.9	2.5	10.5	2.0	8.7	-	-	-	-
Credit unions	1.5	5.4	1.2	5.4	1.3	5.6	1.4	6.1	1.0	6.0	1.0	6.0
GSEs	**14.8**	**54.5**	**12.3**	**54.3**	**13.7**	**57.8**	**13.3**	**58.0**	**11.0**	**53.0**	**10.0**	**45.0**
Agencies and GSEs 5/	6.6	24.4	5.1	22.5	5.6	23.5	4.8	20.9	10.0	45.0	8.0	36.0
Agency- and GSE-backed mortgage pools 6/	8.2	30.2	7.2	31.7	8.2	34.4	8.5	37.2	2.0	8.0	2.0	9.0
“Shadow banking system”	**21.4**	**78.5**	**23.5**	**103.9**	**24.5**	**103.3**	**20.9**	**90.8**	**18.0**	**80.0**	**13.0**	**62.0**
Issuers of ABSs	5.1	18.9	7.3	32.1	6.7	28.4	5.4	23.4	3.0	15.0	2.0	8.0
Money market mutual funds7/	5.8	21.2	4.9	21.5	6.2	26.0	5.2	22.5	4.0	18.0	3.0	15.0
Securities broker-dealers	3.5	12.8	5.0	22.0	3.6	15.4	3.3	14.4	5.0	23.0	4.0	19.0
Finance companies	3.8	13.8	3.1	13.6	3.0	12.8	2.6	11.5	2.0	11.0	2.0	8.0
Real estate investment trusts	0.3	1.0	0.5	2.2	0.4	1.8	0.4	1.8	0.0	2.0	1.0	4.0
Funding corporations 8/	2.9	10.8	2.8	12.4	4.5	18.9	4.0	17.2	2.0	11.0	2.0	8.0
Insurance companies	**11.1**	**40.8**	**10.1**	**44.8**	**9.6**	**40.3**	**9.8**	**42.9**	**10.0**	**44.0**	**9.0**	**44.0**
Life insurance companies	8.7	31.9	8.0	35.2	7.4	31.3	7.7	33.4	8.0	35.0	7.0	35.0
Property and casualty insurance companies	2.4	9.0	2.2	9.7	2.1	9.0	2.2	9.5	2.0	9.0	2.0	9.0
Investment and pension funds	**26.8**	**98.3**	**30.5**	**134.6**	**22.7**	**95.5**	**26.5**	**115.4**	**33.0**	**151.0**	**36.0**	**170.0**
Mutual funds	9.5	34.8	12.6	55.6	8.9	37.6	11.1	48.2	11.0	53.0	15.0	70.0
Closed-end and exchange-traded funds	0.4	1.4	0.5	2.3	0.3	1.4	0.4	1.6	0.0	2.0	0.0	2.0
Private pension funds	9.6	35.1	10.3	45.4	7.6	31.9	8.7	37.9	10.0	44.0	10.0	48.0
State and local government retirement funds	5.0	18.4	5.2	22.8	3.8	16.1	4.3	18.6	7.0	32.0	7.0	31.0
Federal government retirement funds	2.3	8.5	1.9	8.5	2.0	8.5	2.1	9.2	5.0	21.0	4.0	21.0
Total financial system	**100**	**367.3**	**100**	**441.8**	**100.0**	**421.0**	**100.0**	**435.4**	**100.0**	**457.6**	**100.0**	**467.0**

Source: http://www.imf.org/external/pubs/ft/scr/2015/cr15170.pdf

Tab. 2.5: Federal supervisor and regulator of corporate components of banking organizations in the United States

Component	**Supervisor and regulator**
Bank holding companies (including financial holding companies)	FR
Non-bank subsidiaries of bank holding companies	FR/ Functional regulator
National banks	OCC
State banks	
Members-state chartered banks that chose to join the FED	FR
Non-Members	FDIC
Thrift holding companies	OTS
Savings banks	OTS/FDIC/FR
Savings and loan associations	OTS
Edge and agreement corporations	FR
Foreign banks	
Branches and agencies	
State licensed	FR/FDIC
Federally licensed	OCC/FR/FDIC
Representative offices	FR

Source: https://www.federalreserve.gov/pf/pdf/pf_5.pdf

Note: FR= Federal Reserve; OCC= Office of the Comptroller of the Currency; FDIC= Federal Deposit Insurance Corporation; OTS= Office of Thrift Supervision along with overall contribution to GDP. Following the FED the main supervisor of the financial system, note that private depository institutions account for 26 per cent of the financial system in 2014 q3 and hold assets worth 120 per cent to overall GDP. These private depository institutions consist of commercial banks, savings associations and credit unions, of which commercial banks account for the lion's share of the financial system under this category.

Over the period 2002 to 2014 q3 the depository institutions and investment and pension funds maintained their role as dominant agents in the financial system accounting for over half of the system by 2014 q3. Commercial banking continues to dominate the depository institutions accounting for 19 per cent of the system by 2014 q3, a small decline from the 2008 and 2009 levels which saw a mass of banks default in light of the subprime scandal and the ripple effect that was felt through the banking sector.

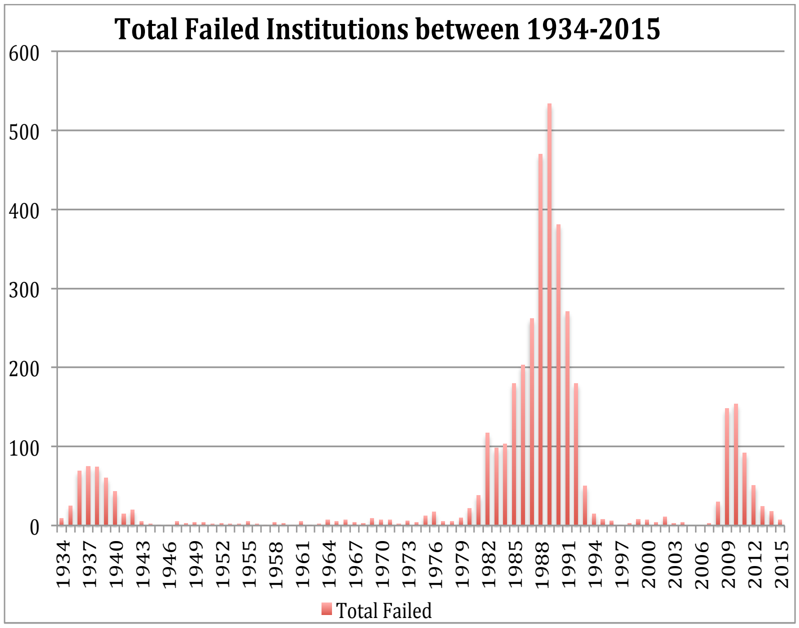
While the depository institutions and the investment and pension funds seem to maintain growth over the period in the table, of great importance is the shadow banking category and its gradual decline from 24.5 per cent in 2008 to a mere 13 per cent in 2014 q3. Shadow banking is defined by Pozsar et al (2010) as "Shadow banks are financial intermediaries that conduct maturity, credit, and liquidity transformation without access to central bank liquidity or public sector credit guarantees. Examples of shadow banks include finance companies, asset-backed commercial paper (ABCP) conduits, limited-purpose finance companies, structured investment vehicles, credit hedge funds, money market mutual funds, securities lenders, and government-sponsored enterprises." The paper goes on to describe this phenomena as being "interconnected along a vertically integrated, long intermediation chain, which intermediates credit through a wide range of securitization and secured funding techniques such as ABCP, asset-backed securities, collateralized debt obligations, and repo." This aspect of the financial system has received much criticism in the role it played in the financial crisis, being accused of saturating the market with liquidity created from risky assets.

2.2.4 Historical overview of bank failures 1934-2015

Figure 2.1 shows the total failures recorded by the FDIC between 1934-2015 in the US banking system. According to the FDIC database this total institution failure figure is inclusive of institutions that were granted assistance from the FDIC, hence some years have greater numbers when compared to table 2.6. The FDIC explains that these institutions were analysed based on systemic risk and seen to warrant assistance.

The chart gives an account of the timeline of events associated with major failure events in US history over the period 1934-2015. Significant occurrences that have impacted the number of failures at any point in time are documented in the timeline. The first spike in bank failure seen in the chart came as a result of the great depression 1929-1939. According to the FDIC historical timeline the depository insurance scheme came into effect in 1934, in that same year approximately 9 FDIC insure banks in that

Fig. 2.1: Total US Bank Failures between 1934-2015



year. During the depression Roosevelt commenced relief programs in an attempt to combat the depression. Between 1937-1938, the administration began cutting relief programs as the belief that the depression was over loomed. The US economy soon slipped back into a recession that saw the default of banks up until 1940.

The second significant spike in the defaulted bank data occurred between 1982-1992 . The weakening US economy see the closures of more banks. According to the historical timeline posted by FDIC, in 1982 "Penn Square Bank in Oklahoma City fails with $511 million in assets. The bank had generated billions of dollars in speculative oil and gas exploration loans, many of which are worthless. To support its rapid growth, the bank had sold participations in energy loans to large regional banks, including Continental Illinois ($1 billion) and Chase Manhattan Bank of New York ($212 million)." In the following years bank failures exceeded 100 due in part to lax regulation and a weakening economic background. In 1989 over 200 banks fail, most of which are situated in Texas. The last round of bank defaults came into being following the 2007 financial crisis.

2.3 Data and Methodology

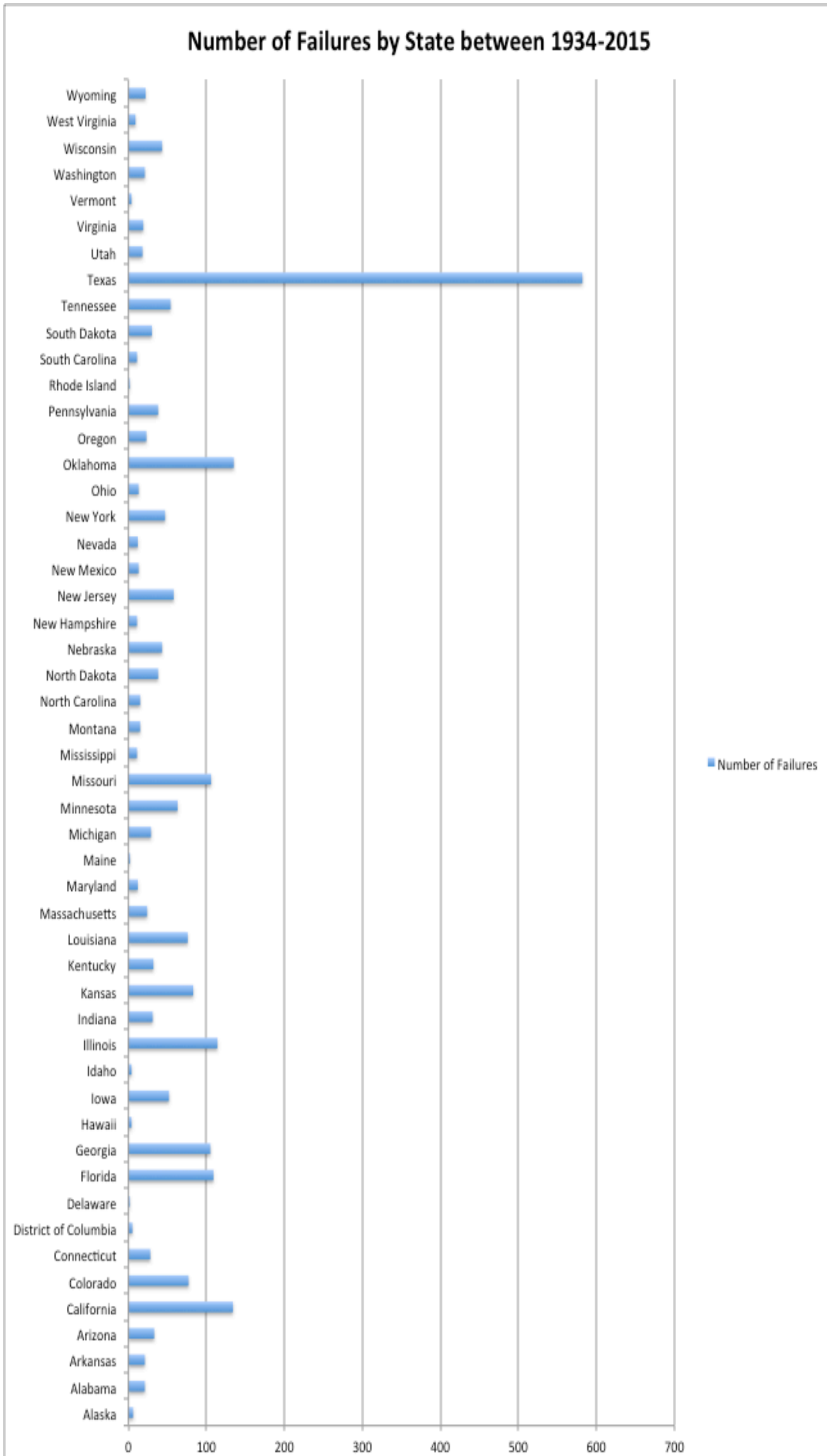
In this section we discuss the data used in the model, the data sources and the methodology used. The paper uses data gathered from the Federal Deposit Insurance Corporation which lists defaulted and non-defaulted banks. The FDIC database lists banks as defaulted when they have ceased operation or been merged with government assistance. Between 1990-2015 the database lists 896 banks as defaulted and provides balance sheets and income statements for these defaulted banks. The data is based on commercial banks from the United States (50 states and DC) and is collected for all funds under the FDIC (these include DIF- deposit insurance fund, BIF- bank insurance fund, SAIF- savings insurance fund) and all failures. The research is developed on quarterly data. A panel logit model is used for both the accounting and structural models. Of note accounting data for failed banks is only available from 1992 and recorded for banks that defaulted in 1993, as such the stata data set is based on a panel data set commencing 1993-2015.

2.3.1 Panel logit model

The logistic model is a binary response model and can be used to give the probability that an event will occur given the variables said to explain the event. In this case the logit model is used in the analysis of bank failure where Y is a Bernoulli distribution such that:

$$p\{Y_t|X\} = \begin{bmatrix} 1 & if\ bank\ year\ t\ is\ the\ year\ of\ default \\ 0 & otherwise \end{bmatrix} \tag{2.6}$$

Fig. 2.2: Total US Bank Failures by State between 1934-2015



Tab. 2.6: Total Commercial Bank Failures between 1990-2015

Failures by Year	
2015	7
2014	14
2013	23
2012	40
2011	84
2010	129
2009	120
2008	19
2007	1
2006	0
2005	0
2004	3
2003	2
2002	10
2001	3
2000	6
1999	7
1998	3
1997	1
1996	5
1995	6
1994	11
1993	42
1992	97
1991	105
1990	158
Total	**896**

Tab. 2.7: Total Commercial Bank Failures by State between 1990-2015

Failures by State		
Alabama	AL	5
Alaska	AK	0
Arizona	AZ	24
Arkansas	AR	6
California	CA	88
Colorado	CO	20
Connecticut	CT	24
Delaware	DE	0
Florida	FL	84
Georgia	GA	91
Hawaii	HI	4
Idaho	ID	1
Illinois	IL	62
Indiana	IN	4
Iowa	IA	3
Kansas	KS	14
Kentucky	KY	1
Louisiana	LA	15
Maine	ME	1
Maryland	MD	7
Massachusetts	MA	16
Michigan	MI	12
Minnesota	MN	24
Mississippi	MS	4
Missouri	MO	24
Montana	MT	2
Nebraska	NE	2
Nevada	NV	11
New Hampshire	NH	10
New Jersey	NJ	14
New Mexico	NM	8
New York	NY	12
North Carolina	NC	8
North Dakota	ND	3
Ohio	OH	6
Oklahoma	OK	19
Oregon	OR	6
Pennsylvania	PA	5
Rhode Island	RI	1
South Carolina	SC	8
South Dakota	SD	1
Tennessee	TN	7
Texas	TX	186
Utah	UT	7
Vermont	VT	2
Virginia	VA	8
Washington	WA	19
	DC	5
West Virginia	WV	2
Wisconsin	WI	8
Wyoming	WY	2
Total		**896**

Tab. 2.8: Commercial Bank Failures by Asset Size between 1990-2015

Year	Small Banks (Under US $1 billion)	Medium Banks (Between US $1-$10 billion)	Large Banks (Over US $10 billion)	**Total**
2015	7			**7**
2014	14			**14**
2013	22	1		**23**
2012	39	1		**40**
2011	81	3		**84**
2010	117	12		**129**
2009	99	19	2	**120**
2008	15	4		**19**
2007	1			**1**
2006				
2005				
2004	3			**3**
2003	2			**2**
2002	9	1		**10**
2001	3			**3**
2000	6			**6**
1999	6	1		**7**
1998	3			**3**
1997	1			**1**
1996	5			**5**
1995	6			**6**
1994	11			**11**
1993	42			**42**
1992	94	3		**97**
1991	99	4	2	**105**
1990	157	1		**158**
Total	**842**	**50**	**4**	**896**

The logit model can predict the likelihood of a bank falling into the defaulted category based on the explanatory variables. Following the evaluation of the probability of default (equation 2.7) and the probability of no default (equation 2.8) we can then calculate the odds ratio. The odds ratio as seen in (equation 2.9) is the probability that a bank year is a defaulted year divided by the probability that it is not.

$$p\{Y=1|X\} = \frac{e^{X\beta}}{1+e^{X\beta}} \tag{2.7}$$

$$p\{Y=0|X\} = 1 - \langle\frac{e^{X\beta}}{1+e^{X\beta}}\rangle = \frac{1}{1+e^{X\beta}} \tag{2.8}$$

The odds ratio is given by equation (7) divided by equation (8)

$$oddsratio = \frac{p\{Y=1|X\}}{p\{Y=0|X\}} = \frac{\frac{e^{X\beta}}{1+e^{X\beta}}}{\frac{1}{1+e^{X\beta}}} = e^{X\beta} \tag{2.9}$$

If we take the natural logarithm of the odds ratio we get the equation below. While probabilities are restricted to values between 0 and 1 this transformation pins the logit model to values on $\mathbb{R}$. Note that as the probability values near 0 the odds ratio is zero meaning the event coded as default is unlikely to occur, in this instance the logistic model will tend to -∞. Conversely as the probability tends to 1 both the odds ratio and the logistic transformation will tend to $+\infty$.

$$ln\langle oddsratio\rangle = ln\langle\frac{\frac{e^{X\beta}}{1+e^{X\beta}}}{\frac{1}{1+e^{X\beta}}}\rangle = ln\langle e^{X\beta}\rangle = X\beta \tag{2.10}$$

2.3.2 Principal component analysis

By nature most accounting variables tend to be highly correlated, as such the logistic accounting model posed some problems as many important accounting variables were deemed insignificant or the signs were not sensible. In an attempt to make use of the accounting variables identified in the following section and to overcome the problem of correlated explanatory variables the paper uses the Principal Component Analysis (PCA) methodology. PCA is essentially a variable reduction method that allows the researcher to reduce the number of explanatory variables in a model while retaining most of the information contained in those variables. As mentioned above the correlation of the explanatory variables can give spurious results and as such we can explore methods to reduce the number of variables by creating “new” variables called principal components. The components that result from this exercise can then be used in the econometric analysis.

The literature defines a principal component “as a linear combination of optimally weighted observed variables”. A principal component for n variables is computed as follows:

$$C_n = \sum \beta_n X_n \tag{2.11}$$

Where:

C_n is the principal component

β_n is the coefficient for the variable X_n (given by solving an eigenequation)

X_n is the first explanatory variable

Of note, a model with n explanatory variables will have n number of principal components. One may then question the idea of PCA being a variable reduction method when the number of components equals the number of explanatory variables. However only the first few components usually three to four are utilised as these tend to explain the majority of variation in the data and are therefore used in the econometric analysis.

The principal components or the 'new' variables have certain characteristics, the first component will explain the majority of the variation in the data and as such will be correlated with the explanatory variables. The second component will explain the variation that was left unexplained by the first component and this too will be correlated with the explanatory variables. Similarly the third component will explain the variation that again was left unexplained by the first two components and this process will carry on until we have n components, with n being equal to the number of explanatory variables, explaining 100 per cent of the variation in the data. More importantly, while the principal components are correlated with the explanatory variables, they are orthogonal to each other.

The chapter uses STATA to run the logistic model and perform the PCA analysis, however the author thought it necessary to give a mathematical analysis of what the PCA method entails and the basic steps behind the transformation of the data.

In the accounting model there are 10 explanatory variables and in the structural model there are 3. The first step the PCA method performs is subtracting the mean of each explanatory variable from each value as such we have $x - \bar{x}, y - \bar{y}, z - \bar{z}$ and so forth. By performing this operation the data set is transformed to one having a zero mean. After which the covariance matrix of the zero mean data set is compiled.

$$cov(y, z) = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(z_i - \bar{z})}{n - 1} \tag{2.12}$$

$$cov(x, y, z) = \begin{bmatrix} xx & xy & xz \\ yx & yy & yz \\ zx & zy & zz \end{bmatrix}$$

Following the compilation of the covariance matrix for the data, the PCA method then extracts the eigenvectors and eigenvalues associated with the covariance matrix. Stata then lists the eigenvalues from largest to smallest with the largest eigenvalue being the first principal component and displaying the strongest relationship with some data. In the explanation of the general PCA methodology above we indicated that the number of principal components extracted are equal to the number of explanatory variables in the data set. As such all principal components are listed with the matching eigenvalues in descending order. Although the number of components are equal to the number of explanatory variables, as explained in the previous section, only the first few principal components usually explain the majority of variation in the data and so usually the first four components or less are chosen to be retained.

The choice of the principal components to be used in the econometric analysis leads to the final step in the PCA process where the original data set is transformed based on the eigenvectors that are retained. Where the final data is the zero mean data set(which is transposed) multiplied by the eigenvector matrix that was retained.

2.3.3 Research variables

Dependent variable

This research uses the year of bank default as the dependent variable. If the bank has defaulted in yr t it is coded as 1 the years of no default is coded as 0. The dependent variable is binary in nature. Bank failure is defined by FDIC as closure of a bank by the federal or state regulatory body.

Independent variables

The independent variables used in this work consist of financial ratios which represent the accounting model approach, structural model variables and macroeconomic variables.

Financial ratios

A total of 118 variables were collected from the FDIC database ranging from balance sheet and income statement variables to performance and condition ratios. The final selection of financial ratios and balance sheet/income statement data was selected based on the CAMEL methodology and existing literature investigating the ability of account data and financial ratios to determine bank default.

The accounting and financial ratios in the model were taken directly from the FDIC database under the balance sheet, income statement, performance and condition ratios. The idea is to utilise the balance sheet, income statement and other performance ratios that can give a sense of the financial soundness of the institution as popularised by the CAMEL rating system and the IMF Financial Soundness Indicators (FSI's). Notably a few of the ratios have been used in other works of a similar nature and have made significant contributions to the existing literature. This section looks at each explanatory variable in the original accounting model and gives an explanation of the financial ratio and its expected sign and contribution to the overall understanding of bank default.

Log Total Assets (lta) according to Cole and White (2012) banks that are relatively smaller in the financial system have a higher probability of failure since they do not have the large capital buffers and support of the governing bodies like their larger counterparts. This lends itself to the "too big to fail" analysis where larger banks despite their investment in many toxic assets generally garner the support from the government and banking regulators to prevent failure.

Cash and due from depository institutions (cash), liquidity is an important aspect of bank default estimation since a liquidity strain caused by bank runs can have devastating effects on bank business. The measurement of liquidity risks has become imperative in the discussion of bank stability and as such this variable is considered in the model. A priori it is expected that the probability of failure will be dampened by banks that hold more liquidity.

Securities (secure) this variable on the balance sheet was included in an attempt to understand the nature of banks "safe" investments as investing in securities was considered less risky that some other investments banks may make. On the other hand the subprime crisis saw banks investing in products that turned out to be toxic and resulted in failure of some banking institutions. This variable is expected to have a negative coefficient since it is expected that investing in securities will minimise the bank's probability of failure.

Goodwill (good) as stated in Cole and White (2012) this variable could have unprecedented power in explaining default for those banks that may have acquired other banks. It looks at the firm value over and above the book value of the bank.

Total bank equity (tbe) this variable is defined as the difference between a bank's assets and liabilities, it stands as the value of the bank to investors. This variable is expected to lower the probability of default of the bank.

Efficiency Ratio (er) this variable looks at the bank's ability to generate revenue from the set of resources at its disposal. It speaks to the overall health of the bank and lower ratios signal improvements in revenue generation. Higher efficiency ratios will be attributed to a higher risk of failure.

Non-current loans and leases (noncurrentll) this represents the monetary value of over due loans and leases on the banks books. The expectation is that an increase in the monetary value of the non-current portfolio should indicate problems in the bank and speak to a higher probability of default. Non-current loans to assets (noncurrentltas) is also included in the analysis.

Non-Interest Expense to Assets (niea) this ratio gives all expenses as a per cent of assets. Expenses include salaries, benefits, bonuses, fixed assets, land and building etc. The excessive growth of expenses in relation to assets and gross income is a concern for institutions particularly where bonuses are excessive and can lead to financial strain on a bank. The expected sign in the model for this financial variable is positive as the ratio increases it is expected that the probability of default also increases. Of course this ratio cannot be analysed in isolation as expenses may increase due to increased acquisition of land and building etc.

Return on Assets (roa) this ratio is computed as net income after taxes as a per cent of assets, it is a profitability ratio and measures an institutions ability to efficiently utilise their assets. The expected sign in the panel logit model is negative, as one would expect the probability of default to decline as ROA increases.

Loss Allowance to Non-current Loans (lancl) is computed by the allowance for losses and leases divided by non-current loans, it measures where losses are accurately being catered for. The expected sign in the logit model is negative. As the ratio falls due to lower allowances or higher non-performing loans there maybe an inherent problem. Increasing non-current loans usually indicate strains on a bank and lower allowances reduce the buffer the bank has to hedge against a deteriorating loan portfolio. As such a lower ratio maybe indicative of higher default probabilities, thus the negative sign.

Non-current Assets plus other real estate to assets (ncaoreta) is another ratio used in the logit model, defined as non-current assets which comprise of assets past due 90 days or more or assets placed in accrual status, as a per cent of assets. With the mortgage problems faced by US banks with the sub-prime crisis it is thought that this ratio is significant. A priori we expect the sign to be positive in the logit model, if the ratio increases due to rising non-current assets or falling assets, this would indicate some possibility of default thereby increasing the default probability.

Non-current Loans to Loans (ncll), non-current loans and leases divided by gross loans. This ratio is a measure of the quality of assets in the bank's portfolio and can be used to identify any possible problems. The expected sign is positive, the ratio may increase due to increasing non-performing loans or a shrinking loan portfolio all of which maybe indicative of problems.

Net Loans and Leases to Core Deposits (nlltcd), loans and leases as a per cent of core deposits. According to the IMF this ratio can be used in the analysis of liquidity problems in an institution, they explain that an excessively high ratio indicating that deposits are falling as core depositors unexpectedly withdraw deposits or the bank experiences a run, may speak to liquidity stress in an institution. As such we expect a positive sign in the logit model.

Tier1 Risk Based Capital Ratio (tier1rbc) this is core capital as a per cent of risk-weighted assets. This ratio is based on the Basel Committee on Banking Supervision's guidelines in capital adequacy measurement. A priori we expect a negative sign with this capital adequacy ratio, as capital increases or risk-weighted assets fall the ratio will increase and the probability of default should decline.

Core Capital Leverage Ratio (cclr), according to the FDIC database this ratio is defined as 'Tier 1 (core) capital as a per cent of average total assets minus ineligible intangibles' and also acts as a capital adequacy measure as such we also expect a negative sign a priori.

Also included in the model are macroeconomic variables in particular the gross domestic product (gdp) and the 3 month t-bill rate (tbill). As the GDP declines suggesting an economic downturn in the economy, one would expect the banking sector to have some response as this sector acts as the lifeline for many other sectors as it channels funds. The inability to channel funds to investment projects due to a slow down in economic growth or economic decline may mean that the banking sector experiences a significant slowdown, which could lead to default.

In investigating the different variables that may influence bank default it is observed that there are some differences between the variables in the years of no default versus the year of default as would be expected the year of default sees some variables exacerbated compared to the year of no default. Table 2.10 gives some summary statistics on the data split into defaulted years versus non-defaulted years. In particular the variable tbe (total bank equity) is significantly lower in the defaulted years registering a mean of \$11,097.58 as opposed to \$35,508.40 in the non- defaulted years possibly indicating the importance of bank equity in analysing the default of a bank. This broad measure of equity capital drops significantly in the year of default. Additionally the variable non-current loans and leases rises drastically in the defaulted years averaging \$54,109.37 versus \$9,458.02 in the non-defaulted years. As one would expect the non-current portfolio tends to give much insight into the banks ability to cope with large loan losses. This variable is usually closely monitored by the regulatory bodies and can give an indication of the possible default of a bank.

Structural model variables

The Merton Model as explicitly explained in the literature review is a framework generally applied to institutions listed on the stock market. Where the volatility of equity, when applied to the Black Scholes option pricing formula, plays a vital role in determining the implied asset values, implied asset volatility, distance to distress and probability of default. In this analysis the banks that are listed on the capital market utilise the general Merton framework to compute the distance to distress, implied asset value and implied asset volatility metrics. However, since most banks in this analysis are not listed on the stock market but are private banks the author engaged an alternative methodology that would allow the inclusion of non-listed banks into the analysis.

Blavy and Souto (2009) developed the Merton risk indicators for the Mexican banking system, despite the fact that most banks in Mexico were not listed. They explained that the analysis relied heavily on the volatility of book value assets as opposed to the volatility in market equity as popularised by the Merton framework. They lament that this method does not have the sophistication of incorporating market information but still grants some useful information in the identification of impending default risk to

Tab. 2.9: Descriptive statistics of variables

Variable	-	Mean	Std. Dev.	Min	Max	Observations	
id	overall	224.5196	135.961	1.000	5.350E+02	N	26141
	between		154.586	1.000	5.350E+02	n	535
	within		0.000	224.520	2.245E+02	T-bar	48.8617
ta	overall	398698.6000	1169660.000	1755.000	2.730E+07	N	17174
	between		940877.400	3228.000	1.720E+07	n	535
	within		529299.800	-15100000.000	1.050E+07	T-bar	32.1009
lta	overall	11.9532	1.261	7.470	1.712E+01	N	17174
	between		1.128	8.079	1.649E+01	n	535
	within		0.674	7.779	1.620E+01	T-bar	32.1009
cash	overall	16853.6300	64986.440	-178.000	2.655E+06	N	17174
	between		33456.210	11.500	5.089E+05	n	535
	within		53510.580	-393685.500	2.362E+06	T-bar	32.1009
secure	overall	59160.8000	220009.100	0.000	5.183E+06	N	17174
	between		164339.000	0.000	2.465E+06	n	535
	within		120922.000	-2110452.000	3.691E+06	T-bar	32.1009
good	overall	3265.0880	31093.970	0.000	1.072E+06	N	17174
	between		21551.960	0.000	4.472E+05	n	535
	within		19721.930	-442784.500	6.277E+05	T-bar	32.1009
tbe	overall	34747.9600	105570.100	-161976.000	2.477E+06	N	17174
	between		82376.990	-2334.000	1.431E+06	n	535
	within		53340.490	-1277821.000	1.081E+06	T-bar	32.1009
noncurrentll	overall	10848.9900	48710.540	0.000	2.625E+06	N	17174
	between		17602.030	0.000	2.535E+05	n	535
	within		44683.390	-242091.700	2.382E+06	T-bar	32.1009
niia	overall	0.0081	0.017	-0.156	4.116E-01	N	17174
	between		0.021	-0.009	3.653E-01	n	535
	within		0.011	-0.217	1.678E-01	T-bar	32.1009
niea	overall	0.0372	0.021	0.000	5.209E-01	N	17174
	between		0.025	0.014	3.248E-01	n	535
	within		0.015	-0.080	4.591E-01	T-bar	32.1009
roa	overall	-0.0029	0.031	-0.795	1.414E-01	N	17174
	between		0.021	-0.131	6.875E-02	n	535
	within		0.028	-0.797	1.392E-01	T-bar	32.1009
er	overall	0.9871	4.912	-355.500	2.538E+02	N	17169
	between		1.264	-11.603	1.640E+01	n	535
	within		4.802	-342.910	2.483E+02	T-bar	32.0916
lancl	overall	9.7899	83.607	0.000	3.513E+03	N	15162
	between		20.507	0.063	2.168E+02	n	534
	within		80.707	-206.815	3.415E+03	T-bar	28.3933
ncaoreta	overall	0.0363	0.060	0.000	6.304E-01	N	17174
	between		0.042	0.000	4.314E-01	n	535
	within		0.055	-0.094	6.216E-01	T-bar	32.1009
nlltcd	overall	1.3562	16.964	-0.123	1.802E+03	N	17162
	between		9.057	0.359	1.632E+02	n	534
	within		16.065	-161.011	1.670E+03	T-bar	32.1386
ccr	overall	0.1085	0.344	-0.130	2.896E+01	N	17173
	between		0.093	-0.049	1.097E+00	n	535
	within		0.336	-0.985	2.852E+01	T-bar	32.0991
tier1rbc	overall	0.1424	0.374	-0.168	3.425E+01	N	17173
	between		0.332	-0.068	7.416E+00	n	535
	within		0.323	-7.244	2.698E+01	T-bar	32.0991
noncurrentltas	overall	0.0256	0.043	0.000	5.946E-01	N	17174
	between		0.027	0.000	3.330E-01	n	535
	within		0.040	-0.070	5.832E-01	T-bar	32.1009
ncll	overall	0.0360	0.059	0.000	7.117E-01	N	17156
	between		0.036	0.000	3.926E-01	n	534
	within		0.056	-0.112	6.806E-01	T-bar	32.1273
gdp	overall	2.5107	2.697	-8.200	7.800E+00	N	26140
	between		0.890	-0.930	4.295E+00	n	535
	within		2.635	-8.588	8.596E+00	T-bar	48.8598
tbills	overall	3.1212	1.878	0.010	6.000E+00	N	26140
	between		0.693	0.286	5.077E+00	n	535
	within		1.781	-0.493	7.432E+00	T-bar	48.8598

Tab. 2.10: Descriptive statistics of defaulted versus non-defaulted years

		Defaulted Bank Years				Non Defaulted Bank Years			
Variable	-	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
id	overall	268.00	154.59	1.00	535.00	223.61	135.40	1.00	494.00
	between		154.59	1.00	535.00		142.75	1.00	494.00
	within		0.00	268.00	268.00		0.00	223.61	223.61
ta	overall	460497.30	1389619.00	3345.00	25500000.00	396711.60	1161892.00	1755.00	27300000.00
	between		1389619.00	3345.00	25500000.00		964710.50	3111.00	17000000.00
	within		0.00	460497.30	460497.30		529200.40	-14900000.00	10700000.00
lta	overall	12.04	1.32	8.12	17.05	11.95	1.26	7.47	17.12
	between		1.32	8.12	17.05		1.11	8.04	16.48
	within		0.00	12.04	12.04		0.68	7.81	16.65
cash	overall	44400.52	135229.10	9.00	1674376.00	15967.91	61212.16	-178.00	2655019.00
	between		135229.10	9.00	1674376.00		32587.44	14.00	482524.70
	within		0.00	44400.52	44400.52		50319.66	-368156.80	2374728.00
secure	overall	54872.83	233737.00	0.00	3988506.00	59298.68	219559.50	0.00	5183085.00
	between		233737.00	0.00	3988506.00		169109.70	0.00	2426281.00
	within		0.00	54872.83	54872.83		121698.50	-2071259.00	3703404.00
good	overall	1539.90	16684.89	0.00	369876.00	3320.56	31446.62	0.00	1071605.00
	between		16684.89	0.00	369876.00		22585.56	0.00	449134.10
	within		0.00	1539.90	1539.90		19963.61	-444710.50	625791.50
tbe	overall	11097.58	52437.05	-161976.00	914497.00	35508.40	106754.90	-16297.00	2477297.00
	between		52437.05	-161976.00	914497.00		86375.50	662.88	1444071.00
	within		0.00	11097.58	11097.58		53303.69	-1290300.00	1068734.00
noncur∼l	overall	54109.37	157352.20	0.00	2625116.00	9458.02	39902.77	0.00	2027892.00
	between		157352.20	0.00	2625116.00		14911.97	0.00	192656.20
	within		0.00	54109.37	54109.37		36553.16	-182671.10	1844694.00
niia	overall	0.00	0.02	-0.16	0.32	0.01	0.02	-0.10	0.41
	between		0.02	-0.16	0.32		0.02	-0.01	0.41
	within		0.00	0.00	0.00		0.01	-0.22	0.17
niea	overall	0.05	0.03	0.01	0.31	0.04	0.02	0.00	0.52
	between		0.03	0.01	0.31		0.02	0.01	0.34
	within		0.00	0.05	0.05		0.02	-0.08	0.46
roa	overall	-0.06	0.06	-0.79	0.07	0.00	0.03	-0.51	0.14
	between		0.06	-0.79	0.07		0.02	-0.11	0.09
	within		0.00	-0.06	-0.06		0.02	-0.44	0.14
er	overall	1.97	13.03	-134.33	201.50	0.96	4.41	-355.50	253.75
	between		13.03	-134.33	201.50		1.05	-12.10	7.73
	within		0.00	1.97	1.97		4.31	-342.45	248.15
lancl	overall	0.66	3.21	0.00	65.67	10.12	85.09	0.00	3513.00
	between		3.21	0.00	65.67		21.86	0.14	222.07
	within		0.00	0.66	0.66		82.05	-211.76	3412.74
ncaoreta	overall	0.16	0.09	0.00	0.49	0.03	0.05	0.00	0.63
	between		0.09	0.00	0.49		0.03	0.00	0.24
	within		0.00	0.16	0.16		0.05	-0.09	0.62
nlltcd	overall	0.94	0.91	0.29	20.69	1.37	17.23	-0.12	1801.77
	between		0.91	0.29	20.69		10.34	0.18	181.27
	within		0.00	0.94	0.94		16.23	-179.03	1659.58
ccr	overall	0.02	0.05	-0.13	0.89	0.11	0.35	-0.10	28.96
	between		0.05	-0.13	0.89		0.10	0.02	1.14
	within		0.00	0.02	0.02		0.34	-1.00	28.51
tier1rbc	overall	0.03	0.10	-0.17	2.02	0.15	0.38	-0.16	34.25
	between		0.10	-0.17	2.02		0.38	0.03	8.24
	within		0.00	0.03	0.03		0.32	-7.97	26.16
noncur∼s	overall	0.11	0.07	0.00	0.49	0.02	0.04	0.00	0.59
	between		0.07	0.00	0.49		0.02	0.00	0.13
	within		0.00	0.11	0.11		0.04	-0.07	0.58
ncll	overall	0.15	0.10	0.00	0.71	0.03	0.05	0.00	0.63
	between		0.10	0.00	0.71		0.02	0.00	0.18
	within		0.00	0.15	0.15		0.05	-0.11	0.61
gdp	overall	1.63	3.08	-8.20	7.10	2.53	2.69	-8.20	7.80
	between		3.08	-8.20	7.10		0.80	-0.98	4.40
	within		0.00	1.63	1.63		2.62	-8.57	8.67
tbills	overall	0.81	1.48	0.01	5.77	3.17	1.86	0.01	6.00
	between		1.48	0.01	5.77		0.71	0.30	5.03
	within		0.00	0.81	0.81		1.76	-0.46	7.45

non listed banks. The method has been successfully employed by Souto (2008) and Souto, Tabak and Vazquez (2008). To assess the volatility in book value assets, it is felt that declining asset values speak more to default than the alternative, as such the method only accounts for falling assets values, which Blavy and Souto term 'downside risks'. A priori we would expect the downward volatility variable to have a positive sign, as asset values become more volatile (downside) the probability of default should rise. The downward volatility of assets is computed as follows below,where σ_A is the asset volatility and A_t is the asset value at time t.

$$\sigma_A = \sqrt{Min(ln(A_t) - ln(A_{t-1}), 0)^2} \tag{2.13}$$

We then compute the distance to distress metric as follows; where D is the distress barrier calculated as total deposits plus half of other borrowed funds and other liabilities and r is the 3 month treasury bill rate. This metric is expected to have a negative sign. As the standard deviations of asset values from the distress barrier become further and further the probability of default is reduced.

$$D2D = \frac{ln(A_t) + (r - \frac{1}{2}\sigma_A^2)T - ln(D_t)}{\sigma_A\sqrt{T}} \tag{2.14}$$

The model also includes the asset value variable. In the banks that were listed on the capital market the Merton model allows this to be computed as the implied asset value, which can be thought of as a truer asset value which accounts for the market capitalization. In the alternative methodology popularised by Blavy and Souto (2008) there is only the book value of assets and as such the model includes this. The expectation from the asset value variable is simple, the original framework explains that as asset values come close to or fall below the distress barrier the probability of default rises, as such we expect a negative sign attached to this variable. As asset values fall the general theory will indicate that the probability of default should rise.

2.4 Results

In this section of the paper we assess the results from the empirical models. Given the discussion in the research variables section we opted to look at a correlation matrix to determine which variables maybe highly correlated and could subsequently be removed from the panel logit model. By nature accounting and finance data tend to be highly correlated, the inclusion of which can lead to spurious results. Table 2.11 gives the correlation matrix for the accounting and financial ratio data.

Endogeneity is an on going concern in many econometric models, the problem concerns correlation of the explanatory variables with the error tem, which may result due to measurement error or dual causality. In this instance we can look at the interconnectedness of banks, for instance as defaults increase due to the interconnectedness of

Tab. 2.11: Correlation Matrix of Accounting and Financial Ratio Data

-	lta	cash	secure	good	tbe	noncurrentll	niia	niea	roa	er	lancl	ncaoreta	nlltcd	ccr	tier1rbc	noncurrentltas	ncll	gdp	tbills
lta	1																		
cash	0.3905	1																	
secure	0.4813	0.4962	1																
good	0.2821	0.3985	0.6138	1															
tbe	0.5475	0.5203	0.8345	0.8244	1														
noncurrentll	0.3335	0.6381	0.3573	0.2031	0.2854	1													
niia	0.0106	0.0220	-0.0095	0.0227	0.0740	-0.0496	1												
niea	-0.2841	-0.0253	-0.1277	-0.0299	-0.0957	-0.0511	0.5870	1											
roa	0.0385	-0.1050	0.0326	0.0219	0.0856	-0.2401	0.2471	-0.2524	1										
er	-0.0205	-0.0021	-0.0152	-0.0070	-0.0210	0.0266	-0.0285	0.0444	-0.1076	1									
lancl	0.0243	-0.0055	-0.0046	-0.0079	0.0120	-0.0264	-0.0125	-0.0391	0.0549	-0.0084	1								
ncaoreta	0.0485	0.0977	-0.0489	-0.0417	-0.0798	0.3495	-0.1441	0.1276	-0.6217	0.1132	-0.0708	1							
nlltcd	0.2629	0.0118	0.0571	0.0391	0.1159	0.0027	0.0198	-0.1118	0.1047	-0.0220	0.0222	-0.1197	1						
ccr	-0.1474	-0.1046	-0.0425	-0.0124	0.0518	-0.1683	0.1893	0.0086	0.4355	-0.0595	0.0471	-0.4533	0.1433	1					
tier1rbc	-0.2716	-0.0894	-0.0405	-0.0277	-0.0167	-0.1539	0.1310	0.0138	0.3477	-0.0435	0.0233	-0.3807	-0.0280	0.8399	1				
noncurrentltas	0.0680	0.1123	-0.0367	-0.0359	-0.0669	0.3999	-0.1191	0.1086	-0.6153	0.1121	-0.0728	0.9345	-0.0852	-0.4164	-0.3521	1			
ncll	0.0466	0.1371	-0.0234	-0.0367	-0.0690	0.4087	-0.1139	0.1281	-0.6188	0.1099	-0.0738	0.9381	-0.1221	-0.4216	-0.3313	0.9815	1		
gdp	-0.1768	-0.0781	-0.0311	-0.0215	-0.0477	-0.1549	0.0973	0.0607	0.2454	-0.0127	0.0303	-0.2304	-0.0970	0.0919	0.1553	-0.2470	-0.2287	1	
tbills	-0.0929	-0.1034	0.0144	0.0156	0.0344	-0.1862	0.1007	-0.0148	0.3985	-0.0604	0.0578	-0.4806	0.0643	0.3201	0.2976	-0.4510	-0.4514	0.3642	1

Tab. 2.12: Shapiro -Wilk test for Normal Data

Variable	Obs	W	V	z	Prob>z
lta	17174	0.99403	47.063	10.452	0
tbe	17174	0.25326	5885.341	23.557	0
noncurrentll	17174	0.18703	6407.339	23.787	0
niea	17174	0.67661	2548.808	21.286	0
er	17169	0.06991	7328.611	24.152	0
lancl	15162	0.07584	6561.674	23.781	0
ncaoreta	17174	0.66556	2635.896	21.377	0
nlltcd	17162	0.00549	7833.561	24.332	0
tier1rbc	17173	0.10444	7057.918	24.05	0
ncll	17156	0.66594	2630.569	21.371	0

the banking sector one may find that the financial variables of other banks alter in an unfavourable way. The interconnectedness in the banking industry can present an endogeniety problem.

As discussed by McLeay and Omar (2000) the possible non-normality of financial data can have implications for the predictive ability of the model. As such we test the normality of the variables we eventually use in the panel logit model. The Shapiro–Wilk and Shapiro–Francia give contradicting results as seen in table 2.12 and table 2.13. The null hypothesis states that the variable is normal, as the results show the Shapiro–Wilk leads to a rejection of the null that all the variables are normally distributed but the Shapiro–Francia gives contradicting results and says that we cannot reject the null. In light of these contradictions we investigate the skewness and kurtosis of each variable, the results are give in table 2.14. Similar to McLeay and Omar (2000) we opt to distinguish between the 'least normal' and 'most normal' variables and attempt a transformation of the 'least normal' variables in an attempt to improve the model.

The transformation of the variables to a normal distribution is believed to improve the predictive ability of the model and is investigated. The data is transformed using various approaches all of which are tested and compared to the ability of the original model to predict failure in the US banking sector. In the first instance the transformation of the 'least normal' variables is done by taking the logs of those variables (results in the appendix table A.1). The predictive ability of the model with this transformed data is reported in the appendix and discussed in the empirical accounting model section.

2.4.1 Empirical accounting models

In this section the results from the panel logit model are analysed. In the following models the dependent variable is coded as 1 if the bank defaulted in that year and 0 otherwise. It is important to note that all the banks in the dataset have defaulted,

Tab. 2.13: Shapiro -Francia test for Normal Data

Variable	Obs	W'	V'	z	Prob>z
lta	17174	0.99404	5.214	0.336	0.36825
tbe	17174	0.25294	653.51	0.387	0.34936
noncurrentll	17174	0.18663	711.52	0.387	0.34936
niea	17174	0.67622	283.234	0.387	0.34945
er	17169	0.06901	814.461	0.387	0.34923
lancl	15162	0.07547	828.744	0.542	0.29396
ncaoreta	17174	0.66622	291.988	0.387	0.34944
nlltcd	17162	0.00527	870.286	0.388	0.34907
tier1rbc	17173	0.10363	784.137	0.387	0.34933
ncll	17156	0.66658	291.727	0.388	0.34902

Tab. 2.14: Normality of Financial Variables

Variable	Variance	Skewness	Kurtosis	Normality
lta	1.5899	0.2971	3.4746	most normal
tbe	1.11E+10	11.9761	202.2829	least normal
noncurrentll	2.37E+09	23.7729	931.8654	least normal
niea	0.0004	4.8341	52.0875	least normal
er	24.1267	-5.6453	2412.0980	least normal
lancl	6990.1340	23.5823	740.1065	least normal
ncaoreta	0.0036	2.6385	11.2546	most normal
nlltcd	287.7796	93.9745	9180.5390	least normal
tier1rbc	0.1402	55.7420	4470.7950	least normal
ncll	0.0035	2.8735	14.1343	most normal

Tab. 2.15: Bounded and Unbounded Ratios

Variable	Bounded (+)	Unbounded (+/-)
lta	*	
tbe		*
noncurrentll	*	
niea	*	
er		*
lancl	*	
ncaoreta	*	
nlltcd		*
tier1rbc		*
ncll	*	

the analysis tries to distinguish the reaction of variables in defaulted quarters versus non-defaulted quarters in an attempt to trace deterioration or changes in particular variables that may indicate bank default. An isolation of such variables can improve monitoring techniques for bank regulators.

The variables which are a combination of financial soundness indicators and CAMELS indicators all have the anticipated signs. Increases in non-current loans to loans (ncll), non-interest expense to assets (niea), non-current assets and other real estate (ncaoreta), non-current loans and leases (noncurrentll) are all associated with increased probability of default as initially expected (Table 2.16). Conversely a larger size of bank as measured by the log total assets variable (lta), efficiency ratio (er), loss allowance to non-current loans (lancl) and tier1 risk based capital (tier1rbc) are all indicative of a lower probability of failure as these variables increase. The a priori expectations have been met by the coefficient signs in explaining bank default.

As regards the significance of the variables in the model there are 5 variables that are significant in this model in particular we find that the log of total asset variable is significant with a p-value of (0.037), the non-current loans and leases (noncurrentll)(0.001), non-interest expense to assets (niea)(0), non-current assets and other real estate to assets (ncaoreta)(0.044), tier1 risk based capital (tier1 rbc)(0). While some variables may have an instantaneous impact on the dependent variable there maybe some instances where it takes some time to work through. The follow through of these impacts can be analysed by assessing the one period lag data, the lagged model is given in table 2.18.

The data from the lagged models shows that two new variables have now become significant, namely the lagged total bank equity variable (ltbe) and lagged efficiency ratio (ler) with p values of 0.063 and 0.067 respectively. This result is interesting since in Cole and White (2012) the authors expressed concern at not having the total bank equity variable register as significant in the model as this was thought to directly influence the default of a financial institution. In the interest of that finding this model was lagged and found that the total bank equity variable (tbe) does indeed display significance in the model with a lagged impact. Similarly the efficiency ratio variable now contributes to the determination of default based on a one period lag.

As regards the classification ability of the non-lagged model table (2.17) shows that the sensitivity of the model which looks at accurately classifying a defaulted quarter as defaulted is 77 per cent in comparison to the specificity which looks at accurately classifying a non-defaulted quarters as such registers at 97 per cent. This in comparison to Cole and White (2012) who were able to classify 82.2 per cent and 99 per cent respectively using annual data and similar explanatory variables. The type 1 errors (misclassifying a defaulted year as non-defaulted) does warrant some concern in comparison to Cole and White (2012) who record a type 1 error rate of 17.8 per cent in comparison to the 23 per cent shown in this model. The difference though small maybe attributed to the difference in methodological approach. The type 2 error rate of 3 per cent recoded in this model is similar to those findings of Cole and White (2012).

After investigating the non-normality of the variables and assessing which variables were most and least normal in table 2.14 we attempted a log transformation of the least normal variables in an attempt to improve the prediction ability of the model as investigated by McLeay and Omar (2000). After applying the panel logit model it was observed that there was a vast increase in the number of variables that were significant in the model. While having the variables explain default is a benefit the ultimate goal is to improve the predictive ability of the model which was not achieved as seen in table A.2 as the specificity (classifying a defaulted bank as defaulted) declined marginally to 64 per cent from 77 per cent with the original data (Table 2.17). Other transformations to normalise the data were investigated, namely the Box-Cox transformation applied to the bounded ratios and the log skew transformations applied to the unbounded ratios, all reported in the Appendix table A.3 and A.4, however the results do not differ materially from those of the log transformed variables.

To further the analysis we apply the principal component methodology to the normalised variables and investigate whether this application improves the classification model. The results are also reported in appendix table A.5, the first 4 principal components are retained as they explain approximately 79 per cent of the variation in the data. All principal components are significant at the 1 per cent level in the default model. Again we lament that having variables significant is a benefit but the ultimate goal is to achieve a classification accuracy well over 95 per cent. In this case only 56 per cent of the defaulted banks are identified as defaulted, while 98 per cent of the non-defaulted banks register as non-defaulted (Table A.6). The application of pca has sought to heighten the amount of information retention in the model and has improved the significance of the explanatory variables but fails to ultimately improve the classification model.

2.4.2 Robustness checks-Accounting and Financial Model

In this section a few robustness checks are carried out on the model. The analysis looks at medium banks as defined by bank asset size between US \$1-\$10 billion and small banks with asset sizes under US \$1 billion (table 2.8). Here the investigation is steered toward the bank size having an influence on default and possibly a change in the variables that impact default between medium and small banks. Further the robustness checks involve delving into the crisis period versus the pre crisis period and analysing how these different periods may have impacted not only bank default but the role the explanatory variables would have played in these times.

Tab. 2.16: Bank Default Estimation Results : Accounting and Finance Ratios

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
lta	-0.137	(0.066)**
tbe	0.000	(0.000)
noncurrentll	0.000	(0.000)***
niea	9.166	(2.445)***
er	-0.002	(0.006)
lancl	-0.025	(0.022)
ncaoreta	2.856	(1.421)**
nlltcd	0.072	(0.097)
tier1rbc	-59.626	(2.460)***
ncll	0.672	(1.409)
gdp	-0.009	(0.021)
tbills	0.282	(0.049)
Intercept	1.185	(0.841)
Equation 2 : lnsig2u		
Intercept	-13.299	(17.865)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. 2.17: Model Classification Accuracy

Classified	Defaulted	Non-Defaulted
Defaulted	77%	3%
Non-Defaulted	23%	97%
Total	**100%**	**100%**

Tab. 2.18: Bank Default Estimation Results : Lagged Accounting and Finance Data

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
llta	0.000	(0.000)**
ltbe	0.000	(0.000)*
lnoncurrentll	0.000	(0.000)
lniea	6.506	(2.841)**
ler	0.018	(0.010)*
llancl	-0.007	(0.014)
lncaoreta	2.042	(1.781)
lnlltcd	0.193	(0.128)
ltier1rbc	-64.344	(3.310)***
lncll	3.739	(1.716)
lgdp	-0.082	(0.019)
ltbills	-0.025	(0.064)
Intercept	0.496	(0.303)
Equation 2 : lnsig2u		
Intercept	-1.213	(0.598)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Medium banks

The results from the panel logit model are given for the subset of medium banks in the dataset. It is important to note that medium banks only accounted for approximately 8 per cent of the entire dataset (all banks) (42/535). A majority of the medium banks defaulted within the crisis period (2009 and 2010), approximately 74 per cent (31/42). As regards the significance of the variables we find that only the niea and tier1rbc variables are significant in the model for medium banks. On the other hand the banks that are of a larger size may not have suffered due to non-current loans and may have had limited impact from the real estate fall out, it would appear from the analysis that the major impact was felt by the small banks. As shown by Antoniades (2015) larger banks tended to hold non-household real estate, that is big real estate projects and more direct and indirect investments in real estate, which is not included in the ncaoreta (non current assets and other real estate to assets) variable. The latter only accounts for household real estate and as such there appears to be limited impact of this variable on the medium banks. This finding supports Antoniades in that medium banks faced less risk in their exposure to household real estate but faced severe problems mainly through their holding of larger real estate investment projects. Given this finding the investigation moves on to assess the impact of the variables on the small banks in the data set in the next section.

Tab. 2.19: Estimation results: Medium Bank Default Estimation Results

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
lta	0.784	(0.668)
tbe	0.000	(0.000)
noncurrentll	0.000	(0.000)
niea	27.096	(14.363)*
er	-0.050	(0.059)
lancl	-0.025	(0.105)
ncaoreta	9.052	(9.231)
nlltcd	0.192	(0.249)
tier1rbc	-69.440	(12.754)***
ncll	-1.552	(9.379)
gdp	0.019	(0.066)
tbills	0.107	(0.244)
Intercept	-11.429	(9.747)
Equation 2 : lnsig2u		
Intercept	-13.981	(583.364)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Small banks

In this section we analyse the panel logit model of default for small banks. From table 2.8 we can see that the small banks command the majority of the data set, in total during the period 1990-2015 there are 842/896 small banks. Our data set which involves the use of data from 1993-2015 has approximately 92 per cent (492/535) small defaulted banks in the set. In the height of the crisis period (2009 and 2010) approximately 44 per cent of small banks defaulted (216/492). In direct contrast to the medium bank data the small bank data should give some sound findings, as there is a substantial data set.

Assessing the signs of the variables gives some insight into their impact on the probability of default. In the first instance we find that the lta variable (log total assets) which represents the size of the bank, has a negative coefficient. This can be interpreted, as smaller banks tend to have a higher probability of default. The latter finding is akin to the "too big to fail" phenomena that plagued the banking sector during the financial meltdown. Do regulators provide assistance to larger banking institutions while allowing their smaller counterparts to manage distressing times on their own? The mere fact that the small bank default data heavily outweighs the medium and large bank data speaks volumes to the approach taken by regulators regarding the "too big to fail" stance.

In terms of the non-current portfolios we find that the variables non-current loans and leases (noncurrentll), non-current assets and other real estate to assets (ncaoreta) and non-current loans to loans (ncll) all have a positive coefficient as expected indicating that increasing these variables tend to increase the probability of default, particularly with small banks. While the capital adequacy coefficient shows that higher holdings reduce the probability of default, Altunbas et al (2007) show that inefficient banks tend to hold higher capital ratios.

The significance of variables mirrors that of the original panel default models with tbe, noncurrenttll, niea, ncaoreta, nlltcd, tier1rbc all registering as significant. This directly contrasts the medium bank results which only showed 2 explanatory variables as significant.

Tab. 2.20: Estimation results: Small Bank Default Estimation Results

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
lta	-0.008	(0.106)
tbe	0.000	(0.000)***
noncurrentll	0.000	(0.000)**
niea	8.711	(2.480)***
er	-0.002	(0.006)
lancl	-0.022	(0.021)
ncaoreta	3.030	(1.454)**
nlltcd	0.186	(0.098)*
tier1rbc	-51.664	(2.830)***
ncll	0.404	(1.527)
gdp	-0.013	(0.023)
tbills	0.301	(0.051)***
Intercept	-0.510	(1.297)
Equation 2 : lnsig2u		
Intercept	-12.048	(14.509)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Crisis period 2008-2015

The number of banks that defaulted in the period demarcated as crisis (2008-2015) gives a total of 436. It is noted that the capital adequacy variable continues to be significant in the results (Table 2.21). The capital adequacy variable is the only variable significant at the 1 per cent level. The importance of capital adequacy has been evaluated by (Canbas et al (2005), Estrella et al (2000)) and the results of this model hold true adhering to the importance of this variable. Surprisingly some of the other variables did not register as significant, in particular the non-current variables which would have played a crucial role during the crisis period.

Tab. 2.21: Estimation results : Crisis Period Default Estimation

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
lta	-0.006	(0.080)
tbe	0.000	(0.000)
noncurrentll	0.000	(0.000)
niea	1.429	(3.611)
er	-0.002	(0.006)
lancl	-0.331	(0.155)
ncaoreta	1.482	(1.548)
nlltcd	0.310	(0.207)
tier1rbc	-66.733	(3.160)***
ncll	-0.276	(1.576)
gdp	-0.043	(0.022)
tbills	-0.284	(0.134)**
Intercept	0.514	(1.059)
Equation 2 : lnsig2u		
Intercept	-14.331	(14.878)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Pre-crisis period 1993- 2007

The data set in the pre crisis model is significantly smaller that the crisis model, here we have approximately 100 banks defaulted. On the other hand we get some interesting results from this model. As with all the models the variable tier1 risk based capital (tier1rbc) remains significant and speaks to the importance of capital in any default assessment model. Of note the non-current loans and leases (noncurrentll), efficiency ratio (er) and non-current assets and other real estate variables are all significant in the pre crisis models. This indicates the importance of these variables in the lead up to the crisis.

2.4.3 Empirical structural models

In this section the structural model is evaluated and its ability to detect default in the banking sector is of critical importance. In an attempt to compare like with like the author used the Blavy and Souto method and applied it to the entire data set. As a result we compute a proxy volatility variable and distance to distress all based on

Tab. 2.22: Estimation results : Pre Crisis Default Estimation

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
lta	0.136	(0.238)
tbe	0.000	(0.000)
noncurrentll	0.000	(0.000)*
niea	5.837	(7.436)
er	0.784	(0.450)*
lancl	0.002	(0.009)
ncaoreta	8.733	(4.761)*
nlltcd	0.091	(0.163)
tier1rbc	-26.671	(4.266)***
ncll	-0.675	(4.391)
gdp	-0.069	(0.113)
tbills	-0.107	(0.127)
Intercept	-1.135	(2.861)
Equation 2 : lnsig2u		
Intercept	-0.706	(0.886)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

the balance sheet of the banking institution. The performance of the model wanes in comparison to the accounting and financial model where the type 2 errors are concerned but performs relatively well in the type 1 error space. Nonetheless the results do present some interesting findings that warrant further investigation.

The first model seen in table 2.23 shows the impact of the total asset values, sigma (volatility) the distance to distress variable on the probability of default. The sigma variable has a positive coefficient meaning higher volatility is associated with a higher probability of default. As regards the significance of the variables in the model it would appear that none of the variables were significant at the 10 per cent or less levels. The distance to distress variable was significant at the 15 per cent level. One main shortcoming may be the way in which the variables are assimilated which is on the balance sheet rather than market data (Blavy and Souto (2009)).

On the other hand it appears that the lagged model seen in table 2.25 registers ld2d (lagged distance to distress) as contributing to the default of a bank. The distance to distress measures how far away a bank's asset values are from some set distress barrier. The further away from this set distress barrier the less likely the bank is to default. The distance to distress plays a significant role in the structural model framework and points to the banks ability to meet its obligations.

With respect to the predictive ability of the original model, the table 2.24 a classification of 99 per cent of defaulted banks were accurate and 1 per cent of non-defaulted. More importantly is the type 1 and type 2 errors which are highlighted, a type 1 error involves classifying a defaulted bank as non-defaulted, this type of error can be costly according to Cole and White (2012) as banks would have to be re-examined by the supervisory authorities. In the structural model the misclassification of this type amounts to 1 per cent (highlighted in blue in the table). The small misclassification of this important error signifies the ability of the model to accurately handle the default classifications based on the explanatory variables used.

Following on from this is the type 2 errors, though less costly; these involve classifying non-defaulted banks as defaulted. The model has a vast type 2 error allocation of 94 per cent (Table 2.24), these type of errors tie up resources as banks will need to be re-examined and ensure that they are functioning as they should. The model does accurately classify the defaulted banks as defaulted and minimises the type 1 errors but does have a large amount of type 2 errors which is less problematic than type1 errors but still warrants some measure of caution.

The classification accuracy of the lagged model (Table 2.26) is quite similar to that of the original model whereby 98 per cent of banks are accurately classified as defaulted but a mere 11 per cent of non-defaulted banks register as non-defaulted. While there are small type 1 errors of 1 per cent the model has a large base of type 2 errors (89 per cent).

Tab. 2.23: Estimation results : Bank Default Estimation Results : Structural Data

Variable	**Coefficient**	**(Std. Err.)**
totalassetsv	0.000	(0.000)
sigma	0.057	(0.044)
d2d	0.000	(0.000)
Intercept	-2.404	(0.056)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. 2.24: Model Classification Accuracy

Classified	Defaulted	Non-Defaulted
Defaulted	99%	94%
Non-Defaulted	1%	6%
Total	**100%**	**100%**

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2.4.4 Robustness checks-Structural Model

In this section the models are subjected to robustness checks. In the first instance the banks are split into medium and small banks based on the data in table 2.8 and then

Tab. 2.25: Estimation results : Lagged Structural Model

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
ltotalassetsv	0.000	(0.000)
lsigma	0.457	(0.571)
ld2d	0.000	(0.000)*
Intercept	-2.384	(0.059)
Equation 2 : lnsig2u		
Intercept	-17.775	(250.121)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. 2.26: Lagged Model Classification Accuracy

Classified	Defaulted	Non-Defaulted
Defaulted	98%	89%
Non-Defaulted	2%	11%
Total	**100%**	**100%**

into cisis period and pre-crisis period, much the same as the accounting and financial model was.

Medium banks

The results for the medium banks based on the structural model indicators are shown in table 2.27 it is immediately noted that the sigma or downward volatility variable is now significant at the 10 per cent level. This finding suggests that for medium banks the downward volatility of assets do influence the probability of default of a bank. The positive coefficient of sigma also suggests that higher downward volatility levels will increase the probability of default for a bank. Banks and regulators can then pay close attention to the movement of assets with a keen eye toward declining asset values. It is important to mention that both the distance to distress (d2d) variable and the total asset values were not significant in the model, similar to the findings of the original model.

This model highlights the importance of analysing movements in asset values for medium banks. As Blavy and Souto (2009) show volatility of assets, in particular downward volatility, do convey important information about the default possibility of a bank, while this variable seems important mainly in the medium bank model it should not be taken for granted as consistent falls in asset values can act as an early warning signal for banks.

Tab. 2.27: Estimation results : Medium Bank Default Estimation Results

Variable	Coefficient	(Std. Err.)
Equation 1 : defaultnodefault		
totalassetsv	0.000	(0.000)
sigma	54.304	(16.957)*
d2d	0.000	(0.000)
Intercept	-2.065	(0.376)
Equation 2 : lnsig2u		
Intercept	-13.212	(29.295)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Small banks

In the case of the small banks in the data set (which accounts for the lion share of the data set) we find that the variables appear insignificant in the model. This finding does pose some concern since default of the small banks would have been thought to be influenced by the volatility in the asset values or even total asset values, but this is not the case as shown by the results in table 2.28.

Tab. 2.28: Estimation results : Small Bank Default Estimation Results

Variable	Coefficient	(Std. Err.)
Equation 1 : defaultnodefault		
totalassetsv	0.000	(0.000)
sigma	0.057	(0.044)
d2d	0.000	(0.000)
Intercept	-2.419	(0.057)
Equation 2 : lnsig2u		
Intercept	-17.855	(255.915)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Crisis period 2008-2015

In this section the investigation focuses on the crisis period 2008-2010 but goes on to extend the data to 2015 as it is felt that there may be some spill over effects from the bubble. While the majority of the data set would have defaulted in the crisis period (approximately 81 per cent) the results show that none of the independent variables are significant in the structural model. The distance to distress (d2d) thought to be the most indicative variable in structural distress models has not proven significant in the distress model for the crisis period. While this result is somewhat alarming it is worth investigating the pre crisis period to further understand the structural model in this context.

Tab. 2.29: Estimation results : Crisis period Estimation Results for the Structural Model

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
totalassetsv	0.000	(0.000)
sigma	-0.253	(0.297)
d2d	0.000	(0.000)
Intercept	-2.465	(0.057)
Equation 2 : lnsig2u		
Intercept	-17.888	(48.225)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Pre crisis period 1993-2007

The pre crisis data accounts for approximately 19 per cent of the overall defaulted bank data as seen in table 2.6, despite this the results indicate that the volatility variable sigma is significant in this smaller data set. This indicates that generally before the subprime mortgage crisis the volatility of assets did play some role in determining bank failure. It is worth noting that many banks reported erroneous asset values coming into the crisis period and these may have hampered the ability of models since banks tended to inflate asset values in the crisis period. The latter maybe one explanation for the importance of the volatility variable in a time where there may have been less benefits associated with erroneous reporting.

Tab. 2.30: Estimation results : Pre Crisis Estimation Results for the Structural Model

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : defaultnodefault		
totalassetsv	0.000	(0.000)
sigma	129.685	(68.695)*
d2d	-0.006	(0.013)
Intercept	-1.824	(0.982)
Equation 2 : lnsig2u		
Intercept	-13.625	(853.136)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

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2.5 Conclusion

This paper took an in depth look at the US banking system and the crisis that ensued. The aim of the study is to investigate the ability of an accounting/financial model compared to a structural model to assess the probability of failure of a bank. The investigation is based on defaulted banks taken from the FDIC database and is then analysed based on defaulted bank quarters versus non-defaulted quarters.

The results suggest that both models present some useful techniques in determining default. As regards the accounting model the ability to record over 70 per cent of defaulted quarters as such while only incorrectly reporting non-defaulted quarters is an achievement for the accounting framework. Additionally the structural model succeeds in classifying defaulted quarters with a 99 per cent accuracy rate but has a very high degree of incorrect classifications for non-defaulted quarters. Both models present interesting findings and can be used to further improve the monitoring process by regulators.

3. PAPER II- DO SOVEREIGN CREDIT RATINGS INFLUENCE BANK CREDIT RATINGS?

3.1 Introduction

"It's not a stretch to say the whole financial industry revolves around the compass point of the absolutely safe AAA rating. But the financial crisis happened because AAA ratings stopped being something that had to be earned and turned into something that could be paid for." Matt Taibbi

According to Standard and Poor's credit ratings "express the agency's opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time" (Guide to Credit Rating Essentials). The credit ratings assigned are used by investors to scrutinize the safety of products offered by different entities and to assess the entities themselves. The widespread dependence on credit ratings to say something about an entity has brought credit rating agencies under scrutiny. Concern over sovereign ratings became illuminated at the pinnacle of the recent financial crisis where sovereigns previously thought to be 'safe' experienced debilitating rating downgrades that caused their economies to haemorrhage.

With the eruption of the Greek debt crisis credit rating agencies fell at the first hurdle being accused of not accurately rating sovereigns. Following which rating changes came quick and fast and the Greek fever spread to other countries in the Euro zone. As the crisis depended countries like Portugal, Italy, Ireland and Cyprus felt the pinch of the rating agencies whom at this point were relentless in their rating downgrades.

The overall impact of the Sovereign debt crisis spread like wildfire through economies and soon the financial sector found itself engulfed in the flames. The financial sector became the focal point of the crisis and the impact the sovereign debt crisis had on this has only been evaluated in the literature by Alsakka et al (2014). Hence this paper poses the research question: Do sovereign rating changes influence bank rating changes and if so to what extent? Were the credit rating agencies downgrading banks because of the jurisdiction they were in or were the banks themselves having problems due to the crisis?

The chapter uses an ordered probit model to ascertain the influence of sovereign ratings on bank ratings. In an attempt to investigate whether or not rating changes are being influenced by the jurisdiction the bank is in, the analysis includes financial data on the rated banks. In conclusion the paper finds that the financial ratios do play a role in determining the overall rating of a bank. The results suggest that bank rating changes in terms of the amount of notches a bank is downgraded by, is heavily influenced by the rating change of the sovereign.

Following the introduction, section 3.2 addresses the literature, section 3.3 discusses the data in the model, section 3.4 the methodology, section 3.5 analyses the results and the chapter concludes in section 3.6.

3.2 Literature Review

3.2.1 How credit ratings affect the market

Even pre crisis, works assess the impact of credit ratings on the market, be it financial markets or other markets. One such paper is by Brooks et al (2004) where the authors analyse the impact on financial markets stemming from changes in sovereign ratings. They evaluate the reaction of stock markets to an upgrade or downgrade of the sovereign. The authors explain that while the efficient market hypothesis (EMH) assumes that stock markets do not respond to sovereign rating changes they find evidence that contradicts this foundation of the EMH. Two trends of discovery in the literature prevail, the first posits that the market is unaffected by rating upgrades, while the second focuses on rating downgrades and offer the finding that only these (downgrades) contain important information which is then absorbed by the market resulting in adverse impacts upon equity markets.

The paper uses data from four main credit rating agencies [1] (CRA's) in its assessment of credit rating impacts. The alteration in credit ratings assigned to a sovereign is analysed based on its impact on the daily market returns over a thirty year period. The methodology employed mirrors that of investigating the impact upon the stock market due to the occurrence of an event, in this case the event is the change in rating of the sovereign. They compute the average abnormal returns, where abnormal market returns are computed as:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}) \tag{3.1}$$

The above equation computes the abnormal market returns as the return (R) on a particular market (i) minus the summation of the parameters α and β by the return on the world market (R_{mt}). Averaging the abnormal returns and adjusting them for risk by standardising it gives the (SAR) standardised abnormal returns.

A substantial part of the analysis focuses on Standard and Poor's since, as the authors explain, they have been in the rating business for quite a number of years and grants a longer data series. Also the local currency rating metric is only available under Standard and Poor's long enough to allow meaningful analysis. The findings

[1] Standard and Poor's, Moody's, Fitch and Thompson.

of the paper in most ways echo the sentiment of much of the existing literature. In particular the authors find that upgrades of sovereigns impart little information to the market and so the market is apathetic to such news. Conversely there seems to be some responsiveness to rating downgrades as the same day effect on returns is negative. It would appear from this analysis that the market responds to negative news more than it does positive news. There work goes on to show that only certain rating agencies, namely Standard and Poors and Fitch have influence over the market in that their ratings get an immediate reaction from the market.

The paper entitled 'PIGS or Lambs? The European Sovereign Debt Crisis and the Role of Rating Agencies' by Gartner et al (2011) takes a closer look at the influence CRA's had in the debt crisis in Europe. They analyse the self reinforcing nature of downgrades and attempt to extract a relationship between CRA sovereign ratings and macroeconomic and structural fundamentals. The paper echoes the sentiment that even CRA's can get it wrong and then turn seemingly healthy economies (lambs) into PIGS[2] up for slaughter, through the self reinforcing prophecy that a downgrade seems to attract.

The authors build a generic model, on 26 OECD countries between 1999 to 2010, thought to be founded upon the macroeconomic principles[3] used by the CRA's in developing sovereign ratings. They devise the following regression that says that the ratings assigned to government the long term debt R_{it} is a function of the macroeconomic principles X_{it}, with α as the intercept and β as a coefficient vector and ϵ being the regression's error term. This part of the analysis is the macroeconomic fundamental part of the sovereign rating, the authors explain there also exists an arbitrary part and want to test if this arbitrary part indeed influences a sovereign rating.

$$R_{it} = \alpha + \beta' X_{it} + \epsilon_{it} \tag{3.2}$$

To test the arbitrary part they assign the above regression (with some alterations) to the PIGS and observe whether the macroeconomic fundamental model is able to exactly replicate the ratings received by the sovereign of the PIGS. If the model cannot exactly replicate then there exists some arbitrary part of the rating analysis by the CRA's that is not captured in the macroeconomic model. They find that there does exist some arbitrary part to the ratings granted by the CRA's and that this arbitrary part drove most of the ratings in and around the crisis, meaning that CRA's pay less attention to macro fundamentals but more attention to other influences. The authors also find that the arbitrary part of credit ratings (i.e. the residual that is left unexplained by macroeconomic variables) do influence the market and as such CRA's have the ability to affect markets by assigning ratings that may be largely arbitrary in part.

[2] Portugal, Ireland, Greece and Spain.

[3] GDP growth, GDP per capita, government surplus, government primary surplus, government debt, government bond yield, credit spread and inflation.

The undue influence of CRA's in the overall economic functioning of economies is an area that has warranted much concern. Gibson et al (2012) echo the sentiment that an arbitrary part of ratings, which they decipher to be downgrades and a dubious political arena put extensive pressure on Greek sovereigns causing spreads to balloon. The authors find, like Gartner et al (2011) that macroeconomic variables exact minimal influence on sovereign spreads, highlighting again the arbitrary part that can possibly drive already ailing economies into a downward spiral.

Afonso et al (2012) analyse the relationship between sovereign credit ratings and CDS spreads, they also investigate the impact of CDS spreads in one country on another i.e. contagion. The paper uses data from three CRA's[4] to develop the analysis which is focused on the EU and spans January 1995 to October 2010. The authors utilise an event study to paint a clear picture of the impact of upgrades, downgrades and CRA outlook on the sovereign yield and CDS spread.

The methodology dissects yields and CDS spreads in a response time of one day prior and post the rating by the CRA, the authors note that this small time span is enacted to reduce the influence of other activities on the yield and CDS spread changes. In line with most event studies done assessing the impact of credit ratings, this paper finds that negative events, that is downgrades or negative outlooks have a greater impact on yields and sovereign spreads. In particular the analysis shows that for all CRA's negative events cause a 0.13 percentage point rise in spreads but positive events only ignite a 0.01 percentage point reduction in spreads, clearly highlighting the markets cynicism regarding positive events. The paper also finds that there does exist contagion among rated countries (split into event and non event countries), in particular there appears to be a greater impact on "non-event" countries who have a higher credit rating as a result of an upgrade/downgrade in the event country.

Becker and Milbourn (2011) investigate the impact of increased competition with the addition of Fitch to the credit rating game. The dominance of Moody's and S&P in the market meant that ratings were distributed these two dominant CRA's and the entrance of Fitch warrants some investigation into how more competition affects the accuracy of ratings. The paper looks at the market share of each CRA and uses a total of 1.1 million bond ratings to define the market share of each CRA. They find that increased competition diminishes the accuracy of ratings, they also explain that when rating are solicited higher levels of competition results in bonds being given significantly higher ratings. The authors suggest that these findings have policy implications regarding the level of entry that should be allowed in the credit rating market.

Rablen (2013) looks at the difference in rating approaches in the market for structured products versus the market for bonds. Prior to the crisis it was found that the ratings assigned to structured products tended to be lacklustre and had limited conservatism versus the bond ratings which appeared to be much more conservative. The

[4] Standard and Poor's, Moody's and Fitch.

CRA's have since been accused if propelling the debt crisis by assigning ratings that were too favourable to products that should not have been graded as investment grade instruments. Rablen (2013) shows that the CRA's were culpable in the events that led to the crisis which speaks to the need for closer monitoring of the activities these entities engage in.

3.2.2 Determinants of bank credit ratings

The literature surrounding credit ratings and banks tends to focus on the determinants of overall bank credit ratings, one such paper is Poon et al (1999). The authors attempt to identify the determinants of the bank financial strength rating put out by Moody's. This rating executed by Moody's was thought to provide an insight into the financial potency of banks. The authors use a total of 100 financial ratios compiled for each bank in the sample.[5] In order to reduce the dimensions of the vast data and to focus on the financial ratios that explain most of the variance in the data, the paper employs factor analysis which results in the retention of three factors that are said to elucidate the bank financial strength rating. These three variables are related to risk, loan provision and profitability. The paper uses a logit model and concludes that the predictive ability of the model including the three identified areas is a good predictor of the ratings assigned to banks by Moody's.

While Poon et al (1999) investigates a relatively new rating put out by Moody's at the time, Poon and Firth (2005) address the claims that banks who receive unsolicited ratings find that there ratings are lower than those who seek out the rating agencies ratings. The authors find that indeed unsolicited ratings tend to be lower but explain that these banks usually have weaker portfolios which in part explain the lower ratings. The paper also constructs a model that aids in the identification of the determinants of ratings that banks receive. Using a sample of banks rated by Fitch and financials on these banks from bank scope, the paper constructs a model of financial variables to determine solicited and unsolicited ratings and uses a range of profitability, asset quality, liquidity, bank size a total of 25 financial variables. To avoid the problem of multicollinearity the authors look at the following ratios:

- Net Interest Margin
- Loan Loss Reserves/ Gross Loans
- Equity to Total Assets
- Return on Assets
- Loans to Total Assets

[5] These ratios cover broad areas such as profitability and efficiency, asset quality, risk, leverage and interest composition.

- Logarithm of book value of Total Assets

The paper by Gogas et al (2014) again looks at forecasting credit ratings by Fitch on their long term ratings. The paper uses data on 92 banks and targets ratings assigned in the year 2012. The use of financial data to determine credit ratings finds the authors using a total of 46 financial variables for each bank in the sample dating from 2008-2011. The authors use an extensive selection criteria that places the four best sets of regressors into varying groups. The methodology involves the computation of the correlation matrix for the 184 regressors, they then place the regressors into groups based on their correlations. Following this the authors identify from each group of correlated variables the ones that contribute the most to the assigned rating. The paper finds that the lagged financial data is instrumental in determining ratings, they also conclude that some variables thought to influence ratings were insignificant in their model, variables such as size and some asset quality ratios. They found that performance ratios and some income statement data played more of a significant role in determining credit ratings.

Other papers like Bissoondoyal-Bheenick and Treepongkaruna (2011) investigate the ratings of banks in the UK and Australia in an attempt to identify factors that play a role in credit ratings. The authors use ratings by three credit rating agencies over the period 2006-2009. The financial variables used fall into 5 categories: credit risk, market risk, liquidity and interest rate, capital adequacy[6] and operating performance, they also include macroeconomic variables in the probit model. The paper finds that the financial ratios with the exception of the market risk ratio are more influential in determining bank credit ratings as opposed to the macroeconomic variables.

In the paper 'Ratings quality over the business cycle' (2013) Bar-Isaac and Shapiro the impact of the economic environment upon the ratings CRA's give is analysed. The paper finds that ratings tend to be counter cyclical, that is in good times ratings tend to be less accurate as CRA's are working to gain traction off the boom period. In a similar arena Bar-Isaac and Shapiro (2011) analysed the ratings analysts gave and the incentives behind those ratings. They highlighted that due to the expectation of increased or continued business analysts put more effort into the ratings but the probability of accuracy tended to be nonmonotonic.

3.2.3 *Shopping for bank credit ratings*

In their paper "Credit ratings failures and policy options" Pagano and Volpin (2010) discuss the role of CRAs in the financial turmoil that categorized the 2008 financial crisis. They explain that one main cause for concern was credit rating shopping which

[6] The variables include: non performing loans and leases to total loan and lease ratio and charge offs to total loans and leases; non interest income as a per cent of operating income; liquid assets as a per cent of average total assets and total loans to core deposits; tier 1 ratio and total capital ratio; return on assets and return on equity.

saw firms seek out CRAs that would give more favourable ratings. The authors also lament that the regulatory bodies did not pay close attention to these problems which resulted in catastrophe for the financial sector. The paper goes on to support a rater pay model but encourages regulations that prevent or minimise the ability of firms to shop for ratings. They suggest that CRAs provide with all necessary information that led to the determination of the rating and issuers in turn provide this information to investors. The latter should improve the transparency of the rating market and ward off the adverse effects of rating shopping.

The paper by Sangiorgi et al (2009) investigates the impact of credit rating shopping by issuers, the authors analyse the issuers ability to choose ratings as this is a critical aspect of the microstructure of ratings. They explain that ratings from different CRAs that tend to diverge result in the issuer opting for the most favourable rating and can lead to "selection" effects in ratings. The paper goes on to analyse notching which occurs when CRAs try to undercut the rating of their rivals this leads to what the author's term as the "winners curse" whereby the issuers opts for the rating that is more favourable to them. They find that the more issuers pay for ratings the more likely it is that the rating received is more favourable in comparison to previous ratings. On the other hand higher cost of ratings results in less ratings being solicited.

The discussion of who pays for solicited ratings is one that again influences the structure of credit ratings. The both models that have been investigated are investor pay and issuer pay models. The assessment of how rater models influence ratings is one that has direct impact on the recent events of the financial crisis. Jiang et al (2012) pay particular attention to Moody's issuer pay model versus S&P's investor pay models. The paper uses data from 1974 on US corporate bonds and focuses on the S&P's change from an investor pay model to an issuer pay model. Moody's remained as an issuer pay model over the course of the research period. It has been argued that issuer pay models can induce rating shopping and encourage CRA's to give more favourable ratings.

The idea of rating shopping is further extended in Sangiorgi et al (2011) where the authors use a rational expectations model to delve into issuers selectively disclose ratings and the inherent bias that tends to be innate in the process. The lack of information regarding contact between the issuer and rating agents can lead to potential rating bias in equilibrium according to Sangiorgi et al (2011).

Skreta and Veldkamp (2009) develop a model to deal with rating inflation, a phenomena that was attributed to the financial crash of 2007. They find that the structure of an asset is directly related to rating shopping. When assets are complex in nature there appears to be increased heterogeneity among rating agent and as such there is increased rating shopping as issuers seek better ratings. The converse is true, the simpler the asset the less heterogeneous (more homogeneous) ratings tend to be and they found that rating shopping in that instance tends to be lower.

Griffin et al (2013) investigate not only rating shopping but allude to the possibility of rating catering by CRAs and the implications of both. Their analysis is developed for CDOs (collateralized debt obligations) which they explain is a market plagued with opacity hence the increased tendency for these occurrences. The model is developed on CDOs rated by both Moody's and S&P between 1997 and 2007.

The paper found that CDOs that received ratings by both CRAs tended to experience default problems more often that those that were only rated by one agent. The authors point to rating shopping that created the environment for this phenomenon. The also explain that the ability of the CRAs to respond to more lax rating methodologies by reducing their ratings was found in the research and pointed to rating catering among the CRAs. The paper points to some unique circumstances that deserve further investigation as regards the CRAs and there rating catering approaches.

In the paper entitled "Tiebreaker: Certification and Multiple Credit Ratings" Bongaerts et al (2012) assess three hypotheses namely rating shopping whereby the issuers seek the most favourable rating from a range of CRAs, information production which looks at having additional raters and the increased benefits from more information on the market and how this influences the ratings. It is thought that the third rater adds more value to the ratings and in this sense can act as a "tiebreaker" when ratings tend to be heterogeneous.

In their 2012 paper "The credit ratings game" Bolton et al address the problematic aspects of the rating industry. They find that CRA's seeking paid ratings tend to give favourable ratings to businesses, those investors who undoubtedly put their faith in credit ratings are tangled in a web of deceit spun by CRA'S regarding credit worthiness of proposed investment products. The paper alludes to the distortions created by this dishonest practice of the CRA's, namely reduced efficiency and rating inflation.

3.2.4 Sovereign credit ratings and banks

While much of the literature surrounding credit ratings tends to sway toward its determinants, market impact or pro (counter) cyclical nature, the existing body of work is mute on the effect sovereign credit ratings have on bank credit ratings. Williams et al (2013) attempt to fill this void by assessing the influence sovereign ratings exact upon bank ratings in emerging markets, while also enlisting other explanatory variables [7] to extrapolate the link between sovereign ratings and bank ratings.

Their data set consists of sovereign and bank ratings from three CRA's for 54 emerging market countries between 1999-2009. They implement a strict timing policy that sees the use of bank ratings that are no more than 3 months post the sovereign rating. The latter is to ensure that no other influences creep in to influence the rating of banks apart from the sovereign rating. The ratings are further classified into a range of ordinal data with the highest possible rating being valued at 1 and the lowest rating

[7] Financial freedom, investment freedom, trade freedom, fiscal freedom, government spending, business freedom, monetary freedom, labour freedom, property rights and freedom from corruption.

having a value of 20.

Since the model incorporates ordinal data the authors employ the ordered probit analysis to evaluate the impact of sovereign ratings[8] on bank ratings. Taken from the paper is the following specification the authors utilise

$$\Delta y^*_{i,a,t} = \Sigma\beta Sch - n_{i,a} + \gamma pw_{i,a} + \lambda w_{i,a} + \vartheta rating_{i,a,t} + \epsilon_i$$

$$\epsilon_i \backsim N(0,1)$$

$y_{i,a,t}$ is measured as

$$y_{i,a,t} = \begin{bmatrix} 0\ if y^*_{i,a,t} \leq \mu_1 (no\ rating\ change) \\ 1\ if \mu_1 < y^*_{i,a,t} \leq \mu_2 (rating\ upgrade/downgrade\ of 1\ notch) \\ 2\ if \mu_2 < y^*_{i,a,t} (rating\ upgrade/downgrade\ of\ 2\ or\ more\ notches) \end{bmatrix}$$

Where $y_{i,a,t}$ is the ordered variable of ratings for banks, the country is represented by i, the rating agency by a and the month by t. The notches are dissected into 0 for no rating change, 1 for and upgrade/downgrade of 1 notch and 2 for a change of 2 or more notches. The parameters $\mu, \beta, \gamma, \lambda$ and ϑ are all to be estimated. The authors further explain that the y ordinal variable looks at the bank being upgraded or downgraded or no change by the CRA based on the explanatory variables listed in the equation above. The explanatory variables are explained as follows,

- $\beta Sch - n_{i,a}$ is a dummy variable assessing the upgrade, downgrade of the sovereign in country i by rating agency a by n notches.
- $pw_{i,a}$ is another dummy variable that looks at whether the sovereign was put on a positive or negative watch 3 months prior to the rating change.
- $w_{i,a}$ is also a dummy variable looking at whether the sovereign is on watch.
- $rating_{i,a,t}$, is the numerical ratings of the sovereign.[9]

The authors explain that a priori the sign attached to the explanatory variables are expected to be positive since any sovereign rating is assumed to influence bank rating be it an upgrade/downgrade or being placed on the negative or positive watch list. The rating variable is seen to account for the state of the sovereign at the time of rating of the banks in country i. They also further evaluate four individual logit regressions to observe how

- The freedom index influences the upgrade or downgrade of a bank.

[8] Upgrades, downgrades and no change.

[9] Coded from 1 representing the highest rating (AAA) to 20 representing the lowest rating (D).

- The freedom index explains the relationship and magnitude of bank rating changes to sovereign rating changes.

- Macroeconomic[10] forces explain the upgrade or downgrade of a bank 3 months after the sovereign.

- The influence of the macro economy (see footnote for variables) on the relationship and magnitude of bank rating changes to sovereign rating changes.

The results of the study indicate that there is a close relationship between the upgrade/downgrade of a sovereign and an associated upgrade/downgrade of a bank in that sovereign state. In an analysis of all the rating agencies the authors found that banks were more likely to be upgraded if the sovereign was upgraded. Particularly, they expound that there is a 63.2 per cent likelihood of a bank being upgraded by 1 notch and 19.3 per cent likelihood of a 2 notch upgrade if the sovereign was upgraded by 1 notch. This likelihood increased to 87.1 per cent of an upgrade for banks if the sovereign had been upgraded by 2 notches or more. While this evidence shows clearly that there appears to be some knock on effects of an upgrade to banks following the upgrade of the sovereign, the authors did not eliminate the likelihood of downgrades and those results lead to some informative conclusions. As previous works have suggested it would appear that the likelihood of downgrades of firms following a downgrade to the sovereign is less likely. This paper found that a bank is 26 per cent likely to be downgraded by 1 notch and 26.7 per cent likely to be downgraded by 2 notches following a 1 notch downgrade of the sovereign. However, if the sovereign is downgraded by 2 notches then banks face a 62.2 per cent likelihood of a downgrade.

The authors perform additional analysis on the results of the model. In the first instance they assess whether the ownership[11] of banks influences the response to sovereign ratings. They find that all are in some way influenced by the rating imposed on the sovereign in which they operate. Moreover, there appears to be a more positive response of locally owned banks to a sovereign upgrade as compared to the other categories, while foreign owned banks respond more to a sovereign downgrade. This observation may raise the question of bias towards locally owned banks in the sovereign state as compared to foreign owned banks, additionally the authors fail to inform the reader of the possible economic state of the sovereign from which the 'foreign bank' is from.

The paper also investigates the bank rating and sovereign rating to understand whether the bank rating[12] compared to the sovereign in some way influences the banks rating when the sovereign rating is changed. They found that if the bank is rated higher than the sovereign, the probability of a 1 notch upgrade for the bank is higher than a 2

[10] GDP per capita, GDP growth, inflation, current account balance, fiscal balance and external debt.
[11] State owned, foreign owned and locally owned.
[12] Bank ratings higher than the sovereign, bank ratings lower than the sovereign or bank ratings equal to the sovereign.

notch upgrade when the sovereign has received a 1 notch upgrade. If the bank is rated lower than the sovereign, then the probability of a 1 notch upgrade is lower than a 2 notch upgrade when the sovereign is upgraded by 1 notch, and finally if the bank rating is equal to the sovereign rating then the probability of a 1 notch upgrade outweighs that of a 2 notch upgrade.

In the case of a 1 notch downgrade of the sovereign it would appear that the probabilities for a 1 notch and 2 notch downgrade for banks are similar when the bank rating is greater than the sovereign rating and equal to the sovereign rating. However, if the bank rating is lower than the sovereign then the probability of a 1 notch downgrade is 50 times lower than the probability of a 2 notch downgrade should the sovereign be downgraded by 1 notch.

The paper also highlights the influence of macroeconomic variables and sovereign ratings on bank ratings. While it is expected that macroeconomic variables will in some way influence bank ratings as the CRA's utilise macroeconomic data to determine bank ratings, the analysis attempts to explain if these macro variables have a greater impact on the banks rating in light of the sovereign rating. The authors found higher GDP growth rates led to banks having a higher probability of a rating upgrade when the sovereign is upgraded, with the converse being true. GDP per capita and current account balance also influence rating changes but more so for state owned and foreign owned banks respectively.

Alsakka et al (2014) performed a similar analysis as discussed previously, with the exception that this model was fitted to European data. They assess the influence of sovereign ratings on bank ratings of European countries to investigate the impact pre and post crisis. The paper uses rating data on long term foreign currency of banks from 21 EU countries. The analysis is segmented into two periods, namely pre crisis which spans January 2003 - December 2007 and crisis period which spans January 2008 - December 2013. The authors fit two models, one where the dependent variable is bank upgrades and the second model's dependent variable is bank downgrades. Both models are a function of sovereign upgrades and downgrades, sovereign watch status and sovereign ratings, the latter being used to give an indication of the financial state of the sovereign.

The authors find that pre crisis, banks and sovereign were rated independently, but during the crisis banks were downgraded within three months of the sovereign being downgraded. The paper concludes that the sovereign downgrade does influence bank downgrades and the authors found the influence to be stronger in Portugal, Italy, Ireland and Greece.

The paper by Huang and Shen (2014) perform a similar analysis where they analyse the influence of the sovereign rating on bank credit ratings by two credit rating agencies Standard and Poor's and Fitch and the model is applied to high income and non high income economies between 2003-2011. They analyse the impact of the sovereign rating, the change in bank variables[13] and macroeconomic variables. They also investigate the impact when the bank ratings exceed, fall below or are matched to the sovereign rating.

The results for the model shows that the sovereign rating is indeed influential in the bank rating changes with the impact of sovereign downgrades having a greater impact. On the other hand when evaluating the non high income countries the study finds that bank rating changes are more responsive to sovereign upgrades and downgrades do not influence bank rating changes. The authors also find that in the crisis period the impacts on banks are magnified due to downgrades of the sovereign.

Correa et al (2014) investigate banks and sovereign of 37 countries between 1995-2011 to observe whether changes in sovereign ratings and government assistance to banks have any significant impact on the ratings assigned to banks stock. The analysis presents major policy implications as it speaks to the direct link between the government health and information on the stability of a bank and the sector in general communicated through the ratings assigned. The paper finds that the stock of banks that are some how impaired and require government assistance are have much more reactionary ratings when the sovereign rating is adversely altered. The latter means that close monitoring of sovereign ratings can signal possible further adverse ratings for banks that are in turmoil or facing some impairment.

Mellios and Blanc (2006) investigate the determinants of sovereign credit ratings, the study adds to the body of existing literature by including more qualitative measures such as corruption they also employ principal component analysis and find that the variables per capita income, government income, the real exchange rate along with inflation are most influential in determining sovereign credit ratings. The ordered logit model is built on the foreign currency ratings for 86 countries by three rating agencies (Moody's Standard and Poor's and Fitch). The time period is set as at December 31, 2003.

3.3 Data

The analysis uses data collected from Bloomberg on 82 banks from Euro zone countries. The bank and sovereign ratings are collected for three credit rating agencies (Moody's, Standard and Poor's and Fitch). Ratings are focused on the foreign long term portfolio of the bank and foreign currency long term debt of the sovereign. It is important to note that other papers that explore the influence of the sovereign rating on the bank rating only utilise the bank rating if it is three months post the rating of the sovereign. The latter time frame is enacted to ensure that the sovereign influence plays a dominant role in the rating of the bank.

This chapter uses two separate data sets the first data set mimics the approach

[13] Change in: Capital adequacy ratio, return on assets, liquid assets to short term funding, loan loss provisions to net interest revenue, cost to income and the natural logarithm of assets

Tab. 3.1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
roa	694	-0.4945	8.8747	197.5215	251.2672
nim	630	2.3750	2.6679	0.1806	53.5357
tier1rbc	618	9.9322	2.4178	-6.1000	24.0000
trbc	589	12.1174	2.4744	-5.3000	24.0000
plltl	563	4.0785	56.7582	-0.5920	1241.4760
npltl	531	7.8736	6.0722	0.0000	41.0108
tltd	598	163.1995	318.1599	22.2602	5676.4020

discussed above where the data set is truncated and only bank ratings that occur three months post the sovereign rating are used. The researcher questioned this approach used by other works since it was felt that this may in some way bias the results. It is believed that by using this approach we force a relationship between the independent and dependent variables leading to bias. As such the second data set used takes into account all bank ratings regardless of their occurrence in relation to the sovereign rating. This would increase the size of the data set since we do not truncate the data in anyway. It is also felt that this would remove the bias from the previous approach. The researcher will compare the output from the two data sets and evaluate the impact of the different data sets on the results. The adjusted model uses the full data sample.

The ratings assigned are coded from 1-20 with the highest rating being assigned a value of 1 and the lowest rating category being assigned a rating of 20. The banks are taken from the methodological note[14] produced by the European Banking Authority, the banks are said to represent approximately 50 per cent of overall banking assets in each jurisdiction.

[14] https://www.eba.europa.eu/documents/10180/669262/Methodological+Note.pdf

3.4 Methodology

Similar to the paper by Alsakka et al (2014) and other works on credit ratings, this paper uses an ordered probit model to investigate the influence of sovereign ratings on bank ratings. The ordered probit model is applied where the outcomes are discrete in nature and have some natural ordering.

If we have an unobservable latent variable y* say, credit worthiness but y* can only be analysed based on an observable variable y say, credit rating categories[15] or rating changes[16].

$$y^* = \alpha + \beta x + \epsilon \tag{3.3}$$

$$y = \begin{bmatrix} 0\ if y^* \leq \gamma_1 \\ 1\ if \gamma_1 < y^* \leq \gamma_2 \\ 2\ if \gamma_2 < y^* \end{bmatrix} \tag{3.4}$$

This chapter attempts to answer the first research question, do sovereign rating changes influence bank rating changes and therefore estimates the following equations for bank downgrades and upgrades similar to Alsakka et al (2014) the following equations are estimated:

$$Bank_{i,c,t} \Downarrow = \alpha_1 Sov_{i,c} \downarrow_1 + \alpha_2 Sov_{i,c} \downarrow_2 + \alpha_3 Sov_{i,c} \uparrow_1 + \alpha_4 Sov_{i,c} \uparrow_2 + \alpha_5 NW_{i,c} + \alpha_6 Srating_{i,c,t} + \epsilon_{i,c,t} \tag{3.5}$$

$$Bank_{i,c,t} \Uparrow = \delta_1 Sov_{i,c} \downarrow_1 + \delta_2 Sov_{i,c} \downarrow_2 + \delta_3 Sov_{i,c} \uparrow_1 + \delta_4 Sov_{i,c} \uparrow_2 + \delta_5 NW_{i,c} + \alpha_6 Srating_{i,c,t} + \epsilon_{i,c,t} \tag{3.6}$$

Where $Bank \Downarrow / Bank \Uparrow$ are the observable variables based on the rating change categories and take the following values: 0=no rating change, 1=upgrade/downgrade of 1 notch, 2=upgrade/downgrade of 2 or more notches.

The dummy variables $Sov \downarrow_1$ and $Sov \downarrow_2$ are the sovereign downgrade variables. This variable has a strict time application of three months following Williams et al (2013) approach, that is it is only included in the data set if the sovereign downgrade occurred three months prior to the bank downgrade. If the sovereign of country i has been downgraded by 1 notch then $Sov \downarrow_1$ will take the value of 1, 0 otherwise. Where the sovereign has been downgraded by 2 or more notches then $Sov \downarrow_2$ will take the value of 1, 0 otherwise.

$Sov \uparrow_1$ and $Sov \uparrow_2$ are also dummy variables in the model and represent sovereign upgrades. This variable also has a strict three month time application. If the sovereign of country i has been upgraded by 1 notch then $Sov \uparrow_1$ will take the value of 1, 0 otherwise. If the sovereign has been upgraded by 2 or more notches then $Sov \uparrow_2$ will take the value of 1, 0 otherwise. In the adjusted model the data set does not have any

[15] Aaa/AAA=1,Aa1/AA+=2, Aa2/AA=3.......C=20.

[16] 0=no rating change, 1= upgrade/downgrade of 1 notch, 2= upgrade/downgrade of 2 or more notches.

strict time requirements, that is we use all available ratings. In the instance where there is no sovereign rating change associated with a bank rating change we simply code the sovereign dummies as 0.

The variable NW is another dummy variable that takes the value of 1 if the sovereign has been placed on the negative watch list three and a half months prior to the bank being downgraded, 0 otherwise. $Srating$ is used as a control variable to give an indication of the overall economic situation since it is the numerical credit rating of the sovereign. The assumption is that better sovereign ratings will be given to economies where the overall economic condition is more favourable.

The first model draws heavily from Williams et al (2013) and Alsakka et al (2014), while the adjusted model attempts to remove this suspected bias in the data. Another limitation in Alsakka et al (2014) is that the authors only analyse the impact of a sovereign downgrade on a bank downgrade, however there may be one event say the financial crisis, that affects both the sovereign and the bank and subsequently leads to a downgrade of both institutions. This paper adds to the existing literature by (1) presenting a less biased data set and (2) asking the question: have otherwise healthy banks been downgraded solely because the sovereign was downgraded. This brings us to the second model of the paper which includes financial variables for the banks in the analysis since we want to evaluate the role the financials play in the bank rating change.

$$Bank_{i,c,t} \Downarrow = \alpha_1 Sov_{i,c} \downarrow_1 + \alpha_2 Sov_{i,c} \downarrow_2 + \alpha_3 Sov_{i,c} \uparrow_1 + \alpha_4 Sov_{i,c} \uparrow_2 + \alpha_5 NW_{i,c} + \alpha_6 Srating_{i,c,t}$$

$$\alpha_7 ROA_{i,c,t} + \alpha_8 NIM_{i,c,t} + \alpha_9 T1RBC_{i,c,t} +$$

$$\alpha_{10} TRBC_{i,c,t} + \alpha_{11} PLLTL_{i,c,t} + \alpha_{12} NPLTL_{i,c,t} + \alpha_{13} TLTD_{i,c,t} + \epsilon_{i,c,t} \tag{3.7}$$

$$Bank_{i,c,t} \Uparrow = \delta_1 Sov_{i,c} \downarrow_1 + \delta_2 Sov_{i,c} \downarrow_2 + \delta_3 Sov_{i,c} \uparrow_1 + \delta_4 Sov_{i,c} \uparrow_2 + \delta_5 NW_{i,c} + \delta_6 Srating_{i,c,t}$$

$$\delta_7 ROA_{i,c,t} + \delta_8 NIM_{i,c,t} + \delta_9 T1RBC_{i,c,t} +$$

$$\delta_{10} TRBC_{i,c,t} + \delta_{11} PLLTL_{i,c,t} + \delta_{12} NPLTL_{i,c,t} + \delta_{13} TLTD_{i,c,t} + \epsilon_{i,c,t} \tag{3.8}$$

The model now includes financial variables that are said to influence ratings of the banks, they include:

ROA - Return on Assets, profitability ratios are always an important aspect of bank health and one such ratio is the return on assets of a bank. Poon et al (1999) identified some variables that are said to duly influence the rating of banks and they emphasised the importance of profitability ratios. Any increase in ROA is expected to positively impact upon the rating of a bank.

NIM - Net Interest Margin, this measures the difference between the interest received by the bank and the interest it pays out, this too is a measure of profitability of a bank and is also identified as contributing to the rating of a bank. One would expect that increasing the margins (with interest receipts outweighing interest payments) would positively impact upon bank ratings.

T1RBC - Tier 1 Risk Based Capital and TRBC - Total Risk Based Capital are both capital adequacy variables in the model. The importance of adequate bank capitalisation has become evident from the crisis. The BIS continue to emphasise the importance of adequate capital for banks. It is expected that improvements in bank capitalisation will favourably influence their credit rating.

PLLTL - Provisions for Loan Losses to Total Loans is defined as an asset quality measure which looks at how much the banks are holding to withstand loan losses. NPLTL - Non Performing Loans to Total Loans is another measure of asset quality and gives information about the banks ability to collect on its outstanding balances. An increasing non performing portfolio is said to have an adverse impact on the bank as the inability to collect on owed balances, particularly where they have not been provisioned for, weakens the credit portfolio. TLTD - Total Loans to Total Deposits is a liquidity measure.

It is important to note that while we analyse these accounting variables independently and assess what the expectations are a priori these variables cannot be looked at in isolation to determine the credit rating of a bank. The analysis of the variables together is the methodology utilised by the CRAs and other monitoring bodies. The CRAs weight the different variables and also include some measure of macroeconomic performance to determine there ratings.

As regards macroeconomic variables in the model these have been subsumed in the sovereign rating component of the model. It is well documented by all CRAs the macroeconomic variables that are used to determine the strength of the sovereign. In this instance one would expect that the macro data will be an integral part of the rating assigned to sovereigns and therefore it is accounted for in the model.

3.5 Results

3.5.1 Interdependence of ratings

The interdependence of bank ratings evaluates the response of other rating agents to a change in the credit rating of the lead CRA. In this instance we evaluate the three CRA's in turn all being the rating leaders and followers at one point. In the first situation we rate Moody's as the rating leader and S&P as the follower, following which S&P becomes the leader and Moody's the follower. The latter is done for all three CRA's and the results are shown in Tables 3.2, 3.3 and 3.4.

The rating methodology is taken from Alsakka (2014) but the results differ slightly due in part to difference in sample size and time frame. The dependent variable is the

Tab. 3.2: Moody's and S&P Interdependence

		Coefficients	Std. Error	Marginal Effects %		
Moody's as leader, S&P as follower				-2	-1	1
Bank Downgrade by Moody's	h=1	-0.7952	0.3888**	20%	19%	18%
	h=2	0.3301	0.3394	-8%	-8%	-7%
	h=3	omitted				
S& P as leader, Moody's as follower						
Bank Downgrade by S&P	h=1	-0.5467	0.5343	21%	21%	-
	h=2	-0.3931	0.4427	15%	15%	-
	h=3	omitted				

*,**,*** statistical significance at the 10%, 5% and 1% levels.

bank rating change of the leader in three time frames (depending on the response of the follower). The follower can respond to the leader's rating change in 1 month, 2-6 months or 7-12 months, he can also respond by a bank downgrade of 1 notch, a bank downgrade of more than 1 notch, an upgrade of 1 or more notches.

In the results we evaluate the likelihood of the follower responding to a rating change of the leader. This idea is an important area of investigation since there are significant implications if one CRA is found to be the rating leader while the others simply respond to those ratings issued. Further to this is the link between possible leaders and issuers shopping for credit ratings. If issuers simply solicit ratings from the agencies that administer favourable ratings and that CRA happens to be the market leader then other agencies may simply assign ratings more in line with the leader CRA. This can continue to propel inaccurate information about issuers and cause investors to make decisions without full information.

The table 3.2 gives the results of interdependence between the ratings issued by Moody's and S&P, the methodology follows that of Alsakka (2014) and the results also indicate similar findings. In the first instance we analyse Moody's as the rating leader and S&P as the follower. Here we look at Moody's downgrading bank i first and the response of S&P within 1 month (h1), 2-6 months (h2) or 7-12 months (h3), the rating categories are downgrade by more than 1 notch (-2), downgrade by 1 notch (-1) and upgrade by 1 notch (1). We also investigate the marginal effects of such rating changes.

The results show that there is a higher probability of a multiple notch downgrade by Moody's between 2-6 months following a bank downgrade by S&P (15 per cent). Additionally a downgrade of 1 notch also appears more likely between 2-6 months when Moody's is the follower (15 per cent). Interestingly, when Moody's is the leader it appears that S&P sometimes gave upgrades (18 per cent) despite the leader (Moody's) downgrading the bank. The results (similar to Alsakka (2014)) suggest that between Moody's and S&P, the latter tends to lead the rating game, it also appears that S&P is more independent with the ratings assigned since they were willing to give upgrades within 1 month of Moody's downgrading banks.

Tab. 3.3: S&P and Fitch Interdependence

		Coefficients	Std. Error	Marginal Effects %		
S&P as leader, Fitch as follower				-2	-1	1
Bank Downgrade by S&P	h=1	-0.2253	0.5540	8.4%	8.4%	-
	h=2	-0.2379	0.5468	8.9%	8.9%	-
	h=3	omitted				
Fitch as leader, S& P as follower						
Bank Downgrade by Fitch	h=1	0.5724	0.5102	-19.6%	-19%	-
	h=2	-0.2203	0.4294	7.5%	7.3%	-
	h=3	omitted				

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. 3.4: Fitch and Moody's Interdependence

		Coefficients	Std. Error	Marginal Effects %		
Moody's as leader, Fitch as follower				-2	-1	1
Bank Downgrade by Moody's	h=1	0.0769	0..5938	2.1%	2.1%	-
	h=2	0.1224	0.5312	3.4%	3.4%	-
	h=3	omitted				
Fitch as leader, Moody's as follower						
Bank Downgrade by Fitch	h=1	1.1904	0.5945**	43.5%	42.0%	-
	h=2	0.0954	0.4418	3.4%	3.4%	-
	h=3	omitted				

*,**,*** statistical significance at the 10%, 5% and 1% levels.

The results from table 3.3 for S&P and Fitch indicate that where Fitch leads the rating the likelihood of a downgrade from S&P is higher than the converse (-19.6% versus 8.4%) in a month time period. This indicates that S&P administers much harsher ratings within a 1 month and 2-6 month (h2) period when Fitch downgrades a bank first. On the other hand Fitch appears less reactionary to rating downgrades made by S&P. In the end we can conclude that Fitch has a 8.4 per cent probability of downgrading a bank by 1 or more than 1 notch following a rating downgrade by S&P.

3.5.2 Bank downgrade model

This section evaluates the role sovereign upgrades and downgrades play in the downgrade of banks by the credit rating agency. The analysis investigates all three rating agencies together, results shown in table 3.5. While the initial research sought to divide the data set into pre-crisis (2003-2007) and crisis periods (2008-2013) the researcher found that similar to Alsakka et al (2014) the pre crisis dataset is empty. There were no bank rating changes 3 1/2 months post the sovereign rating change during the pre-crisis period. This indicates that bank rating changes and sovereign rating changes seem to be independent pre-crisis.

The sovereign upgrades have been omitted from the model due to multicollinearity implying that sovereign upgrades have little influence in the bank downgrades assigned as expected. The sovereign downgrade variables however are statistically significant at the 5 per cent and 1 per cent levels. This result stands in support of that found by Alsakka (2014) that sovereign downgrades do influence the downgrades assigned to banks by the CRA's.

The way in which Alsakka's model is developed does elicit some concerns as it implies that only the sovereign rating dummies have undue influence on the rating a bank receives. In an attempt to improve the model and drawing on what the rating agencies themselves claim to do we include financial variables in the model. The influence of financial variables on ratings assigned to institutions have been well investigated in the literature (Poon et al 1999, Poon et al 2005).

As regards statistical significance we find that only the sovereign downgrade dummies, negative watch and sovereign rating variables are significant in the model. The implication is that the change in rating is heavily influenced by these variables. If a bank is downgraded the variables alluded to are the major drivers behind the amount of notches the bank is downgraded by. It would be interesting to investigate the ratings assigned (bank level model) to see whether the financial variables play a more influential role there.

Tab. 3.5: Estimation results : Bank downgrade model

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : bankdowngrade		
Sov $\uparrow_1$	0.000	(0.000)
Sov $\uparrow_2$	0.000	(0.000)
Sov $\downarrow_1$	0.316	(0.138)**
Sov $\downarrow_2$	1.185	(0.132)***
negativewatch	-0.812	(0.121)***
sovereignrating	0.032	(0.010)***
Equation 2 : cut1		
Intercept	-0.177	(0.068)
Equation 3 : cut2		
Intercept	1.207	(0.077)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

3.5.3 Bank upgrade model

This section looks at the bank upgrade model where the dependent variable is now bank upgrades. As one can imagine following the financial crisis bank upgrades tended to be few and far in between. The results indicate that bank upgrades were in part influenced by sovereign upgrades of 1 notch and the rating assigned to the sovereign.

Tab. 3.6: Estimation results : Bank downgrade model with financial variables

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : bankdowngrade		
Sov $\uparrow_1$	0.000	(0.000)
Sov $\uparrow_2$	0.000	(0.000)
Sov $\downarrow_1$	0.540	(0.181)***
Sov $\downarrow_2$	1.165	(0.171)***
negativewatch	-0.829	(0.154)***
sovereignrating	0.044	(0.017)*
roa	0.003	(0.019)
tier1rbc	0.014	(0.033)
plltl	0.077	(0.169)
npltl	-0.001	(0.016)
tltd	0.002	(0.002)
Equation 2 : cut1		
Intercept	0.317	(0.490)
Equation 3 : cut2		
Intercept	1.673	(0.495)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

In an attempt to deepen the investigation the model is extended to include financial ratios of which roa and tier1rbc are of statistical significance.

3.5.4 Bank level model

While the previous models look at the bank's rating change, this model looks at the ratings assigned to the bank by the CRA the alphabetic ratings have been transformed to numerical ratings for the purpose of the ordered probit model. In table 3.9 we apply the same methodology looking at the influence of sovereign rating changes and ratings along with the negative watch status on the rating assigned to banks. Here we see that both the sovereign downgrade of 1 notch and more than 1 notch are both statistically significant, along with the sovereign rating variable. This is no surprise since CRA's do claim to assess the sovereign to which the bank is attached as this will determine the possible support the bank will receive in times of financial and economic turmoil. If the sovereigns cannot keep their house in order it is highly unlikely to assist any failing banks.

In an attempt to deepen the investigation we apply the financial variables that are said to explain credit rating assignments. Table 3.10 gives the results, here we find that only the sovereign downgrade of 2 notches, the sovereign rating and non-performing variables are statistically significant. Similar works have found the return on assets to

Tab. 3.7: Estimation results : Bank upgrade model

Variable	Coefficient	(Std. Err.)
Equation 1 : bankupgrade		
Sov $\uparrow_1$	0.807	(0.468)*
Sov $\uparrow_2$	0.000	(0.000)
Sov $\downarrow_1$	-0.790	(0.671)
Sov $\downarrow_2$	-4.550	(225.151)
negativewatch	-0.219	(0.498)
sovereignrating	-0.079	(0.023)***
Equation 2 : cut1		
Intercept	-0.329	(0.125)
Equation 3 : cut2		
Intercept	1.143	(0.146)
Equation 4 : cut3		
Intercept	1.942	(0.237)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. 3.8: Estimation results : Bank upgrade model with financial variables

Variable	Coefficient	(Std. Err.)
Equation 1 : bankupgrade		
Sov $\uparrow_1$	1.561	(0.929)
Sov $\uparrow_2$	0.000	(0.000)
Sov $\downarrow_1$	-4.935	(549.671)
Sov $\downarrow_2$	-5.376	(820.208)
negativewatch	-1.756	(378.450)
sovereignrating	0.103	(0.092)
roa	1.266	(0.320)***
tier1rbc	-0.473	(0.159)***
plltl	-2.328	(1.480)
npltl	-0.027	(0.061)
tltd	-0.009	(0.006)
Equation 2 : cut1		
Intercept	-5.116	(1.693)
Equation 3 : cut2		
Intercept	-3.084	(1.553)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

be an important variable in rating determination but this is not the case here. The non-performing loan variable is used by regulatory agents to assess the health of a bank (along with other indicators). As such its statistical significance is expected. The sign associated with the npltl is positive, as such if the ratio goes up due to higher non-performing loans the independent variable also increases and higher numerical values are associated with rating downgrades.

Tab. 3.9: Estimation results : Bank level model

Variable	Coefficient	(Std. Err.)
Equation 1 : banklevel		
Sov $\uparrow_1$	-0.077	(0.379)
Sov $\uparrow_2$	0.000	(0.000)
Sov $\downarrow_1$	-0.319	(0.122)***
Sov $\downarrow_2$	-0.294	(0.109)***
negativewatch	-0.131	(0.094)
sovereignrating	0.374	(0.012)***

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. 3.10: Estimation results :Bank level model with financial variables

Variable	Coefficient	(Std. Err.)
Equation 1 : banklevel		
Sov $\uparrow_1$	-0.173	(0.501)
Sov $\uparrow_2$	0.000	(0.000)
Sov $\downarrow_1$	-0.184	(0.161)
Sov $\downarrow_2$	-0.333	(0.142)**
negativewatch	-0.046	(0.126)
sovereignrating	0.509	(0.023)***
roa	-0.023	(0.017)
tier1rbc	-0.030	(0.024)
plltl	-0.191	(0.133)
npltl	0.045	(0.012)***
tltd	-0.001	(0.001)
Equation 2 : cut1		
Intercept	-2.168	(0.546)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. 3.11: Comparison of Fitch viability rating and all in rating

Variable	Obs	Mean	Std. Dev.	Min	Max
Viability rating	156	10.43	4.68	2	21
All in rating	398	7.28	3.26	1	17

3.5.5 Standalone bank rating model

Looking at the viability rating for Fitch and the standalone bank rating for Moody's give a sense of the financial strength of the bank excluding any possible assistance from the regulatory or governing bodies. It is believed that these ratings are of immense importance since it presents the rating based solely on the bank's merit. This approach, given the European debt crisis where in many instances the sovereign problems plagued the banks, should illuminate the ability of the bank's to stand on their own.

In an attempt to evaluate this approach we determine the ability of our existing model to determine the standalone and viability rating for both Fitch and Moody's both done on a 21 point alphabetic rating scale, transformed to numerical ratings scale for use in an ordered probit model. Similar to the paper by the BIS (2016) we attempt to trace the influences on the rating and run a comparative analysis between this and the all in rating to assimilate whether rating catering has occurred. In this approach we also understand the prime role of the sovereign rating in the analysis and then observe whether there are major differences between the standalone ratings assigned and the all in ratings used.

When looking at the statistics comparing the Fich vability rating to their all in rating we find that the standard deviation tended to be higher for the viability rating compared to the all in rating. On average banks tend to have lower ratings when they are assessed excluding outside assistance (standalone/ viability rating).

Table 3.12 gives the results of the ordered probit model using the viability and standalone ratings for Fitch. By applying the same model as we did previously we note some differences. With the standalone approach we now find that the explanatory variables namely (return on assets (roa), tier 1 risk based capital (t1rbc), non-performing loans to loans (npltl), and total loans to deposits (tltd) are all statisticlly significant in the model. These variables explain the standalone rating assigned to banks by Fitch.

Tab. 3.12: Estimation results : Standalone rating

Variable	**Coefficient**	**(Std. Err.)**
	Equation 1	
roa	-0.056	(0.022)**
t1rbc	-0.227	(0.103)**
plltl	-0.291	(0.241)
npltl	0.048	(0.024)**
tltd	-0.014	(0.004)***

3.6 Conclusion

This chapter presents the question of whether or not the downgrade of the sovereign overwhelmingly influences the downgrade of the banks in their jurisdiction. The paper attempts to analyse pre crisis and crisis periods but finds that pre crisis, the rating of banks and sovereign are independent. Highlighting the fact that the sovereign rating changes in no way influence bank rating changes in the pre crisis time. Conversely, analysis of the crisis time period illuminates three fundamental conclusions.

Firstly, like other papers we find that the sovereign downgrades do influence bank downgrades in their jurisdiction for all three credit rating agencies. For all three CRA'S both the sovereign downgrade of 1 notch and the sovereign downgrade of 2 or more notches explained the change in rating for banks in the crisis period.

The paper did not eliminate the possibility of one event having a major influence on both the sovereign and bank leading to their downgrades. As such we included financial variables in the model to asses whether the banks were being downgraded solely because of the jurisdiction they were in. The latter brings us to the second conclusion that the accounting information of banks do play some role in determining the rating change but it was still found that the sovereign still had a greater influence on the rating change of a bank.

To solidify the analysis we investigated the role the accounting variables play on the rating a bank receives. This paved the way for the final conclusion that the accounting variables determine the overall rating a bank receives say Aaa/AAA or C, but in terms of determining how many notches to downgrade a bank by, it was found that the sovereign variable is more influential.

4. PAPER III- BANK CREDIT RATINGS MODELS

4.1 Introduction

The dependence on credit ratings issued by agencies continues to be questioned in the wake of the financial crisis. The impacts are still being felt by many economies left to rebuild their financial systems after the devastation brought on by the recent crisis. Credit ratings play an integral role as they are believed to give an insight into the ability of institutions to repay debt and can foster investor confidence in a firm or have the opposite effect. It is with this notion that many investors trust and rely upon credit rating agencies to give some indication about the financial ability of an institution.

The self reinforcing nature of credit ratings has been researched and documented where the mere downgrade by the rating agency is the catalyst for pushing institutions into the eye of a problematic storm. But how much do the public know about rating methodologies used by CRA's and how reliable are the rating information granted by theses agencies? Many have attempted to answer these questions and most with a quite cynical tone as researchers are usually unable to replicate ratings with 100 per cent accuracy.

While this chapter evades the debate of the trustworthy nature of credit rating agencies it does focus on the ability to replicate credit ratings posted by the three rating agencies. Even more than replicating ratings based on financial information, I assess the ability of 4 statistical models to accurately classify bank credit ratings. I compare an ordered probit, multiple discriminant analysis, ordinary least squares and artificial neural network models to determine which statistical model is better at classifying ratings. The analysis adds to the existing literature by attempting to include a univariate statistical model amongst the multivariate models. It also compares the ability of each model to determine rating using financial variables and principal components.

The chapter finds that the multiple discriminant analysis model supersedes the other models in its ability to accurately classify credit ratings. Moreover the model with variables tend to outperform the model with principal components. In the next section we discuss the relevant literature, section 4.3 explains the data and 4.4 details the methodology. The results are presented in section 4.5 and the paper concludes in section 4.6.

4.2 Literature Review

4.2.1 Moody's bank rating methodology

In the rating methodology for global banks document put out by Moody's in May 2013, they give a comprehensive analysis of their methodology for rating global bank securities and other bank instruments. The report focuses on the methodology applied to the Bank Financial Strength Rating (BFSR) and the Baseline Credit Rating Assessments (BCA). This section of the paper attempts to dissect the methodology by the rating company in order to replicate the rating models and test the ability of varying rating models to adequately determine bank credit ratings.

The report explains that bank credit ratings comprise of a combination of indicators both internal and external to bank strength. Internal ratings are based on franchise value, risk positioning, operating environment, financial fundamentals and regulatory environment. The external component is said to include; external support factors and currency deposit ceilings. While it is easier to focus on the measurable financial ratios of a bank to understand the credit ratings assigned we cannot ignore the fundamental factors described by the Moody's report. Despite some of these factors being subject to rater judgement. Additionally data to measure some components may not be readily available.

The report explains that franchise value is based on the market share held by the bank and its ability to diversify its products. The idea is that a bank with a large market share and well diversified products that have a far global reach can sustain itself under abnormal market pressures. They also suggest that this diversification of product will lead to greater earning stability as one area can compensate for shortfalls in another.

Risk positioning as an internal rating component focuses on how the bank manages the risks the bank and industry face. Moody's focuses on six subsections under risk positioning namely; corporate governance, controls and risk management, financial reporting transparency, credit risk concentration, liquidity management and market risk appetite. Under corporate governance Moody's claim to observe a wide range of relationships between the board, management and shareholders they also observe organization practices of the bank such as remuneration structures and other related party risks.

The ability of the bank to manage and control operation and other risks is also analysed by Moody's. The controls and risk management subsection takes into account risk management by evaluating the four pillars of risk management assessment[1] (RMA). Moody's also claim to assess the timeliness, frequency and accuracy of financial reporting of banks being rated. Another area that the rating agency focuses on, as do many banking regulators, is the concentration of credit risk among large borrowers and

[1] risk governance, risk management, risk measurement and risk infrastructure and intelligence.

industries. These large exposures give details on the possible financial problems banks can face if they are unable to recoup loan payments from large borrowers.

Another critical area of evaluation according to Moody's is the regulatory and operating environment. If the bank is supervised by a regulator that can ensure best practice and can enforce the rules that support a safe banking system Moody's explains that these banks will receive better ratings. It is felt that the regulators are the guardians for depositors and seek to ensure the safety of deposits. The operating environment which the bank is subject to, according to Moody's will have influence on the rating they receive. Banks that are subjected to financial and politically distressing environments will have weaker ratings. To measure these Moody's look at economic stability as measured by GDP, integrity and corruption by using the World Banks corruption index and finally the legal system in the country.

The next and probably most used rating factor in the existing literature is the financial fundamentals. Due mainly to the ease with which this accounting information can be collected. According to the Moody's report financial fundamentals are based on the CAMEL approach and Moody's assess five main areas namely; profitability, liquidity, capital adequacy, efficiency and asset quality.

The profitability component is of great importance in the rating analysis as Moody's explain that this can act as a buffer for banks should they encounter financial stress. The report explains that Moody's places great emphasis on return on equity, earnings per share, income before taxes and loan loss provisions as a per cent of risk weighted assets and net income as a percent of risk weighted assets.

4.2.2 Standard and Poor's bank rating methodology

Standard and Poor's issued a rating methodology guideline on their approach to rating banks and some major and minor overhauls to their approach in November 2011. The figure 4.1 gives a visual breakdown of the approach used by this rating agency. We can immediately identify some similarities and stark differences with the Moody's approach.

In the first instance Standard and Poor's note that rating the banks' commences with an analysis of the macro factors further subdivided into the economic risk factors and the industry risk factors. The economic risk factors range from problems arising out of political and economic instabilities to the risk associated with households in an economy. The countries are placed into groups from very low risk (group 1) to extremely high risk (group 10) as stated in the Standard and Poor's rating manual. According to Standard and Poor's a bank's economic risk score is heavily dependent upon the amount of business the bank has in the said country, in that case they weight the economic risk of each country the bank is operational in where the bank has in excess of 5 per cent of its business operations.

The industry risk as explained by Standard and Poor's is based on the operation of the banking industry where the bank carries out its main activities. The risks associated with the banking industry are rationalized as the ability of regulators to adequately monitor and manage the banking system along with their efficient and effective handling of any crisis situations that threaten banking stability. The role of the last resort elements to add liquidity to the market should any undue situations arise and the use of complex financial instruments in banking.

From figure 4.1 we observe that following the macro factor analysis the rating methodology then looks at the bank specific factors, these are made up of business position, capital and earnings, risk position, funding and liquidity. The business position rating category is further subdivided into three areas of interest (1) business stability, (2) concentration or diversity and (3) management and corporate strategy.

Business stability assesses the ability of the bank to withstand major financial and economic changes. Standard and Poor's claim that they analyse the revenue generation to understand the bank's capacity to deal with liquidity runs and lack of access to funding markets. Where revenue can sustain the banks funding requirements and position the bank to handle any financial distress the bank will receive a better rating. They also address the command of the market that the bank has and its customer base, with banks having larger market share and a greater customer base being in a better position.

The second element of the business position criteria is the concentration or diversity. This element addresses the business of the bank in terms of its concentration or diversification. As is expected banks that are diversified or have different lines of business are expected to better withstand many economic and financial shocks since they have different areas to absorb losses made in another. It is expected that diversified banks will have stronger ratings than those that are less diversified.

The final component in the business position factor looks at the management of the bank and their performance based on governance of the bank. The report highlights that this element is qualitative and emphasise the importance of the management team to adequately steer the bank toward success. They explain that past performance of the bank is used as a gage with regard to this measure. The bank's performance is also compared to other banks with similar business in the industry and their performance.

In reference to figure 4.1 we see that the next element in the bank rating methodology is capital and earnings. This section of the rating methodology assesses the banks ability to absorb losses in times of economic ills. It focuses on the bank meeting regulatory requirements, specific capital ratios that give a sense of loss absorption abilities, the class of capital and the earnings capacity of the bank. The fundamental investigation of whether the bank can meet or surpass regulatory requirements in terms of its capital holdings is imperative to its rating category. Standard and Poor's emphasise that banks that at least meet the regulators requirements would be in a stronger position than banks that continually fall short of the regulators set standards.

Apart from the regulatory framework set the bank must also ensure it is in a strong position regarding its capital holdings. In order to determine this Standard and Poor's monitor the Risk Adjusted Capital (RAC) ratio which is computed as Total Adjusted Capital/ Risk Weighted Assets. The next step in the analysis is evaluating the quality of capital a bank is holding. This process, according to the Standard and Poor's rating guide, will capture any weaknesses in the capital holdings that may have been missed by the evaluation of the RAC ratio. It looks at the ability of capital to absorb normalised losses allowing the bank to stand firm in times of economic turmoil.

The third pillar under the bank specific rating factors is the risk positioning of the bank. Here Standard and Poor's address the risks associated with the bank, risks range from the concentration or diversification of bank business, the ability to handle challenges and how the evolving economic environment would alter the risk structure of the bank.

Finally the bank specific factors take account of funding and liquidity for the bank, a measure that is of immense importance in banking business as evidenced by the recent financial crisis. As stated in the report the funding analysis attempts to evaluate the banks ability to continue its business in trying financial times and it takes an introspective look at the funding mix the bank is operating under. Things like the mix of core deposit and short term funding, the loan to deposit ratio, the banks ability to gain support form the central bank being some of the quantitative aspects of the foundation.

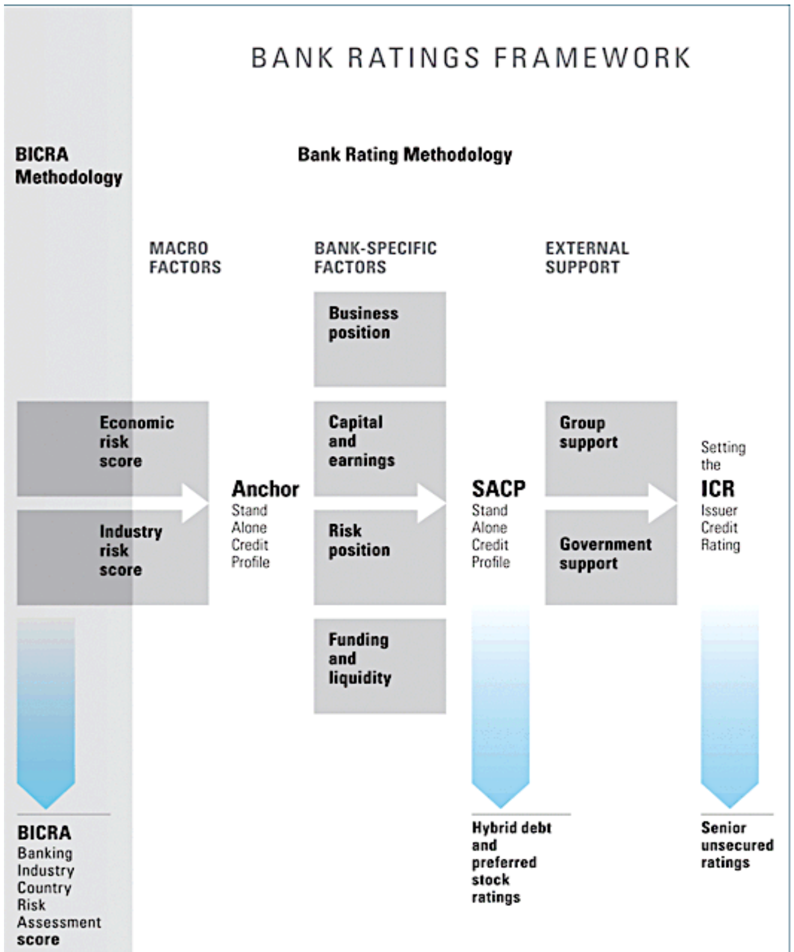
The last element in the rating analysis is the external support component. The ability of the regulators, government etc. to provide a safety net in order to cushion the blow of any impending crisis. This is an import component in bank stability as was witnessed with the most recent financial crisis. The importance of the authority's ability to provide support in catastrophic events will significantly impact the rating a bank receives since this goes to the heart of sector stability.

4.2.3 Credit rating studies

Credit rating studies have taken different approaches in the vast literature. Some studies focus on the determinants of credit ratings giving specific attention to financial ratios and other publicly available information to accurately predict credit ratings. Other studies take the determinants as given and focus on the ability of different multi and univariate statistical methods to predict credit ratings. Models such as probit and logit models, multiple discriminant analysis, neural networks, support vector machines have been detailed in the literature.

One of the earliest deterministic model approaches is found in Fisher (1959) where he uses ordinary least squares to determine the risk premium on corporate bonds. The author lists 4 independent variables that are said to determine the risk premium; earnings variability, period of solvency, equity to debt ratio and outstanding bonds. Fisher found that approximately 81 per cent of the variation in risk premiums were

Fig. 4.1: Standard and Poor's Rating Methodology



Source: Standard and Poor's Rating Methodology Guideline 2011.

explained by the estimated regression equation.

Horrigan (1966) addresses the question of financial ratios being able to determine corporate bond ratings. Even at this time Horrigan makes note that accounting data has suffered severe criticism in the literary field as its ability to determine ratings was thought to be inadequate. Nonetheless Horrigan investigates whether financial ratios can shed any light on the determination of credit ratings.

The data sample consists of 201 Moody's ratings and 151 Standard and Poor's firm ratings during the period 1959-1964. The author analysed financial ratios[2] and compiled a basic correlation between the independent variables and the dependent variable (bond ratings) is analysed from which the variables with the highest correlations are ascertained. The analysis then looks at using ordinary least squares to investigate different combinations of the explanatory variables. In the end 5 variables were found to be the best predictors of credit ratings.

- net worth to total debt
- sales to working capital
- total assets
- sales to net worth
- net operating profit to sales

West (1970) goes on to criticize Horrigan's methodology and proposes an alternative methodological approach. He argues that the methodology employed by Horrigan has no theoretical backing and the results can be much improved by exploring Fisher's approach. The application of Fisher's approach saw the author regress the coded company rating on the four independent variables identified by Fisher. The results show that the author was able to accurately predict 62 and 60 per cent of the credit ratings over two time periods.

While most of the early papers focused on the ordinary least squares method of rating classification Pinches and Mingo (1973) put forward the use of multiple discriminant analysis to classify ratings of industrial bonds. They used a sample of 180 bonds of which 48 bonds were used as the hold out sample on which to test the discriminant function. The authors used 6 independent variables thought to influence bond ratings they were; net income to interest, net income to total assets, long term debt to total assets, year of dividend payments, size of issue and a dummy variable for subordination

[2] Cash plus marketable securities to current debt, current assets less inventory to current debt,current assets to current debt, net worth to total debt, net worth to long term debt,net worth to fixed assets,net operating profits to interest, sales to accounts receivable, sales to inventory, sales to working capital,sales to fixed assets,sales to total assets,sales to net worth, net operating profit to sales, net profits to sales, net operating profits to total assets,net profits to net worth, total assets.

status. They were able to accurately classify approximately 65 per cent of bond ratings from the hold out sample.

Other papers such as Pinches and Mingo (1973), Pinches and Mingo (1975), Altman and Katz (1976) all utilise the multiple discriminant analysis methodology to determine credit ratings. In some cases the determination of the dependent variables for the discriminant function are arbitrary since the multiple discriminant methodology does not assign significance to the enlisted variables. Nonetheless it appears that this methodology is always (in the case of these papers) able to estimate 65 per cent and over of the rating classifications. In particular Altman and Katz (1976) were able to accurately classify an astonishing 80 to 90 per cent of the ratings in the entire sample with a 76 per cent accuracy on the hold out sample.

Kaplan and Urwitz (1979) investigate the popular methodological approaches, at the time, used to predict bond ratings. They argue that the OLS and multiple discriminant analysis methods suffer from limiting assumptions and do not account for important features of bond ratings. The authors argue that the inability of the OLS model to account for the importance in the ordinal nature of bond ratings means that this approach omits important information. As a result the OLS method cannot distinguish between the least risky bonds rated as Aaa, those rated as A which are less risk than B but more risky than Aaa.

The multiple discriminant method as explained by Kaplan and Urwitz (1979) also entails some limiting assumptions. Apart from the assumptions of normality the multiple discriminant analysis method does not allow the researcher to observe or test the importance of the variables used to develop the discriminant function. The authors argue that this is one reason Altman and Katz (1976) started with models containing 30 variables and had no methodological basis of reducing these to 14 variables. In an attempt to correct the limitations presented by the OLS and multiple discriminant methodology the authors propose the use a probit methodology in the classification of ratings. They find that the probit approach eliminates the limiting assumptions in the OLS and multiple discriminant methods and is able to classify bonds ratings with approximately 67 per cent accuracy.

Early research in computer learning models boasted of the ability of models to learn from data and claimed to eliminate the restrictive assumptions placed on data structures by models such as OLS, MDA and the like. The enthusiasm about computers mimicking the human brain was established in the 1960's but was in limited use since they were fraught with problems. Improvements saw the genesis of artificial neural networks (ANN) with hidden layers following on to present time and we now have ANN's using looping methodologies such as back propagation, the use of deep learning procedures which entail a multitude of hidden networks etc.

Some early works like Dutta and Shekar (1988), Hongkyu et al (1997), Maher and Sen (1997), Chaveesuk et al (1999) all used some form of neural network structure to classify ratings. The accuracy results in these papers show that the ANN method is well placed in the rating classification literature with all results giving rating classifications in excess of 50 percent reaching as high as 88 per cent classification accuracy.

In the paper by Bennell et al (2006) the authors compare the ability of neural networks and ordered probit models to accurately classify sovereign ratings. The authors find that the neural network methodology is able to outperform the ordered probit analysis. The neural network approach was able to accurately classify 42.4 per cent of sovereign ratings compared to 31.8 per cent by the ordered probit model.

The analysis by Bennell et al is developed on sovereign long term foreign currency ratings spanning 70 sovereigns across 11 rating agencies from the US, Europe, Canada and Japan. The authors explain that the sample includes 1,383 data points between the period 1989-1999. The sovereign long term foreign currency rating is transformed to a numerical scale from 16 to 1 (best to worst). The authors follow Cantor and Packer (1996) and Trevino and Thomas (2000, 2001) and include seven explanatory variables[3] determined to explain sovereign credit ratings.

Hill et al (2010) look at the diferences in ratings among three rating agents, namely Moody, Fitch and S&P as regards their sovereign ratings between the period 1990-2006. The investigation utilises an ordered probit model and a hazard model to determine the importance of the independent variables in the different rating methodologies applied by the CRAs. Hill et al pay close attention to the outlook and watch status of the CRAs and investigate whether these encapsulate all information. They conclude that ratings among agencies tend to be heterogenious but only differe marginally, that is by 1 or 2 notches. They also found that possibility of rating changes increase at lower rating levels for all CRAs.

Ogut et al (2012) investigate the ability of four statistical models to adequately classify the Moody's bank financial strength rating based on 26 financial variables. The authors explain that the data set is constructed for the period 2003-2006 and is developed for the Turkish banking sector. Given the large number of explanatory variables the authors undertake factor analysis to minimise the number of explanatory variables. They run a comparison of the model with variables alongside those with factors. The statistical models compared include an ordered logit model, multiple discriminant analysis, probabilistic neural networks and support vector machines. They conclude that the models with variables in each case outperformed the models with factor scores as inputs. Additionally they found that both the multiple discriminant analysis and support vector machine models were able to classify 65.11 per cent of the ratings correctly compared to classifications of 62.79 per cent by the other models.

Jones et al (2015) take a unique approach in the credit rating literature, they investigate a wide range of binary classifiers (similar to this paper) to extract a classifier that

[3] IMF development indicator, external debt to export, external balance, fiscal balance, rate of inflation, GDP per capita, GDP growth

approximates the ratings closely. The authors look at clasifiers such as logit/probit, discriminant analysis, neural networks, support vector machines, generalised boosting, AdaBoost and random forecasts. The paper concludes that different classifiers are able to predict better on different samples. For example the test sample saw improved classification from models like the discriminant analysis and the logit and probit. While the classifiers developed around nerual networks and the like tend to be more robust and are better predictors for a wider array of samples.

Doumps et al (2015) similar to the first chapter of this thesis, take the stance that both accounting and structural information contain a wealth of information that can explain rating changes assigned. In an unprecedented work the authors seek not only to include accounting data to determine the rating assigned to banks they also include data of a structural nature. The analysis is developed on European firms between the period 2002-2012.

Agha and Faff (2014) seek to highlight how firms costs alter due to a change in ratings. Their sample is based on non-financial firms between 1985-2009. The authors find that financially flexible firms experience lower costs when the ratings are stable. In particular they found a lower cost of capital as investor sentiment is stable, good ratings warrant some level of investment. One important conclusion is the reaction to financially inflexible firms. An upgrade to inflexible firms warrants little to no change in cost while a downgrade sees a significant rise in costs.

An analysis of the effectiveness of different classifiers is undertaken by Zhong et al (2014). The paper compares the ability of ELM, I-ELM, SVM and BP to accurately determine the ratings from Moody's and S&P. The model uses financial data of the firms and the paper finds that SVM models perform well when looking at the output distribution.

The firm specific characteristics and the ability of different models using these characteristics to predict accurate credit ratings is investigated by Mizen and Tsouka (2012). In their baseline model which is a linear model they find that any improvement in the firm characteristics tends to improve the rating received by the firm. Mizen and Tsoukas (2012) examine a various group of probit models to determine the importance of specific variables that may aid in the prediction of credit ratings. The authors skillfully look at the ageing of bonds, whereby the length of time a bond has had a specific rating enters their model. They also take into account momentum and drift of the bond. The allowance for non-linear arguments improve the model. The model is based on US bonds between 2000-2007 rated by Fitch.

Niemann et al (2008) seek to develop prediction models for multinational corporations and base it on financial data, due in part to the limited number of defaults they developed a model that seeks to limit heterogeneity in the financial data associated with groups.

Along the lines of using ratings to predict events Sy (2004) investigates whether we can use sovereign ratings to predict a currency crisis. The author establishes that there is no lead relationship between sovereign rating changes and a currency crisis but instead sovereigns tend to be downgraded following a currency crisis. Both Xia (2014) and Kraft (2015) examine the broader area of rating agencies catering. In Xia's work the change in behavior of an issuer pay rating firm when an investor pay firm enters the market is observed. While the vast array of literature points toward deterioration in rating quality, Xia argues the opposite. He finds that ratings of the issuer pay firm actually improve with the entry of an investor pay firm.

4.2.4 Investment grade vs. speculative grade ratings

General rating theory seems to suggest that credit ratings do convey important information to the market, if this is indeed the case then the grade of credit rating as in investment versus speculative grade should also hold some important infomation. Leading on from that idea is the non-linearity among ratings, suggesting that a change from one lower investment grade to a higher grade may carry less important infomation than a change from investment to speculative grade. The idea that movement within the bands have differing effects have been investigated in the literature and are expounded in this section.

According to Jorion and Zhang (2005), the information content of ratings is twofold. The amount of defaults that have occurred in a rating class can speak to the information content that the ratings carry. If issues that have a poor rating tend to default then it says that the market takes into account the ratings and the information it carries and responds. The authors explain that much of the literature examines the information content attached to a change in rating. If ratings do carry important inforation then one would expect goods news (improved ratings) to be concomittant with higher stock and bond prices reflection the improvement in ratings. While the latter has been investigated and found to be of minimal truth, in that bad news seems to carry more information content than good news.

Jorion and Zhang (2005) argue that one important variable that is missing from the models is the initial rating or starting point of ratings for the institution. The claim that a change in rating of the investment grade ratings to higher or lower investment grades carry less information than a change in the speculative grade ratings. Historically it has been shown that downgrades tend to be statistically significant in models addressing information content of ratings.

The importance of negative information as it pertains to the information content of ratings have also been investigated by Goh and Ederington (1998). They propound that firms may willingly disclose good news and therefore good news contains little information since firms will not hide good news. On the other hand firms maybe more reluctant to share bad news and so the information content in downgrades becomes more valuable. Another thought put forward is that the analysis into worsening financials is more indepth and would have more resourses assigned by the CRA since failure to detect possible defaults can adversely affect their reputation. As such one may find that downgrades warrant more attention than upgrades and inherently have more informational content.

According to the paper by Jaramillo and Tejada (2011) which look at assessing whether or not investment grade influences the costs associated with borrowing by a sovereign. They find that spreads on investment grade issues tend to be 36 per cent lower than simply utilising macroeconomic fundamentals. This means that higher grade sovereigns experience cheaper borrowing costs.The data set is based on 35 emerging economies over the period 1997-2010.

The paper by Arezki et al (2011) delves into the impacts on finncial markets stemming from sovereign rating news. As in other studies the paper concludes that negative news had a significant impact on financial markets. The authors also suggest that the overall extent of the spillover is directly related to a number of critical factors of which the country being downgraded and the agency where the news came from seem to be important factors that influence the size of spill over effect. If the news is about a country already experiencing serious economic trials then the spill over to financial markets is extreme as one would expect from more developed countries such as those in Europe.

Older studies done by Sarig and Warga (1989), Fons(1994), Longstaff and Schwartz (1995) and Jarrow et al (1997) all suggest that investment grade issues tend to have yield curves that trend in an upward direction versus speculative grade issues which tend to have a yield curve which slopes in a downward direction.

4.3 Data

In this section we discuss the data upon which the analysis is built. The study is developed on data collected from Bloomberg for three credit rating agencies; Moody's, Standard and Poor's and Fitch. For Moody's, Standard and Poor's and Fitch we use data on a sample of banks from Euro zone countries spanning 2003-2013. The dependent variable is bank credit ratings on the foreign long term portfolio and the independent variables are listed below. Similar to Ogut et al (2012) this study tests the ability of both the variables and the principal components (derived from the variables) to accurately predict credit ratings.

As the vast literature on credit ratings shows the CRA's use an array of quantitative and qualitative data to arrive at ratings for the firms they rate. In an attempt to replicate ratings with as much accuracy as posible we too employ data of a financial nature leaving room for error where rater judgement is concerned. Similar to Amato and Furfine, (2004) and van Gestel et al. (2007) the varables included vary from profitability, asset quality, capital adequacy and liquidity ratios to more balance sheet figures, an array that should give a sound financial look at any institution.

- Sovereign Rating (Srat)- This gives the rating assigned to the sovereign. The main assumption is that higher sovereign ratings should feed into higher bank ratings and the converse is true.

- Return on Assets (ROA)-is a profitability ratios and is assessed when looking at bank health. Any increase in ROA is expected to positively impact upon the rating of a bank.

- Return on Common Equity (ROE)- Though closely related we also include ROE in the correlation matrix, if this variable and ROE are highly correlated which we expect one would be eliminated. Return on Equity, also a profitability ratio, this variable measure the returns from shareholder investments and is also a significant measure of the health of a bank. This profitability ratio is expected to positively influence the rating of a bank. This variable was also identified as an important determinant in bank ratings in Poon et al (2005).

- Net Interest Margin (NIM)- Another profitability variable is the net interest margin. This measures the difference between the interest received by the bank and the interest it pays out, this too is a measure of profitability of a bank.

- Efficiency Ratio (ER)- The efficiency ratio, as the name suggests looks at the bank turning its resources into revenue, a lower the ratio signals higher efficiency.

- Tier 1 Risk-Based Capital Ratio(T1RBC) and Total Risk-Based Capital Ratio (TRBC) are both capital adequacy variables.

- Provisional Loan Losses/Total Loans (PLLTL)- Provisions for Loan Losses to Total Loans is defined as an asset quality measure which looks at how much the banks are holding to withstand loan losses.

- Reserve for Loan Losses/Total Loans (RLLTL)- This ratio gives the banks funds set aside to absorb losses from bad loans and loans expected to go bad (reserves for loan losses) against the total loan portfolio.

- Non-Performing Loans/Total Loans (NPLTL)- Is a measure of asset quality and gives information about the banks ability to collect on its outstanding balances. An increasing non performing portfolio is said to have an adverse impact on the bank as the inability to collect on owed balances, particularly where they have not been provisioned for, weakens the credit portfolio.

- Total Loans/Total Deposits (TLTD)- This acts as a liquidity measure.

- Total Loans/Total Assets (TLTA)- Similar to TLTD this variable also acts as a measure of liquidity.

- Deposits/Assets (DA)- This ratio looks at the banks coverage of its liabilities in particular whether the deposits can be covered by the existing asset base.
- Earning Assets (EA)- These are assets that earn income, for example stocks, bonds, interest paying accounts etc.
- Log Assets (logassets) and Total assets (TA)- measure bank size as they will be correlated to each other we simply use log assets in the model going forward.

Financial ratios tend to be highly correlated and to minimise the problems that such correlations can cause (spurious results) the author ran a correlation matrix with the 16 financial variables reported below. One expects some correlation with financial variables particularly where ratios use similar accounting data to compute them as such we look for correlations on the higher end of 65 per cent and over.

The bank credit ratings are coded for the purpose of the model. The researcher transforms the alphabetic ratings into numerical ratings between 1 to 20, with 1 being the best rating and 20 the worst. Consider table 4.2 which gives the transformation of bank credit ratings. This method is also applied to the sovereign ratings which also ranges between 1 to 20 that is from best to worst.

Tab. 4.1: Financial Variables Correlation Matrix

	ROA	ROE	NIM	ER	T1RBC	TRBC	PLLTL	RLLTL	NPLTL	TLTD	TLTA	DA	DF	TA	EA	LogA
ROA	1															
ROE	0.9551	1														
NIM	0.1922	0.1268	1													
ER	-0.4446	-0.3662	-0.3932	1												
T1RBC	0.0282	0.0045	0.0605	0.039	1											
TRBC	-0.1568	-0.1406	-0.1442	0.2959	0.7927	1										
PLLTL	-0.2043	-0.2668	0.2707	-0.1969	0.0214	-0.131	1									
RLLTL	0.0576	0.0285	0.2156	-0.1427	0.0248	-0.0369	0.0757	1								
NPLTL	-0.5959	-0.6026	0.0366	0.1083	-0.0954	0.1316	0.1734	0.1194	1							
TLTD	-0.4534	-0.4239	-0.205	0.2104	-0.2046	0.0824	0.0183	-0.0513	0.5574	1						
TLTA	-0.0333	-0.0801	0.1731	-0.2477	-0.3173	-0.3349	0.172	0.2715	0.2968	0.5424	1					
DA	0.3778	0.2867	0.4512	-0.4617	-0.086	-0.3833	0.1602	0.3504	-0.197	-0.4156	0.5064	1				
DF	0.4382	0.3645	0.3001	-0.2749	0.1638	-0.1424	-0.0327	0.2695	-0.3902	-0.8042	-0.1238	0.7236	1			
TA	0.1285	0.1574	-0.1968	0.1496	0.3538	0.4018	-0.2151	-0.197	-0.2944	-0.4683	-0.8663	-0.4759	0.1416	1		
EA	0.1209	0.1441	-0.1982	0.112	0.2917	0.3698	-0.2035	-0.198	-0.2619	-0.4109	-0.8083	-0.4686	0.0785	0.9649	1	
LogA	0.0681	0.0912	-0.1464	0.0917	0.3608	0.4634	-0.212	-0.238	-0.1521	-0.2587	-0.7156	-0.4787	0.0015	0.8999	0.9156	1

Tab. 4.2: Credit Rating Transformation

Rating	Moody's	Standard & Poor's	Fitch	Rating Grade	Description
1	Aaa	AAA	AAA	Investment	Minimal risk
2	Aa1	AA+	AA+	Investment	Minimal risk
3	Aa2	AA	AA	Investment	Very low credit risk
4	Aa3	AA-	AA-	Investment	Very low credit risk
5	A1	A+	A+	Investment	Very low credit risk
6	A2	A	A	Investment	Low credit risk
7	A3	A-	A-	Investment	Low credit risk
8	Baa1	BBB+	BBB+	Investment	Low credit risk
9	Baa2	BBB	BBB	Investment	Moderate credit risk
10	Baa3	BBB-	BBB-	Investment	Moderate credit risk
11	Ba1	BB+	BB+	Speculative	Substantial credit risk
12	Ba2	BB	BB	Speculative	Substantial credit risk
13	Ba3	BB-	BB-	Speculative	Substantial credit risk
14	B1	B+	B+	Speculative	Substantial credit risk
15	B2	B	B	Speculative	High credit risk
16	B3	B-	B-	Speculative	High credit risk
17	Caa1	CCC+	CCC	Speculative	High credit risk
18	Caa2	CCC	DDD	Speculative	Very high credit risk
19	Caa3	CCC-	DD	Speculative	Very high credit risk
20	Ca and below	CC and below	D	Speculative	Very high credit risk

4.4 Methodology

This section describes the different multivariate and univariate statistical models used to predict credit ratings. Here we analyse the ordered probit, multiple discriminant analysis, ordinary least squares and artificial neural networks models and explain how the models using variables and principal components are developed.

Ordered Probit

The ordered probit model is the first statistical model evaluated, since ratings are discrete in nature and have an ordinal outcome this multivariate statistical model should adequately account for the nature of the dependent variable. There exists an unobserved latent variable y^*, for example credit worthiness y^* is dependent on the independent variables and some error term. Despite y^* being unobservable we can observe the ordinal variable y in this case the credit ratings, these can take a value from 1-20 with 1 being the best possible rating and 20 the worst.

$$y^* = \alpha + \beta x + \epsilon \tag{4.1}$$

$$y = \begin{bmatrix} 0 \; if y^* \leq \gamma_1 \\ 1 \; if \gamma_1 < y^* \leq \gamma_2 \\ 2 \; if \gamma_2 < y^* \end{bmatrix} \tag{4.2}$$

The bank rating in the following equations is the dependent variable and can take any value between 1-20 depending on he rating assigned by the rating agency. The rating the bank receives is determined by the financial ratios (the independent variables) listed on the right hand side of the equation these financial ratios are used by the rating agencies along with other information to determine the rating a bank receives. Due to identified subjectivity by the rating agencies in some of the measurement tools this paper and others like it tend to focus on publicly available information that is less subjective. In using the financial fundamental ratios we come up against multicollinearity problems with the finance data which can give spurious results. To correct for the latter principal component analysis is applied to the finance data and the principal components become the independent variables as see in the equation 4.4. The ability to build both models in this way also presents the researcher with a platform to test not only different statistical approaches to forecast bank ratings but within each statistical approach to analyse whether using the variables or transformed variables (principal components) are better at forecasting bank credit ratings.

$$Bankrating_{i,c,t} = \alpha_1 Srating_{c,t} + \alpha_2 ROA_{i,c,t} + \alpha_3 ROE_{i,c,t} + \alpha_4 NIM_{i,c,t} + \alpha_5 T1RBC_{i,c,t}$$

$$+\alpha_6 TRBC_{i,c,t} + \alpha_7 PLLTL_{i,c,t} + \alpha_8 NPLTL_{i,c,t} + \alpha_9 TLTD_{i,c,t} + \alpha_{10} TLTA_{i,c,t} + \alpha_{11} DA_{i,c,t} + \epsilon_{i,c,t} \tag{4.3}$$

$$Bankrating_{i,c,t} = \alpha_1 PC1_{i,c,t} + \alpha_2 PC2_{i,c,t} + \alpha_3 PC3_{i,c,t} + \alpha_4 PC4_{i,c,t} + \alpha_5 PC5_{i,c,t}$$

$$+\alpha_6 PC6_{i,c,t} + ...\alpha_n PCn_{i,c,t} + \epsilon_{i,c,t} \tag{4.4}$$

Multiple Discriminant Analysis

Another multivariate statistical model used to predict ratings is multiple discriminant analysis (MDA). MDA is used when the dependent variable under analysis is of a categorical nature and there exist two or more categories which are distinguishable. The main aim of MDA is to discriminate among groups based on the independent variables. For example we may expect banks that have the best credit ratings (AAA) to have high return on assets and return on equity, be well capitalised and have low non performing loans. As such these independent variables can be used to discriminate those banks that have high credit ratings and those that have ratings on the lower end. One shortcoming of this particular model is that there are approximately 18 categories of ratings and therefore at some point distinguishing a rating of 14 to a rating of 15 might become onerous since there is no vast difference between the two categories (just a 1 notch downgrade). The ability of the MDA to discriminate groups then adds to the predictive ability of the model whereby the researcher can attempt to forecast the group new cases will belong to based on the discriminant function.

The MDA is built on the foundation that there exists at least two groups which can be easily distinguished and the groups are mutually exclusive. The model is built as seen in the following equation, where: D is the discriminant function, v the discriminant coefficient, X is the variable score and c is a constant.

$$D = \sum v_n X_n + c \tag{4.5}$$

Ordinary Least Squares

The ordinary least squares method is a statistical technique which attempts to explain the relationship between the dependent and independent variables by fitting a line. The OLS estimation procedure gives the line of best fit which is taken as the best approximation of the data.

$$y = \beta_0 + \beta_1 x + u \tag{4.6}$$

Where y is the dependent variable, β_0 is the constant term or the intercept term and β_1 being the slope parameter, x is the independent or explanatory variable and u is known as the error term in the regression equation and represents other variables that may affect y not accounted for by the regression equation. The regression estimation is built on the following assumptions;

- $E(u) = 0$
- $Cov(x, u) = E(xu) = 0$

In the case of the bank rating model we investigate the ability of the OLS technique to predict bank ratings. The first equation uses financial ratios along with the sovereign rating variable as explanations for bank credit ratings, the second equation looks at the principal components as the explanatory variables in the bank rating model.

$$Bankrating_{i,c,t} = \beta_1 Srating_{i,c,t} + \beta_2 ROA_{i,c,t} + \beta_3 ROE_{i,c,t} + \beta_4 NIM_{i,c,t} + \beta_5 T1RBC_{i,c,t}$$

$$+\beta_6 TRBC_{i,c,t} + \beta_7 PLLTL_{i,c,t} + \beta_8 NPLTL_{i,c,t} + \beta_9 TLTD_{i,c,t} + \beta_{10} TLTA_{i,c,t} + \beta_{11} DA_{i,c,t} + u_{i,c,t} \tag{4.7}$$

$$Bankrating_{i,c,t} = \beta_1 PC1_{i,c,t} + \beta_2 PC2_{i,c,t} + \beta_3 PC3_{i,c,t} + \beta_4 PC4_{i,c,t} + \beta_5 PC5_{i,c,t}$$

$$+\beta_6 PC6_{i,c,t} + ...\beta_n PCn_{i,c,t} + u_{i,c,t} \tag{4.8}$$

Artificial Neural Networks

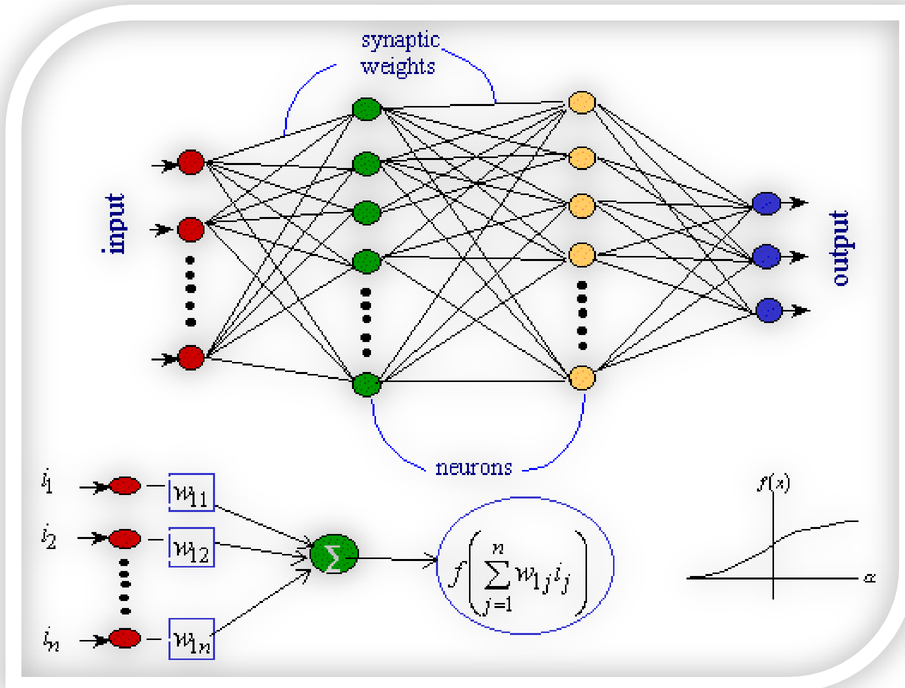
Artificial neural networks finds its home in the broad area of computer learning and proposes to mimic the working of the human brain, in essence learning from the data. To premise the discussion of artificial neural networks one must first grasp the basic workings of the human brain, which in the literature is argued to be too complex to understand thoroughly. Figure 4.2 gives a graphical representation of the neural pathway in the human brain. Inputs or information is sent to the neurons, when this information amalgamates pass a certain point it triggers an electrical impulse from the neurons. Neurons communicate with other neurons via synapses (electrical signals) that elicit some action. These synapses represent the synaptic weights attached to the artificial neural network models.

The popularity of neural networks springs from the lack of restrictions preceding data learning, that is to say we do not have to pose limiting assumptions on the data as in other statistical techniques like ordinary least squares and other such models. The neural network model learns the relationships between the dependent and independent variables during the training process. The researcher is no longer plagued with pre-determining the existing relationships. The flexibility allowed by the neural network does come at a price since it is cumbersome to understand and interpret the synaptic weights.

The neural network has different structures for example back propagation where the network is made up of connections that flow forward and loop back, feed forward networks where the connections flow forward without any backward loops. This analysis uses the multilayer perceptron (MLP)architecture. For a visual representation of the network structure see Appendix C.1, the structure consists of:

- inputs also known as independent variables
- synaptic weights which link the inputs to the hidden layer and link the hidden layer to the output
- a hidden layer which contains the activation function to be used
- the output

Fig. 4.2: Neural Networks



Source: http://www.ndt.net

4.5 Results

4.5.1 Ordered Probit

This section of the results reports on the ability of the ordered probit model to accurately classify bank credit ratings for the three credit rating agencies (Moody's, Standard and Poor's and Fitch). The results are given for the ordered probit model using financial variables and are compared with the ordered probit model using the principal components. This section of the analysis will assess the ability of the model with variables to outperform the model with the principal components in accurately classifying bank credit ratings. The researcher approaches the variables model first and attempts to build a significant model based on 16 financial ratios for each rating agency (see data section). After compiling the most useful model the researcher then compiles the confusion matrix to assess the classification of the model with variables. Following this we build an ordered probit model with principal components (the principal components are derived from the best fit model with variables) and test the ability of the principal component model to accurately classify bank credit ratings.

As regards the confusion matrix the statistical program (in some cases STATA in others SPSS) compiles the probabilities of attaining each rating category, this gives us the probability of obtaining a 1, 2, 3, 4,....18 for each observation. After which we assign the category with the highest probability as the predicted rating category for that observation. We then compare the predicted rating category to the actual rating category for each observation.

Moody's

The ordered probit model has 12 financial variables all said to influence credit ratings in some way. Many of the variables were either used in previous literature or highlighted by the rating agency as being used in the determination of credit ratings. The model with all significant variables is model 5 (Table 4.3). Model 5 has 163 observations and gives a log likelihood of -200.1089, the chi square value is 438.23 which is significant at the 1 per cent level.

In order to evaluate the performance of the model in accurately classifying bank credit ratings assigned by the credit rating agency Moody's, we construct the confusion matrix seen in table 4.4. The confusion matrix gives the number of observations accurately classified in each rating category. We can see this figure down the main diagonal of the matrix. In total the model accurately classified 83/163 observations an accuracy rate of approximately 52 per cent.

Upon further investigation of the individual rating categories we find that the ratings between 2-4 (Aa1-Aa3) are all classified with 60 per cent and over accuracy. Despite the rating category 1 having 0 accurate classifications we must observe that there was only 1 observation in this category and the model incorrectly classified it as a 3 as opposed to a 1 (Table 4.4). Barring this it appears that the model is better able to classify the higher rating categories (those associated with the better ratings) compared to the middle ratings (Table 4.5). Further to this we also find that the model classifies the rating category of 16 with 100 per cent accuracy, and the categories 11 and 13 are also accurately classified by 85.7 per cent.

After evaluating the Moody's ordered probit model with variables we then apply principal component analysis to the variables. Following this, the same methodology is then followed where we run the ordered probit model with the principal components and then develop the confusion matrix to assess whether we can improve the classification of bank ratings using principal components.

The relationship between the principal component and the financial variables are analysed based on the correlation matrix seen in table 4.6, we take the correlations that are 30 per cent and over to indicate some significant relationship between the two. As such pc1 appears to be correlated with the sovereign rating variable (Srat),total loans to total assets (TLTA) and log total assets (logassets). The correlation matrix shows that pc2 is correlated to 5 financial variables in the model (ROE, NPLTL, TLTD, DA). As regards pc3 there exist correlations with Srat, NIM, T1RBC and TLTD. Pc4 can be described as the capital adequacy variable since it is highly correlated with T1RBC, it is also correlated to PLLTL and TLTA. Pc7, pc9 also have correlations that will be further discussed in the analysis.The components, now treated as variables, are placed in the ordered probit model as explanatory variables. Table 4.7 shows the results, pc1, pc4, pc7, pc9 are all significant in model 6.

We can now analyse both the correlation matrix and the ordered probit model to ascertain whether our principal components make sense. In analysing pc1, we see that the principal component in the ordered probit model (Table 4.7) has a positive coefficient, this means that if pc1 increases then the bank numerical rating increases translating to a worsening of the rating/a bank downgrade. Pc1 is positively correlated to the sovereign rating variable and the total loans to total assets (TLTA). As such any increase in these variables will increase pc1, and any increase in pc1 will worsen the bank's credit rating.

Higher numerical sovereign ratings mean a worsening of the sovereign credit rating since sovereign credit ratings are translated on a similar rating scale (1-20 with 1 being the best and 20 the worst). It is important to note that the ratio TLTA can increase due to a fall in asset values thereby reducing the denominator which can adversely affect bank credit ratings. However this ratio can also increase if we have an increase in total loans while a higher loan portfolio may signal a growth in business it also means that banks now have to hold higher reserves depending on the type of loans and it also makes risk weighted assets higher.

Pc1 is inversely related to both total asset and log total assets. This suggests that as these variables increase pc1 will fall, as pc1 falls the numerical bank rating will also fall say from 5 to 3 indicating an improvement in the rating since lower numerical values are associated with better ratings. This result stands in line with a priori expectations since we expect higher asset values to improve the overall rating of the bank since it increases the buffer the bank has should problems arise.

The second principal component pc2 has a positive sign in the ordered probit model as seen in table 4.7. This suggests that any increase in pc2 will result in an increase in the numerical bank rating. It must be noted that an increase in the numerical bank rating say from 3 to 6 signals a worsening in the overall rating while the opposite is true. The first financial variable pc2 has a strong correlation to is ROE (Table 4.6), the relationship is inverse therefore any increase in ROE results in a fall in pc2 while a fall in pc2 is synonymous with a fall in the numerical bank rating pointing to an improvement in the overall rating (Table 4.7). This result is concomitant with a priori expectations since we expect higher returns on equity to put the bank in a more favourable position and thereby improve its credit rating.

The principal component pc2 also has a positive relationship to NPLTL and TLTD this means that any increase in these variables will lead to an increase in pc2. From the ordered probit model results (table 4.7) we know that pc2 has a positive coefficient and as such any increase in pc2 will increase the numerical bank rating pointing to a worsening of the credit rating. We can understand how an increase in non-performing loans and the total loans to total deposits ratios may worsen the bank credit rating.

The final variable to be highly correlated to pc2 is DA (deposits to assets) the variables are inversely related so that a higher deposits to assets ratio will reduce pc2 and a fall in pc2 results in a fall in the numerical bank rating which is synonymous to an overall improvement in the bank credit rating. While higher deposits might bode well for the bank it seems unlikely that falling asset values could lead to improved credit ratings.

The third principal component pc3 is positively correlated with Srat. Higher sovereign ratings lead to higher values of pc3 and from the ordered probit model in table 4.7 we see that higher values of pc3 lead to increases in the numerical bank rating. This means that as the sovereign rating increases, that is the sovereign is downgraded this contributes to a bank downgrade. I have closely evaluated and proven this in the previous chapter.

Surprisingly pc3 is also positively correlated to NIM and T1RBC which means any increase in these variables will serve to worsen the credit rating of the bank. A priori we expect any increase in T1RBC to have a positive impact on the credit rating a bank receives. Upon closer examination of NIM we see that the ratio can increase due to a fall in the denominator (average earning assets) if this occurs we would expect higher NIM to be likened to a weaker credit rating. As regards TLTD we find this variable is inversely related to pc3, the effect is opposite to that identified with pc2, here any increase in the ratio will decrease pc3 and any fall in pc3 will lead to a fall in the numerical bank rating, that is it will lead to an upgrade for the bank.

Pc4 has a negative coefficient in the ordered probit model, this means that any increase in pc4 will lead to a decrease in the bank numerical rating implying that the bank has been upgraded. The correlation between pc4 and T1RBC is positive and any increase in this variable will increase pc4. As mentioned any increase in pc4 will lead to a decrease in the numerical rating suggesting a bank upgrade. This stands in line with a priori expectations since we anticipate an increase in the capital adequacy ratios improving the overall credit ratings of the bank. The variable TLTA also has a positive sign in the correlation table with pc4 and so we conclude that increases in this ratio will improve bank credit ratings.

On analysing pc7 in the ordered probit model we observe a negative coefficient. In creases in pc7 will result in a decrease in the numerical rating of the bank (the dependent variable), associated with an improvement in the bank rating. Further analysis of pc7 in table 4.6 shows the principal component to be inversely related to Srat, therefore higher sovereign ratings will lead to a fall in pc7 and a fall in pc7 as seen in table 4.7 will result in a rise in the numerical bank rating. From this we can conclude that a sovereign downgrade influences a bank downgrade.

The variables PLLTL and NPLTL are both positively correlated to pc7. An increase in PLLTL can come from rising loan loss provisions (a non cash expense) which can occur to cover increased risky loans being put on the books by banks. The ratio may also increase on account of decreasing total loans (the denominator). From the model a rise in PLLTL will be followed by an increase in pc7. As pc7 increases we find that the numerical bank rating should fall. Similar is the case for an increase in NPLTL which is suggested to result in an increase in pc7 and an improvement in the overall bank rating. Contrary to a priori expectations the results of pc7 suggest that an increase in the variables PLLTL and NPLTL will result in an improvement in the bank credit rating.

As regards the principal component pc9 we observe from table 4.7 that this component has a positive coefficient in the ordered probit model. From table 4.6 the component is positively correlated to both Srat and ROE. A priori we would expect an increase in Srat to adversely affect the bank rating while an increase in ROE should improve the bank rating. Closer observation suggests that an increase in both variables will increase pc9 which will worsen bank credit ratings. Before disputing the results the argument must be made that the financials of the banks are assessed in unison by the rating agency and so it is difficult to expect each variable to behave as expected. The bank may have rising ROE but other aspects that Moody's deem important may suggest that the bank should be downgraded. Being that pc9 is also positively related to NPLTL suggests that any increase in this variable will worsen the overall bank rating.

Following the analysis of the principal components and the variables the confusion matrix with principal components is built the main diagonals are assessed to get the classification accuracy. This can be seen in table 4.8, the horizontal ratings are the bank ratings issued by the rating agency Moody's while the vertical ratings are the ratings predicted by the model. After running the ordered probit model STATA lists the probability of receiving the ratings (3,4,5,.....18) based on the explanatory variables. We then choose the highest probability in each case so for example STATA may give the probability of receiving a 3 based on the explanatory variables as 0.99, the probability of a 4 is 0.30 and a 5 is 0.69 and so on then we choose 3 for that observation since it has the highest probability. We then compare the predicted ratings with the ratings issued by the rating agency, this is seen along the main diagonals in table 4.8.

For the principal component analysis we find that the model can only accurately classify 51 per cent of the data (83/163) this is close to the ordered probit model with variables which was able to accurately classify 52 per cent of the data (84/163). A closer look at the confusion matrix with principal components shows that the category with the best classification was 18 and 11 with a classification of 100 per cent (8/8)and 71 per cent (10/14) respectively. Categories 13, 3 and 2 registered classifications of 79, 67 and 60 per cent respectively.

If we analyse the off diagonals of the confusion matrix we see that the models struggle to discriminate 1 notch above and 1 notch below the actual ratings, for example we have the actual rating category of 3 being misclassified as a 4. This trend is observed throughout the off diagonal (1 above and 1 below) for the matrix. This points to the difficulty the models have in the discriminations of rating categories that are close.

With the ordered probit model for Moody's we find the classification with variables out performs that with principal components in the determination of ratings by a small margin. Nonetheless an overall classification of 52 per cent is still weak and we now apply the methodology to other rating agencies and analyse the results on their data. It may be that we are unable to adequately capture the rating methodology utilised by Moody's in determining their credit ratings, or that the rating process is quite subjective and therefore is difficult to replicate with 100 per cent accuracy. Despite Moody's admitting to many ratings being subject to rater judgement one wonders how raters can distinguish ratings that are 1 notch above or below, since it appears that the models struggle with this.

Tab. 4.3: Moody's Ordered Probit Model with Variables

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variables	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Srat	0.6883	0.000	0.6908	0.000	0.6900	0.0000	0.6816	0.000	0.6741	0.000
	(0.0573)		(0.0571)		(0.0570)		(0.0563)		(0.0558)	
ROE	-0.0660	0.050	-0.0673	0.045	-0.0653	0.0510	-0.0718	0.028	-0.0238	0.024
	(0.0337)		(0.0336)		(0.0334)		(0.0327)		(0.0105)	
NIM	-0.2979	0.027	-0.2992	0.026	-0.2854	0.0330	-0.2840	0.034	-0.2456	0.062
	(0.1348)		(0.1348)		(0.1337)		(0.1341)		(0.1314)	
ER	-0.0070	0.420	-0.0080	0.340						
	(0.0087)		(0.0084)							
T1RBC	0.1863	0.056	0.1709	0.065	0.1926	0.0320	0.1892	0.035	0.1863	0.038
	(0.0974)		(0.0927)		(0.0899)		(0.0898)		(0.0896)	
PLLTL	-0.9109	0.027	-0.8873	0.030	-0.8227	0.0410	-0.7956	0.049	-0.7031	0.077
	(0.4118)		(0.4095)		(0.4034)		(0.4040)		(0.3976)	
RLLTL	-0.0088	0.384	-0.0100	0.315	-0.0098	0.3210				
	(0.0102)		(0.0099)		(0.0099)					
NPLTL	0.2272	0.000	0.2274	0.000	0.2250	0.0000	0.2138	0.000	0.2159	0.000
	(0.0403)		(0.0403)		(0.0402)		(0.0385)		(0.0384)	
TLTD	-0.0174	0.048	-0.0176	0.046	-0.0161	0.0630	-0.0145	0.087	-0.0151	0.074
	(0.0088)		(0.0088)		(0.0086)		(0.0085)		(0.0085)	
TLTA	0.0400	0.158	0.0450	0.092	0.0456	0.0880	0.0371	0.142	0.0429	0.086
	(0.0284)		(0.0267)		(0.0267)		(0.0253)		(0.0250)	
DA	-0.0363	0.427	-0.0553	0.044	-0.0498	0.0640	-0.0467	0.080	-0.0475	0.074
	(0.0457)		(0.0275)		(0.0268)		(0.0267)		(0.0266)	
DF	-0.0180	0.602								
	(0.0345)									
logassets	-1.7444	0.000	-1.7292	0.000	-1.6808	0.0000	-1.6309	0.000	-1.5788	0.000
	(0.2640)		(0.2623)		(0.2572)		(0.2520)		(0.2487)	

Standard errors in parentheses

Tab. 4.4: Moody's Confusion Matrix from Ordered Probit Model with Variables

Predicted Rating	Actual Rating																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	18	**Predicted Total**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
2	0	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
3	1	2	12	3	0	0	0	0	0	0	0	0	0	0	0	0	0	**18**
4	0	0	1	13	4	4	1	0	0	0	0	0	0	0	0	0	0	**23**
5	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	**2**
6	0	0	0	3	8	10	6	0	0	0	0	0	0	0	0	0	0	**27**
7	0	0	0	0	0	6	6	1	4	3	0	0	0	0	0	0	0	**20**
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
9	0	0	0	0	0	0	4	2	6	4	1	0	0	0	0	0	0	**17**
10	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	**3**
11	0	0	0	0	0	0	0	0	1	3	12	2	1	0	1	0	0	**20**
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
13	0	0	0	0	0	0	0	0	0	0	1	1	12	2	1	0	0	**17**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
16	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	8	2	**11**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Actual Total	**1**	**5**	**15**	**19**	**13**	**21**	**17**	**3**	**13**	**11**	**14**	**3**	**14**	**2**	**2**	**8**	**2**	**163**

Tab. 4.5: Percentage of Ratings Accurately Classified with Variables

Numerical Rating	Rating Assigned by Moody's	Per cent Accurately Classified
1	Aaa	0.0
2	Aa1	60.0
3	Aa2	80.0
4	Aa3	68.4
5	A1	7.7
6	A2	47.6
7	A3	35.3
8	Baa1	0.0
9	Baa2	46.2
10	Baa3	9.1
11	Ba1	85.7
12	Ba2	0.0
13	Ba3	85.7
14	B1	0.0
15	B2	0.0
16	B3	100.0
18	Caa2	0.0

Tab. 4.6: Moody's Correlation between Explanatory Variables and Principal Components

Variable	Pc1	Pc2	Pc3	Pc4	Pc5	Pc6	Pc7	Pc8	Pc9	Pc10
Srat	**0.3066**	0.2168	**0.3297**	-0.1913	0.1926	0.0209	**-0.6666**	0.1488	**0.3933**	-0.2125
ROE	-0.2255	**-0.4516**	-0.1530	0.2374	**0.3383**	0.0643	0.0514	-0.1982	**0.6976**	0.0588
NIM	0.1719	-0.1898	**0.4134**	0.0989	**0.3823**	**0.7078**	0.1699	0.0369	-0.2691	-0.0080
T1RBC	-0.1486	0.1942	**0.4339**	**0.4933**	0.1230	-0.2838	-0.1821	-0.1261	-0.1060	**0.5927**
TRBC	-0.2839	**0.3400**	0.1834	**0.4518**	0.1039	-0.1160	0.1943	-0.0154	0.0174	**-0.7084**
PLLTL	0.2548	0.0720	0.2971	**-0.4123**	**0.3913**	**-0.4533**	**0.5377**	-0.0987	0.1104	0.0300
NPLTL	0.1456	**0.4979**	0.0961	0.0173	**-0.4333**	**0.3665**	**0.3087**	-0.1483	**0.4563**	0.1981
TLTD	0.0439	**0.4134**	**-0.4490**	0.0679	**0.3887**	0.1238	0.0573	0.1221	-0.0688	0.1198
TLTA	**0.3898**	0.0303	-0.2495	**0.3327**	0.1461	-0.1262	0.0808	**0.5986**	0.0710	0.0877
DA	0.2768	**-0.3576**	0.2603	0.2478	**-0.4001**	-0.1311	0.1764	**0.3188**	0.0883	-0.0843
TA	**-0.4505**	-0.0117	0.1746	-0.2755	-0.0378	-0.0077	-0.0491	**0.3415**	-0.0307	0.0216
logassets	**-0.4510**	0.0830	0.1247	-0.1639	0.0391	0.1107	0.1597	**0.5457**	0.1893	0.1687

Tab. 4.7: Moody's Ordered Probit Model with Principal Components

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Variables	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
pc1	1.5535	0.000	1.5534	0.000	1.5524	0.000	1.5399	0.000	1.5231	0.000	1.5084	0.000
	(0.1110)		(0.1110)		(0.1109)		(0.1098)		(0.1083)		(0.1072)	
pc2	1.1033	0.000	1.1031	0.000	1.1020	0.000	1.0933	0.000	1.0846	0.000	1.0729	0.000
	(0.0909)		(0.0908)		(0.0907)		(0.0902)		(0.0895)		(0.0886)	
pc3	1.0734	0.000	1.0734	0.000	1.0772	0.000	1.0694	0.000	1.0558	0.000	1.0420	0.000
	(0.0950)		(0.0951)		(0.0952)		(0.0945)		(0.0936)		(0.0925)	
pc4	-0.5974	0.000	-0.5972	0.000	-0.6063	0.000	-0.6016	0.000	-0.5914	0.000	-0.5811	0.000
	(0.0976)		(0.0975)		(0.0974)		(0.0970)		(0.0964)		(0.0959)	
pc5	-0.1067	0.322	-0.1065	0.322								
	(0.1077)		(0.1076)									
pc6	-0.0073	0.954										
	(0.1272)											
pc7	-2.6132	0.000	-2.6135	0.000	-2.6066	0.000	-2.5930	0.000	-2.5649	0.000	-2.5332	0.000
	(0.2264)		(0.2264)		(0.2260)		(0.2254)		(0.2232)		(0.2207)	
pc8	-0.2253	0.143	-0.2252	0.143	-0.2272	0.140						
	(0.1538)		(0.1539)		(0.1538)							
pc9	1.1169	0.000	1.1161	0.000	1.1112	0.000	1.1120	0.000	1.1044	0.000	1.0878	0.000
	(0.2100)		(0.2095)		(0.2090)		(0.2087)		(0.2083)		(0.2078)	
pc10	-0.3562	0.132	-0.3559	0.132	-0.3599	0.128	-0.3587	0.128	-0.3625	0.124		
	(0.2364)		(0.2363)		(0.2362)		(0.2358)		(0.2356)			

Standard errors in parentheses

Tab. 4.8: Moody's Confusion Matrix from Ordered Probit Model with Principal Components

Predicted Rating	Actual Rating																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	18	**Predicted Total**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
2	0	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
3	1	2	10	4	0	1	0	0	0	0	0	0	0	0	0	0	0	**18**
4	0	0	3	11	4	3	1	0	0	0	0	0	0	0	0	0	0	**22**
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
6	0	0	0	4	8	12	5	0	0	0	0	0	0	0	0	0	0	**29**
7	0	0	0	0	1	5	7	1	2	3	0	0	0	0	0	0	0	**19**
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
9	0	0	0	0	0	0	4	2	7	4	1	0	0	0	0	0	0	**18**
10	0	0	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0	**4**
11	0	0	0	0	0	0	0	0	1	3	12	2	2	1	1	0	0	**22**
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
13	0	0	0	0	0	0	0	0	0	0	1	1	11	1	1	0	0	**15**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
16	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	8	1	**10**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
Actual Total	**1**	**5**	**15**	**19**	**13**	**21**	**17**	**3**	**13**	**11**	**14**	**3**	**14**	**2**	**2**	**8**	**2**	**163**

Standard and Poor's

This section gives the results from Standard and Poor's. The results from using the financial variables are analysed. Based on the significance of the variables the researcher chooses model 6 as the optimal model, where all the variables are found to be significant (Table 4.9). Model 6 has 9 explanatory variables all said to influence the credit rating a bank receives in some way. With the exception of net interest margin all the other variables are significant in the model, with 7 variables being significant at the 1 per cent level and 1 variable at the 5 per cent level (Table 4.9). The model has 142 observations with a log likelihood function of -157.702 and a chi square ratio of 397.67, significant at the 1 per cent level.

The ability of the ordered probit model to accurately classify the ratings based on the explanatory variables is then evaluated in the confusion matrix. Overall the model accurately predicts 47 per cent of the ratings (67/142). Upon closer analysis some interesting facts are revealed. Within the time period being evaluated no bank was rated AAA or AA+ as a result we do not have 1 or 2 rating categories. The model closely predicts 5 out of the 14 categories (Table 4.10). It would appear that the highest and lowest rating categories (3 (AA) and 18 (CCC))are the best predicted categories in the model. Other categories such as 7, 12 and 15 also attain accuracy over 60 per cent. The model lacked the ability to determine the rating category 13 and performed poorly at rating the categories 4 and 5.

Drawing from the model's inability to classify some categories we can take a closer look at the confusion matrix. The main diagonal of the matrix gives the ratings that were accurately classified. However if we observe the off diagonals we see some interesting points. It would appear that the model lacks the ability to discriminate 1 notch above and 1 notch below the rating categories it is attempting to predict. For example if we look at rating category 6 which only had a 46.2 per cent classification accuracy (Table 4.11) we observe that the model inaccurately classified almost half the data as a category of 5 (1 notch below), similarly the rating category of 8 inaccurately classified most of the ratings at a 9 (1 notch above the actual rating) and finally the rating category of 9 incorrectly classified the majority of ratings as either 1 notch above or 1 notch below. This speaks to the inability of the model to discriminate against 1 notch above and 1 notch below the actual rating. This too might speak to the limited segregation that exists between rating categories a problem that may be better addressed if we group rating categories.

Another point of note about the confusion matrix and the off diagonals is that the dispersion when looking at the off diagonals is not vast. This means that while the model may have trouble discriminating 1 or 2 notches above or below the actual rating, the error does not go beyond that, as such we don't inaccurately predict a 4 to be a 10 or a 9 to be a 18 etc.

In an attempt to test whether principal component analysis can improve the classifi-

Tab. 4.9: Standard and Poor's Ordered Probit Model with Variables

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Variables	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Srat	0.8419	0.000	0.8429	0.000	0.8423	0.000	0.8427	0.000	0.8438	0.000	0.8341	0.000
	(0.0739)		(0.0737)		(0.0736)		(0.0735)		(0.0734)		(0.0723)	
ROE	-0.0672	0.009	-0.0675	0.008	-0.0676	0.008	-0.0687	0.006	-0.0687	0.006	-0.0648	0.009
	(0.0255)		(0.0255)		(0.0255)		(0.0251)		(0.0251)		(0.0248)	
NIM	-0.2230	0.144	-0.2218	0.146	-0.2227	0.144	-0.2155	0.150	-0.2064	0.163	-0.1932	0.188
	(0.1526)		(0.1525)		(0.1524)		(0.1496)		(0.1479)		(0.1467)	
ER	-0.0013	0.869										
	(0.0079)											
T1RBC	0.4824	0.000	0.4869	0.000	0.4877	0.000	0.4922	0.000	0.4826	0.000	0.4907	0.000
	(0.1137)		(0.1105)		(0.1104)		(0.1088)		(0.1060)		(0.1056)	
PLLTL	0.1008	0.809	0.1026	0.806	0.1024	0.806						
	(0.4180)		(0.4179)		(0.4179)							
RLLTL	-0.0016	0.872	-0.0016	0.871								
	(0.0100)		(0.0100)									
NPLTL	0.2789	0.000	0.2801	0.000	0.2795	0.000	0.2801	0.000	0.2769	0.000	0.2776	0.000
	(0.0374)		(0.0366)		(0.0365)		(0.0364)		(0.0354)		(0.0354)	
TLTD	-0.0506	0.001	-0.0507	0.001	-0.0508	0.001	-0.0512	0.000	-0.0525	0.000	-0.0443	0.000
	(0.0147)		(0.0147)		(0.0147)		(0.0146)		(0.0142)		(0.0115)	
TLTA	0.0697	0.073	0.0702	0.069	0.0700	0.070	0.0706	0.067	0.0770	0.028	0.0671	0.045
	(0.0388)		(0.0386)		(0.0386)		(0.0385)		(0.0351)		(0.0336)	
DA	-0.1619	0.019	-0.1613	0.019	-0.1617	0.019	-0.1615	0.019	-0.1797	0.001	-0.1512	0.000
	(0.0690)		(0.0689)		(0.0689)		(0.0689)		(0.0517)		(0.0427)	
DF	-0.0095	0.770	-0.0104	0.747	-0.0110	0.732	-0.0125	0.690				
	(0.0326)		(0.0322)		(0.0320)		(0.0313)					
logassets	-1.1657	0.000	-1.1596	0.000	-1.1526	0.000	-1.1551	0.000	-1.1016	0.000	-1.3177	0.000
	(0.3124)		(0.3102)		(0.3071)		0.3070		(0.2758)		(0.1668)	

Standard errors in parentheses

Tab. 4.10: Standard and Poor's Ordered Probit Model Confusion Matrix from Model with Variables

Predicted Choice	Actual Bank Level														
	3	4	5	6	7	8	9	10	11	12	13	14	15	18	**Predicted Totals**
3	5	1	0	1	0	0	0	0	0	0	0	0	0	0	**7**
4	1	1	2	0	0	0	0	0	0	0	0	0	0	0	**4**
5	0	3	1	3	0	0	0	0	0	0	0	0	0	0	**7**
6	0	0	6	6	2	0	0	0	0	0	0	0	0	0	**14**
7	0	0	0	3	9	4	1	0	0	0	0	0	0	0	**17**
8	0	0	0	0	3	5	6	1	0	0	0	0	0	0	**15**
9	0	0	0	0	0	7	8	5	1	0	0	0	0	0	**21**
10	0	0	0	0	0	0	5	6	2	1	0	0	0	0	**14**
11	0	0	0	0	0	0	1	1	4	2	0	0	0	0	**8**
12	0	0	0	0	0	0	0	0	4	12	4	1	1	0	**22**
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
14	0	0	0	0	0	0	0	0	0	0	1	2	0	0	**3**
15	0	0	0	0	0	0	0	0	0	0	0	2	4	0	**6**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	4	**4**
Actual Totals	**6**	**5**	**9**	**13**	**14**	**16**	**21**	**13**	**11**	**15**	**5**	**5**	**5**	**4**	**142**

Tab. 4.11: Percentage of Ratings Accurately Classified

Numerical Rating	Rating Category	Per cent Accurately Classified
3	AA	83.3
4	AA-	20.0
5	A+	11.1
6	A	46.2
7	A-	64.3
8	BBB+	31.3
9	BBB	38.1
10	BBB-	46.2
11	BB+	36.4
12	BB	80.0
13	BB-	0.0
14	B+	40.0
15	B	80.0
18	CCC	100.0

cation of ratings we use the best model from the variable analysis in table 4.9 and apply principal component analysis. Table 4.12 gives the relationship between the principal components and the explanatory variables.

The sovereign rating variable has a strong relationship to both pc1, pc3, pc6 and pc7. The sovereign rating variable gives the numerical rating of the sovereign at the time of bank rating. The correlation table shows that any increase in this variable (Srat) will increase both pc1, pc3 and pc7 but decrease pc6. The return on common equity (ROE) variable is highly correlated to pc1, pc2 and pc7 . The sign attached to pc1 for these variables is negative indicating that any increase in ROE will decrease pc1. The converse holds for pc2 since the coefficient signs are positive, as such any increase in ROE will increase pc2. The variables net interest margin (NIM) is positively related to pc3 and pc5 any increase in these variables will then lead to an increase in pc3. On the other hand NIM is inversely related to pc7.

Further examination of the explanatory variables shows that T1RBC is positively correlated to both pc3 and pc4. This variable also loads on pc9 but with differing signs. The non-performing loan variable loads on pc1, pc5, pc6 and pc7. While the total loans to deposits ratio (TLTD) and the total loans to assets ratio (TLTA) both load on pc1, pc4. The last two variables deposits to assets (DA) and log assets are both correlated to pc2. Of note log assets is also correlated to pc1 and pc5 and DA is also correlated to pc6.

To further analyse the principal components we put them into the ordered probit model as explanatory variables and assess the output seen in table 4.13. The coefficient attached to pc1 is positive meaning any increase in pc1 will result in an increase in the bank numerical rating, note that higher numerical ratings means an overall worsening of the rating (see table 4.13). Now we can analyse pc1 in terms of its relationship to the explanatory variables with which it is highly correlated.

The variable Srat is positively correlated to pc1, any increase in this variable for example higher sovereign rating levels (which corresponds to a worsening of the sovereign rating) will lead to an increase in pc1. Following from table 4.13 any increase in pc1 leads to an increase in the overall numerical bank rating level, also corresponding to a worsening of the overall rating for the bank.

The rating variable ROE is inversely related to pc1 which means increases in this variable translates to a decrease in pc1. As observed by the ordered probit model in table 4.13, any fall in pc1 will lead to a fall in the numeric overall bank rating. Such a fall translates to an improvement in the overall bank credit rating since lower rating numeric values are associated with better ratings for example a numeric rating of 3 is AA while 18 is CCC. This result is consistent with a priori expectations since improvements in profitability is expected to translate into improved ratings ceteris paribus.

Non-performing loans to total loans (NPLTL) is also positively correlated to pc1 so that any increase in this ratio will increase pc1 and any increase in pc1 leads to an increase in the numeric bank rating. As such we can conclude that an increasing non performing loan ratio will serve to deteriorate the bank credit rating.

As regards the liquidity ratio total loans to total deposits (TLTD), we know that deposits are used to make loans by banks and mismatch on the maturity term is usually where banks make their money. If we have a situation where long term deposits are falling while short term loans are rising the bank could find itself in a liquidity strain baring the availability of the other measures that such institutions have available (short term funding market etc). The ratio in the model is positively related to pc1 and gives the indication that any increase in this ratio will worsen a banks credit rating. The ratio total loans to total assets (TLTA) also acts as a liquidity barometer and is positively related to pc1 and so we can conclude the same that a rise in this ratio will worsen a banks credit rating.

The log total assets variable is used as a measure of the size of the institution. It is assumed that bigger banks will have better buffers to sustain them against any impending risk. The too big too fail phenomena has been well investigated. The coefficient of this variable is negatively related to pc1 meaning any increase in log assets, which would result from an increase in total assets, would result in a fall in pc1. As pc1 falls the overall bank level rating will also fall. We know that a lower numeric value for bank ratings is associated with an improvement in the rating.

When we analyse the correlation between the principal components and the financial ratios we find that pc2 is also correlated to ROE, the relationship this time is positive as opposed to pc1. This means that if ROE increase then pc2 will increase and from the ordered probit model in table 4.13 any increase in pc2 (due to its positive coefficient in the model) will lead to an increase in the numeric bank rating. We know that higher bank ratings are associated with the bank being worse off. The behaviour of pc2 and ROE , stands in direct contrast with pc1.

The variable deposits to assets (DA) also loads on pc2 with a positive coefficient meaning that increases in this ratio will increase pc2 and worsen the overall bank rating. This ratio can be seen as a measure of the banks ability to cover any draw down on its deposits with its assets. While higher deposits may increase the banks ability to grant loans a possible draw down on deposits means that the existing assets should be able to cover. Log assets is also inversely related to pc2 as it is to pc1 and therefore the analysis remains much the same as discussed above.

If we analyse the third principal component pc3, we find that the variable Srat loads on pc3 with a positive coefficient. This means that any increase in Srat will lead to an increase in pc3 and will increase the numeric bank rating level. This analysis is synonymous with pc1 since any increase in Srat means an overall worsening of the sovereign rating and will therefore lead to a worsening in the bank rating. The net interest margin (NIM) is also positively correlated to pc3, the NIM variable measures the amount of interest earned against the interest paid out relative to earning assets. The results suggest that higher NIM leads to higher bank ratings (a worsening of the banks credit rating). Upon closer examination of the ratio we observe that the NIM ratio may increase due to higher interest income or lower interest payments thereby increasing the numerator. One would expect that this would improve the overall standing of the bank since this suggests an improvement in bank performance. However the ratio may also increase if the denominator (average earning assets) declines and would suggest that the bank is facing some problem situations.

The final variable that loads on pc3 is the capital adequacy variables (T1RBC) it is positively related to pc3, suggesting any increase in this variable would lead to an increase in pc3. From the ordered probit model we see that pc3 has a positive coefficient meaning that any increase in pc3 leads to an increase in the overall bank level rating. This result is somewhat unexpected since we expect higher capital levels to improve the rating of the bank. It must be noted that the impact of the variables on the rating of the bank is not in isolation meaning that while the capital may be increasing, some other aspect maybe deteriorating simultaneously, as a result we need to address the complete picture of the banks financial fundamentals.

Pc4 this component is positively related to both T1RBC, which means that any increase in this variable would increase pc4. In the ordered probit model pc4 has a negative sign attached to the coefficient therefore any increase in pc4 would reduce the overall bank level meaning an improvement in the bank rating. This result stands in line with a priori expectations as we would expect higher capital levels to improve the overall credit rating of the bank. Both the liquidity measures TLTD and TLTA are also positively related to pc4 and any increases in these variables are then said to improve the overall bank rating.

Pc5 is positively related to NIM, NPLTL and logassets (Table 4.12) from the ordered probit model we see that pc5 has a negative coefficient. We can then conclude that any increase in NIM, NPLTL and logassets will reduce the numerical rating (the dependent variable in the ordered probit model) meaning an improvement in the bank rating. While this result maybe expected for NIM and logassets it seems unlikely that an increasing non-performing loan portfolio will improve credit ratings.

On further investigation of the principal components we find that pc6 is inversely related to Srat and TLTD but positively correlated to NPLTL and DA. Since pc6 has a negative coefficient in table 4.13 we can hypothesise that as Srat and TLTD increase pc 6 will fall and the numerical bank rating will rise; that is the bank will be downgraded. On the other hand as NPLTL and DA rise pc 6 will also rise resulting in a fall in the numerical bank rating, signalling a bank upgrade. This result appears a bit alarming as we do not expect rising non performing loans to result in the upgrade of a bank but must be reminded that each financial variable is not considered in isolation by the rating agencies and so it is not wise to conclude that any one variable has an overwhelming influence on a rating upgrade or downgrade.

The principal component pc7 is positively related to Srat, ROE and NPLTL. From the ordered probit model pc7 has a positive coefficient therefore as these variables increase pc7 will increase and results in a bank downgrade. This finding for Srat and NPLTL is in line with a priori expectations, however, this is not the case for ROE. Pc7 is inversely related to NIM and increases in this variable translate into an improvement in bank ratings. Pc9 is now analysed since pc8 was eliminated from the ordered probit model due to insignificance. Pc9 is negatively related to T1RBC. The ordered probit model shows that pc9 has a negative coefficient which means that an increase in T1RBC will result in a bank downgrade.

Post the analysis of the principal components relationship to the financial variables and their behaviour in the ordered probit model we can analyse the confusion matrix for the ordered probit model using the principal components. The confusion matrix gives the amount of banks that were correctly classified in the ordered probit model based on the explanatory variables, in this case the principal components. In table 4.14 the correct classification is highlighted along the main diagonal, where the predicted rating matches the actual bank rating. In terms of this matrix we find that 47 per cent (67/142) of the data is accurately classified when we use principal components as opposed to variables. This model gives the same result as the ordered probit model with variables which was also able to accurately classify approximately 47 per cent of the data.

Tab. 4.12: Standard and Poor's Correlation Matrix between Variables and Principal Components

Variable	Pc1	Pc2	Pc3	Pc4	Pc5	Pc6	Pc7	Pc8	Pc9
Srat	**0.3323**	0.1534	**0.4087**	-0.2535	-0.0801	**-0.5221**	**0.4248**	**0.3728**	0.1865
ROE	**-0.3697**	**0.3235**	-0.1365	0.2863	0.2044	-0.1736	**0.3452**	-0.0205	0.0794
NIM	0.0456	0.2646	**0.4932**	-0.0847	**0.6577**	-0.0781	**-0.4275**	-0.2328	0.0129
T1RBC	-0.2213	-0.2233	**0.5428**	**0.3283**	-0.2552	-0.1232	0.0047	0.0137	**-0.6419**
NPLTL	**0.3842**	-0.2195	0.1065	0.0764	**0.3779**	**0.4702**	**0.6028**	-0.1798	-0.1650
TLTD	**0.3650**	-0.2018	-0.2467	**0.4545**	0.2411	**-0.3100**	-0.1811	0.1844	-0.0428
TLTA	**0.3743**	0.2639	-0.0424	**0.4861**	-0.0524	0.1375	-0.1835	**0.3407**	-0.0286
DA	0.0440	**0.4686**	0.2751	0.0589	-0.2702	**0.5312**	-0.0601	0.2080	0.1226
logassets	**-0.3506**	**-0.3111**	0.0258	-0.1704	**0.3636**	0.2221	-0.0525	**0.7512**	-0.0052

Tab. 4.13: Standard and Poor's Ordered Probit Model with Principal Components

	Model 1		Model 2	
	Coefficient	P-value	Coefficient	P-value
pc1	1.7671	0.000	1.7593	0.000
	(0.1415)		(0.1413)	
pc2	0.5797	0.000	0.5766	0.000
	(0.0677)		(0.0676)	
pc3	1.6316	0.000	1.6199	0.000
	(0.1440)		(0.1430)	
pc4	-0.9800	0.000	-0.9706	0.000
	(0.1183)		(0.1177)	
pc5	-0.7051	0.000	-0.7075	0.000
	(0.1315)		(0.1310)	
pc6	-1.5383	0.000	-1.5344	0.000
	(0.1910)		(0.1905)	
pc7	2.4616	0.000	2.4516	0.000
	(0.2456)		(0.2455)	
pc8	-0.2662	0.159		
	(0.1889)			
pc9	-1.2069	0.000	-1.1855	0.000
	(0.3119)		(0.3109)	

Standard errors in parentheses

Tab. 4.14: Standard and Poor's Confusion Matrix from Ordered Probit Model with Principal Components

Predicted Rating	Actual Rating														
	3	4	5	6	7	8	9	10	11	12	13	14	15	18	**Predicted Total**
3	3	1	0	1	0	0	0	0	0	0	0	0	0	0	**5**
4	3	1	2	0	0	0	0	0	0	0	0	0	0	0	**6**
5	0	3	1	2	0	0	0	0	0	0	0	0	0	0	**6**
6	0	0	6	7	2	0	0	0	0	0	0	0	0	0	**15**
7	0	0	0	3	9	4	1	0	0	0	0	0	0	0	**17**
8	0	0	0	0	3	5	4	1	0	0	0	0	0	0	**13**
9	0	0	0	0	0	7	11	5	1	0	0	0	0	0	**24**
10	0	0	0	0	0	0	3	6	2	1	0	0	0	0	**12**
11	0	0	0	0	0	0	2	1	5	1	0	0	0	0	**9**
12	0	0	0	0	0	0	0	0	3	13	4	1	1	0	**22**
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
15	0	0	0	0	0	0	0	0	0	0	1	4	2	0	**7**
18	0	0	0	0	0	0	0	0	0	0	0	0	2	4	**6**
Actual Total	**6**	**5**	**9**	**13**	**14**	**16**	**21**	**13**	**11**	**15**	**5**	**5**	**5**	**4**	**142**

Fitch

This section gives the result for Fitch rating data. Table 4.15 shows the ordered probit model with financial variables all said to influence the bank credit rating assigned by Fitch. Model 7 gives the best results with 5 of the financial variables being significant all at the 1 per cent level. The researcher opts to retain model 7 and proceeds the analysis on this model. The model has 122 observations with a log likelihood ratio of -105.05. It is important to note that the variables which were highly influential in the Moody's and Standard and Poor's models do differ slightly in the Fitch model.

After we obtain the best model we then run the confusion matrix in Stata to obtain the classification matrix based on the ordered probit model with variables. The confusion matrix is given in table 4.16, 60 per cent of the ratings are accurately classified (73/122). In comparison with the other rating agencies it appears that the ordered probit model was best in classifying the Fitch data set since the Moody's and Standard and Poor's models with variables correctly classified 52 and 47 per cent respectively.

As with the models built for the other rating agencies we find that the highest category (that is the worst ratings) in this case 14 and 16 are able to achieve 100 per cent classification. Despite the few observations in the categories it would appear that the models are better able to discriminate among the worst rating categories. Noteworthy are also the lower categories, in this case category 3 and 4 achieve 67 per cent accuracy in the rating classifications. Higher categories such as 9 and 10 were also able to attain an accurate classification of 79 per cent and 80 per cent respectively.

As with the previous analysis we now investigate the application of principal component analysis to see if this methodology can in anyway improve the classification of the bank credit ratings by Fitch. The application of principal component analysis to the 10 explanatory variables taken from the best ordered probit model with variables (Table 4.15). Table 4.17 gives the correlations of the explanatory variables and principal components.

The first principal component to be analysed is pc1. From the ordered probit model in table 4.18 we see that pc1 has a positive coefficient. Then rises in pc1 translate to rises in the numerical bank rating, that is a bank downgrade. We now assess the relationship between pc1 and the explanatory variables. In the first instance we find that pc1 is inversely related to ROE. As this variable increases pc1 will fall and the dependent variable in the ordered probit model will also fall signalling a bank upgrade. This result is as expected since higher ROE should impact positively on the bank rating. On the other hand we find that ER, PLLTL and NPLTL are all positively related to pc1, as these variables increase we expect pc1 to increase which should translate into a rating downgrade due to the positive coefficient attached to pc1 in the ordered probit model.

Pc2 being the second principal component carries a positive coefficient in the ordered probit model seen in table 4.18. From the correlation table 4.17 we observe a positive relationship between Srat and pc2. As the sovereign is downgraded (that is the numerical rating increases) we find that pc2 will also increase triggering an increase in the dependent variable (numerical bank credit ratings). An increase the numerical bank rating signals a bank downgrade since higher numerical values are associated with lower rating categories. Pc2 is also positively correlated to DA and DF and increases in these variables trigger higher values of the numerical bank rating, that is a bank downgrade.

Pc3 has been eliminated from the ordered probit model due to insignificance and so the analysis continues with pc4. We find that pc4 has a positive coefficient in the ordered probit model in table 4.17. This means that any increase in pc4 will result in an increase in the dependent variable meaning a bank downgrade. From the correlation table we find that pc4 is positively correlated to Srat, and ROE and any increases in these variables will increase pc4 which will in turn increase the dependent variable, that is cause a bank downgrade. While we expect higher values of the variable Srat to translate to a bank downgrade it seems unlikely that higher ROE should have the same effect.

For the principal component pc5 which carries a negative sign in the ordered probit model we observe an inverse relationship between Srat. This means that any increase in these variables will translate into a bank downgrade. The converse is true for ER, as the efficiency ratio increases we find that pc5 will increase triggering a decrease in the dependent variable in the ordered probit model.

Pc6 and pc7 both carry positive coefficients in the ordered probit model (Table 4.18). Pc6 is positively related to Srat and ER while pc7 is positively related to ER and TA. Increases in these variables will increase the principal components and any increase in the principal components will translate into an increase in the dependent variable, that is a bank downgrade. On the other hand the principal components are inversely related to PLLTL and NPLTL suggesting that increases in these variables will lead to a bank upgrade.

The confusion matrix seen in table 4.19 shows the accurate classification of ratings along the diagonal. We find that the model is able to replicate the ratings assigned by Fitch up to 53 per cent (65/122). As compared to the model with variables which was able to classify 60 per cent we see that the model with principal components is comparatively weaker.

Tab. 4.15: Fitch Ordered Probit Model with Variables

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Variables	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Srat	1.0275	0.000	1.0267	0.000	1.0248	0.000	1.0160	0.000	1.0258	0.000	1.0053	0.000	0.9984	0.000
	(0.1042)		(0.1041)		(0.1041)		(0.1033)		(0.1023)		(0.0985)		(0.0964)	
ROE	0.0455	0.158	0.0451	0.161	0.0440	0.170	0.0459	0.150	0.0456	0.152	0.0481	0.129	0.0395	0.092
	(0.0323)		(0.0321)		(0.0320)		(0.0319)		(0.0318)		(0.0317)		(0.0235)	
NIM	-0.1159	0.537	-0.1131	0.545	-0.1396	0.441	-0.1320	0.465	-0.1503	0.399				
	(0.1879)		(0.1869)		(0.1812)		(0.1805)		(0.1781)					
ER	-0.0131	0.078	-0.0131	0.078	-0.0127	0.086	-0.0121	0.098	-0.0123	0.091	-0.0121	0.096	-0.0111	0.098
	(0.0074)		(0.0074)		(0.0074)		(0.0073)		(0.0073)		(0.0073)		(0.0067)	
T1RBC	-0.1226	0.319	-0.1213	0.323	-0.1086	0.368	-0.1045	0.386	-0.1351	0.231	-0.1325	0.239		
	(0.1229)		(0.1226)		(0.1207)		(0.1205)		(0.1128)		(0.1126)			
PLLTL	-1.2121	0.011	-1.2002	0.011	-1.2128	0.010	-1.2339	0.008	-1.2369	0.008	-1.2500	0.008	-1.1879	0.000
	(0.4774)		(0.4705)		(0.4699)		(0.4681)		(0.4672)		(0.4676)		(0.2964)	
RLLTL	-0.0103	0.440	-0.0105	0.430	-0.0077	0.535								
	(0.0134)		(0.0133)		(0.0124)									
NPLTL	0.2684	0.000	0.2674	0.000	0.2672	0.000	0.2664	0.000	0.2603	0.000	0.2632	0.000	0.2559	0.000
	(0.0487)		(0.0482)		(0.0481)		(0.0481)		(0.0472)		(0.0470)		(0.0434)	
TLTD	-0.0131	0.321	-0.0131	0.321	-0.0084	0.420	-0.0101	0.315	-0.0095	0.343	-0.0102	0.304		
	(0.0132)		(0.0132)		(0.0104)		(0.0100)		(0.0100)		(0.0099)			
TLTA	0.0226	0.563	0.0227	0.561										
	(0.0391)		(0.0390)											
DA	0.1273	0.070	0.1277	0.069	0.1520	0.007	0.1471	0.009	0.1550	0.005	0.1440	0.007	0.1669	0.001
	(0.0703)		(0.0702)		(0.0566)		(0.0560)		(0.0548)		(0.0531)		(0.0503)	
DF	-0.1492	0.002	-0.1497	0.002	-0.1594	0.000	-0.1599	0.000	-0.1608	0.000	-0.1566	0.001	-0.1551	0.000
	(0.0487)		(0.0486)		(0.0457)		(0.0457)		(0.0456)		(0.0453)		(0.0440)	
EA	0.0000	0.884												
	(0.0000)													
logassets	-0.6235	0.493	-0.6498	0.466	-0.6722	0.450	-0.6360	0.474						
	(0.9088)		(0.8909)		(0.8903)		(0.8878)							

Standard errors in parentheses

Tab. 4.16: Fitch Confusion Matrix from Ordered Probit Model with Variables

Predicted Rating	Actual Rating													
	2	3	4	5	6	7	8	9	10	11	12	14	16	**Predicted Total**
2	0	1	1	0	0	0	0	0	0	0	0	0	0	**2**
3	2	2	0	0	0	0	0	0	0	0	0	0	0	**4**
4	0	0	4	0	2	0	0	0	0	0	0	0	0	**6**
5	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
6	0	0	1	3	8	5	1	0	0	0	0	0	0	**18**
7	0	0	0	0	5	4	5	0	0	0	0	0	0	**14**
8	0	0	0	0	0	7	9	1	0	0	0	0	0	**17**
9	0	0	0	0	0	0	6	17	1	0	0	0	0	**24**
10	0	0	0	0	0	0	0	1	15	5	0	0	0	**21**
11	0	0	0	0	0	0	0	0	1	5	1	0	0	**7**
12	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
14	0	0	0	0	0	0	0	0	0	0	0	4	0	**4**
16	0	0	0	0	0	0	0	0	0	0	0	0	5	**5**
Actual Totals	**2**	**3**	**6**	**3**	**15**	**16**	**21**	**19**	**17**	**10**	**1**	**4**	**5**	**122**

4.5.2 Multiple Discriminant Analysis

This section follows the same methodology in the previous section but uses multiple discriminant analysis as the multi variate tool.

Moody's

In this section we opted to use the best model taken from the Moody's ordered probit model with variables, this was model 5 (Table 4.3). Table 4.20 gives the confusion matrix from the application of multiple discriminant analysis. The model is able to accurately classify 66 per cent of the ratings (107/163). It would appear that the multiple discriminant analysis model performs better that the ordered probit model with variables as this model could only classify 52 per cent of the ratings accurately.

Upon closer evaluation of the MDA we find that out of the 17 rating categories 16 were classified accurately by more than 50 per cent. The rating categories of 1, 12, 14, 15 and 18 were all classified with 100 per cent accuracy based on the MDA. The category with the weakest classification is the numerical rating 6, if we analyse the off diagonals of this category we also observe that 5 observations were predicted as a 5 and 5 observations predicted as a 4, it is obvious that the model was unable to discriminate ratings 1 notch above and 1 notch below this category.

To test whether we can improve the classification by the use of principal components, table 4.21 gives the classification of ratings (the confusion matrix) from principle components. As we can see this model accurately classifies 57 per cent of the credit ratings accurately (93/163). The application of principal component analysis in this instance weakens the classification of credit ratings almost halving the classification of

Tab. 4.17: Fitch Correlation between Explanatory Variables and Principal Components

	Pc1	Pc2	Pc3	Pc4	Pc5	Pc6	Pc7
Srat	0.1140	**0.3809**	0.1243	**0.4832**	**-0.5747**	**0.4592**	0.1504
ROE	**-0.4499**	-0.1402	0.2014	**0.3467**	0.1099	-0.1356	0.2690
ER	**0.3938**	-0.1660	-0.0448	-0.0120	**0.4951**	**0.4381**	**0.5989**
TRBC	0.0465	**-0.3410**	**0.6813**	0.0575	0.1640	**0.3763**	**-0.4930**
PLLTL	**0.4249**	0.1329	0.2789	0.0075	0.0187	**-0.5182**	-0.0009
NPLTL	**0.4128**	0.0563	**0.3515**	0.2651	-0.0120	**-0.3505**	0.1887
DA	-0.1841	**0.5293**	0.2340	-0.2325	0.2214	0.0346	0.0152
DF	-0.1917	**0.4835**	**0.3259**	-0.3395	0.1397	0.0936	0.1667

Tab. 4.18: Fitch Ordered Probit Model with Principal Components

	Model 1		Model 2		Model 3	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
pc1	0.6060	0.000	0.6065	0.000	0.6006	0.000
	(0.0811)		(0.0810)		(0.0806)	
pc2	2.0725	0.000	2.0695	0.000	2.0572	0.000
	(0.1982)		(0.1982)		(0.1978)	
pc3	0.0730	0.512				
	(0.1114)					
pc4	2.9463	0.000	2.9254	0.000	2.9124	0.000
	(0.3037)		(0.3016)		(0.3002)	
pc5	-1.8070	0.000	-1.8031	0.000	-1.7953	0.000
	(0.2066)		(0.2063)		(0.2054)	
pc6	1.1549	0.000	1.1625	0.000	1.1495	0.000
	(0.1974)		(0.1969)		(0.1960)	
pc7	0.4633	0.078	0.4267	0.097	0.4373	0.088
	(0.2630)		(0.2568)		(0.2560)	

Standard errors in parentheses

Tab. 4.19: Fitch Confusion Matrix for Ordered Probit Model with Principal Components

Predicted Rating	Actual Rating													
	2	3	4	5	6	7	8	9	10	11	12	14	16	**Predicted Total**
2	0	2	1	0	0	0	0	0	0	0	0	0	0	**3**
3	2	0	0	0	0	0	0	0	0	0	0	0	0	**2**
4	0	1	4	0	2	0	0	0	0	0	0	0	0	**7**
5	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
6	0	0	1	3	7	4	1	0	0	0	0	0	0	**16**
7	0	0	0	0	6	5	7	0	0	0	0	0	0	**18**
8	0	0	0	0	0	7	6	3	0	0	0	0	0	**16**
9	0	0	0	0	0	0	7	15	1	0	0	0	0	**23**
10	0	0	0	0	0	0	0	1	14	5	0	0	0	**20**
11	0	0	0	0	0	0	0	0	2	5	1	0	0	**8**
12	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
14	0	0	0	0	0	0	0	0	0	0	0	4	0	**4**
16	0	0	0	0	0	0	0	0	0	0	0	0	5	**5**
Actual Total	**2**	**3**	**6**	**3**	**15**	**16**	**21**	**19**	**17**	**10**	**1**	**4**	**5**	**122**

the model with variables.

In this model the categories that were classified with 100 per cent accuracy were the rating category of 1,12 and 18. When comparing both models some stark differences are observed. It appears that the model with variables is better able to classify the higher rating categories 14, 15 and 16. Thus far for Moodys we see that the application of principal component analysis only weakens the classification ability of the model in both the ordered probit model and the multiple discriminant analysis model. In the next section we apply the ordinary least squares method and evaluate the model with variables and the model with principal components.

Tab. 4.20: Moody's Confusion Matrix from Multiple Discriminant Analysis with Variables

Predicted Rating	Actual Rating																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	18	**Predicted Totals**
1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
2	0	3	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
3	0	2	13	2	0	0	0	0	0	0	0	0	0	0	0	0	0	**17**
4	0	0	1	10	2	1	2	0	0	0	0	0	0	0	0	0	0	**16**
5	0	0	0	2	7	5	2	0	0	0	0	0	0	0	0	0	0	**16**
6	0	0	0	1	2	9	0	0	0	0	0	0	0	0	0	0	0	**12**
7	0	0	0	2	2	5	9	1	1	0	0	0	0	0	0	0	0	**20**
8	0	0	0	0	0	1	3	2	2	1	0	0	0	0	0	0	0	**9**
9	0	0	0	0	0	0	0	0	8	2	2	0	0	0	0	0	0	**12**
10	0	0	0	0	0	0	1	0	2	7	0	0	0	0	0	0	0	**10**
11	0	0	0	0	0	0	0	0	0	0	12	0	2	0	0	0	0	**14**
12	0	0	0	0	0	0	0	0	0	1	0	3	0	0	0	0	0	**4**
13	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	**11**
14	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	**3**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	**2**
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	**6**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	**4**
Actual Totals	**1**	**5**	**15**	**19**	**13**	**21**	**17**	**3**	**13**	**11**	**14**	**3**	**14**	**2**	**2**	**8**	**2**	**163**

Tab. 4.21: Moody's Confusion Matrix from Multiple Discriminant Analysis with Principal Components

Predicted Rating	Actual Rating																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	18	**Predicted Total**
1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
2	0	4	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	**6**
3	0	1	12	3	1	0	0	0	0	0	0	0	0	0	0	0	0	**17**
4	0	0	1	6	1	2	0	0	0	0	0	0	0	0	0	0	0	**10**
5	0	0	1	5	8	4	2	0	0	0	0	0	0	0	0	0	0	**20**
6	0	0	0	1	1	8	4	0	0	0	0	0	0	0	0	0	0	**14**
7	0	0	0	2	2	4	5	1	1	3	0	0	0	0	0	0	0	**18**
8	0	0	0	0	0	3	3	2	1	2	0	0	0	0	0	0	0	**11**
9	0	0	0	0	0	0	3	0	9	2	1	0	0	0	0	0	0	**15**
10	0	0	0	0	0	0	0	0	2	3	0	0	0	0	1	0	0	**6**
11	0	0	0	0	0	0	0	0	0	0	13	0	2	1	0	0	0	**16**
12	0	0	0	0	0	0	0	0	0	1	0	3	0	0	0	0	0	**4**
13	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	**10**
14	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	**2**
15	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	**3**
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	**5**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	**4**
Actual Total	**1**	**5**	**15**	**19**	**13**	**21**	**17**	**3**	**13**	**11**	**14**	**3**	**14**	**2**	**2**	**8**	**2**	**163**

Standard and Poor's

This section looks at the application of multiple discriminant analysis to the Standard and Poor's data. We use financial ratios similar to those from model 6 in table 4.9. Based on the MDA output we compile the confusion matrix seen in table 4.22. The MDA model accurately classified 64 per cent of the credit ratings (92/142).

From the confusion matrix we observe the improved classification of the MDA technique. Out of 14 rating categories 11 are classified with a rating accuracy of 60 per cent and over. Once again the best classified category is 18 where all the ratings are accurately classified (100 per cent). The rating categories 3 and 15 are accurately classified with 83 per cent and 80 per cent respectively. Interestingly the off diagonals which represent misclassification only register at most 4 ratings misclassified at any one time compared to the confusion matrix for the ordered probit model with variables which had as much as 7 ratings misclassified at any one point.

To continue the analysis as outlined in the previous section we apply MDA to the principal component analysis. Note that the results from the application of principal component analysis will be same as that in the ordered probit model approach since we use the same financial ratios. The confusion matrix from the MDA with principal components is seen in table 4.23 which shows that the model only accurately classifies 58 per cent of the observations (82/142). The result from this model with the principle components is much improved over the ordered probit model which found an accuracy classification of 47 per cent.

Tab. 4.22: Standard and Poor's Multiple Discriminant Analysis Confusion Matrix from Variables

Predicted Rating	Actual Rating														
	3	4	5	6	7	8	9	10	11	12	13	14	15	18	**Predicted Total**
3	5	1	0	0	0	0	0	0	0	0	0	0	0	0	**6**
4	0	3	1	0	0	0	0	0	0	0	0	0	0	0	**4**
5	1	1	4	1	0	0	0	0	0	0	0	0	0	0	**7**
6	0	0	4	8	3	0	0	0	0	0	0	0	0	0	**15**
7	0	0	0	3	9	2	1	0	0	0	0	0	0	0	**15**
8	0	0	0	1	1	11	4	2	0	0	0	0	0	0	**19**
9	0	0	0	0	0	2	11	2	0	0	0	0	0	0	**15**
10	0	0	0	0	1	1	2	9	2	1	0	0	0	0	**16**
11	0	0	0	0	0	0	3	0	5	1	0	0	1	0	**10**
12	0	0	0	0	0	0	0	0	2	13	2	1	0	0	**18**
13	0	0	0	0	0	0	0	0	1	0	3	0	0	0	**4**
14	0	0	0	0	0	0	0	0	1	0	0	3	0	0	**4**
15	0	0	0	0	0	0	0	0	0	0	0	1	4	0	**5**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	4	**4**
Actual Total	**6**	**5**	**9**	**13**	**14**	**16**	**21**	**13**	**11**	**15**	**5**	**5**	**5**	**4**	**142**

Tab. 4.23: Standard and Poor's Confusion Matrix from Multiple Discriminant Analysis Model with Principal Components

Predicted Rating	Actual Rating													
	3	4	5	6	7	8	9	10	11	12	13	14	15	18	**Predicted Total**
3	5	1	0	0	0	0	0	0	0	0	0	0	0	0	**6**
4	0	3	0	1	0	0	0	0	0	0	0	0	0	0	**4**
5	1	1	4	0	0	0	0	0	0	0	0	0	0	0	**6**
6	0	0	5	8	3	0	0	0	0	0	0	0	0	0	**16**
7	0	0	0	3	9	2	1	0	0	0	0	0	0	0	**15**
8	0	0	0	1	1	11	4	2	0	0	0	0	0	0	**19**
9	0	0	0	0	0	2	10	2	0	0	0	0	0	0	**14**
10	0	0	0	0	1	1	2	9	2	1	0	0	0	0	**16**
11	0	0	0	0	0	0	3	0	6	2	0	0	1	0	**12**
12	0	0	0	0	0	0	1	0	1	12	2	1	0	0	**17**
13	0	0	0	0	0	0	0	0	1	0	3	0	0	0	**4**
14	0	0	0	0	0	0	0	0	1	0	0	3	0	0	**4**
15	0	0	0	0	0	0	0	0	0	0	0	1	4	0	**5**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	4	**4**
Actual Total	**6**	**5**	**9**	**13**	**14**	**16**	**21**	**13**	**11**	**15**	**5**	**5**	**5**	**4**	**142**

Fitch

The multiple discriminant analysis method is now applied to the Fitch data to investigate the performance of this statistical method against other. In the first instance we opt to use the best model with variables taken from the ordered probit analysis (Table 4.15). The multiple discriminant analysis finds that this model with variables is able to accurately classify the ratings assigned by Fitch with a 62 per cent (76/122) level of accuracy (Table 4.24).

To further investigate whether the best model with principal components from table 4.18 can improve the analysis we apply multiple discriminant analysis to model 3 which omits pc3 due to insignificance. The results from the confusion matrix are seen in table 4.25. We find that the model only accurately classifies 60 per cent (73/122) of the Fitch ratings as compared to 62 per cent classified by the model with variables.

Tab. 4.24: Fitch Confusion Matrix from Multiple Discriminant Analysis with Variables

Predicted Rating	Actual Rating													
	2	3	4	5	6	7	8	9	10	11	12	14	16	**Predicted Total**
2	2	1	1	0	0	0	0	0	0	0	0	0	0	**4**
3	0	2	0	0	0	0	0	0	0	0	0	0	0	**2**
4	0	0	4	0	3	0	0	0	0	0	0	0	0	**7**
5	0	0	0	1	0	0	0	0	0	0	0	0	0	**1**
6	0	0	1	2	10	4	3	0	0	0	0	0	0	**20**
7	0	0	0	0	2	7	5	0	0	0	0	0	0	**14**
8	0	0	0	0	0	5	11	4	0	0	0	0	0	**20**
9	0	0	0	0	0	0	0	12	1	0	0	0	0	**13**
10	0	0	0	0	0	0	2	3	12	3	0	0	0	**20**
11	0	0	0	0	0	0	0	0	3	5	0	0	0	**8**
12	0	0	0	0	0	0	0	0	1	2	1	0	0	**4**
14	0	0	0	0	0	0	0	0	0	0	0	4	0	**4**
16	0	0	0	0	0	0	0	0	0	0	0	0	5	**5**
Actual Total	**2**	**3**	**6**	**3**	**15**	**16**	**21**	**19**	**17**	**10**	**1**	**4**	**5**	**122**

Tab. 4.25: Fitch Confusion Matrix from Multiple Discriminant Analysis with Principal Components

Predicted Rating	Actual Rating													
	2	3	4	5	6	7	8	9	10	11	12	14	16	**Predicted Total**
2	2	1	1	0	0	0	0	0	0	0	0	0	0	**4**
3	0	2	0	0	0	0	0	0	0	0	0	0	0	**2**
4	0	0	4	0	3	0	0	0	0	0	0	0	0	**7**
5	0	0	0	1	0	0	0	0	0	0	0	0	0	**1**
6	0	0	1	2	9	4	2	0	0	0	0	0	0	**18**
7	0	0	0	0	3	7	6	1	0	0	0	0	0	**17**
8	0	0	0	0	0	5	10	3	0	0	0	0	0	**18**
9	0	0	0	0	0	0	1	12	0	0	0	0	0	**13**
10	0	0	0	0	0	0	2	3	12	4	0	0	0	**21**
11	0	0	0	0	0	0	0	0	4	4	0	0	0	**8**
12	0	0	0	0	0	0	0	0	1	2	1	0	0	**4**
14	0	0	0	0	0	0	0	0	0	0	0	4	0	**4**
16	0	0	0	0	0	0	0	0	0	0	0	0	5	**5**
Actual Total	**2**	**3**	**6**	**3**	**15**	**16**	**21**	**19**	**17**	**10**	**1**	**4**	**5**	**122**

4.5.3 Ordinary Least Squares

This section of the results looks at applying ordinary least squares to the data and determining if this univariate model is similar in terms of its classification ability to the multi variate cases. In using the OLS approach we must be aware of the shortcomings of these type of univariate models in comparison to the multi variate counter parts. In the first case the OLS statistical approach does not account for the ordinal nature of the data whereas the ordered probit models take into account the ordering of the data. Additionally the OLS approach generates continuous values when predictions for bank ratings are generated. To overcome the latter we round up the predicted bank rating to whole numbers, barring these shortcomings we apply the OLS approach.

Moody's

In the case of the OLS model we apply the same basic principle as seen in the other statistical models. Table 4.26 give the output from the application of OLS to variables said to influence bank credit ratings the variables that are found to be insignificant are eliminated from the model and we choose model 4. Using model 4 we tabulate the probability of receiving each numerical credit rating based on the explanatory variables, this is given in the confusion matrix in table 4.27.

The highlighted main diagonal gives the number of bank credit ratings accurately predicted. In the case of the OLS model we find that 62/163 ratings were accurately predicted (38 per cent). The OLS technique does not perform as well as the previous two statistical techniques since the ordered probit analysis with variables was able to predict 52 per cent of ratings accurately and the multiple discriminant analysis with variables was able to accurately classify 66 per cent of the ratings.

In an attempt to investigate whether or not the principal component method would strengthen the classification we apply principal component analysis to the data and build the classification matrix. We take the best OLS model from the analysis with variables (Model 4) (Table 4.26). The principal components are developed based on these variables since we want the model with variables and the model with principal components both to contain the same information.

From the ordinary least squares model with principal components seen in table 4.29 we find that pc3, pc5 and pc8 have all been eliminated due to insignificance in Model 4. The analysis of the principal components correlation to the explanatory variables and the impact they have on the dependent variable are now analysed.

In the case of pc1 we find that this variable has a negative coefficient in the ordinary least squares model. This means as pc1 rises the dependent variable falls indicating a bank upgrade. From table 4.28 we see that pc1 is negatively related to Srat and PLLTL which suggests that any increase in these variables will decrease pc1 and subsequently increase the dependent variable which translates into a bank downgrade. This component is, however, positively related to ROE, and logassets and any increase in these variables will translate into a bank upgrade. The findings associated with pc1 seem to fall in line with a priori expectations.

As regards the second component we see that pc2 carries a positive coefficient in the ordinary least squares model. The correlation table 4.28 shows that pc2 is positively correlated to T1RBC, and NPLTL therefore any increase in these variables will increase pc2. From the ordinary least squares model we know that an increase in pc2 will increase the numerical bank rating (the dependent variable) meaning a bank downgrade. While increases in NPLTL could translate into a bank downgrade it seems unlikely that higher capital holdings will have the same effect. Nonetheless a bank can have higher capital holdings and still be subject to a growing non performing portfolio and drying up liquidity. On the other hand pc2 is inversely related to ROE which suggests that rises in this variable translate to rating upgrades.

The correlation between principal components and explanatory variables seen in table 4.28 shows that pc4 is negatively correlated to T1RBC this suggests that any increase in this variable will decrease pc4. From the OLS model seen in table 4.29 we see that pc4 has a positive coefficient and as such any decrease in pc4 will decrease the dependent variable (numerical bank ratings) suggesting a bank upgrade. Pc4 is found to be positively related to PLLTL and so any increase in this variable will trigger a bank downgrade as suggested by the OLS model.

The next principal component to be analysed is pc6 since pc 5 was eliminated from the OLS model due to insignificance. Pc6 which carries a negative sign in the OLS model (Table 4.29) is inversely related to the variable Srat. This suggest that as the sovereign numerical rating increases (a sovereign downgrade), pc 6 will decrease and the bank numerical rating will increase. This analysis suggests that as the sovereign is downgraded it is likely to influence a bank downgrade. Pc6 is positively related to the variables PLLTL and NPLTL (Table 4.28), the OLS model seems to suggest that increases in PLLTL and NPLTL will result in an improvement in the bank credit rating (an upgrade) this result seems contradictory since we would expect higher non performing loans to adversely affect the credit rating.

Pc7 which carries a positive coefficient in the OLS model is positively correlated to Srat, ROE and NPLTL. Increases in these variables will increase pc7 and thereby trigger an increase in the numerical bank rating (the dependent variable) which translates to a bank downgrade.

The final part of this analysis involves the compilation of the confusion matrix from the OLS model with principal components, this is seen in table 4.30. The principal component analysis application correctly classifies approximately 36 per cent (58/163) of the bank credit ratings accurately. The application of principal component analysis marginally weakens the classification of ratings as compared to the methodology using the variables which was able to accurately classify 38 per cent of the credit ratings accurately.

Tab. 4.26: Moody's Ordinary Least Squares Model with Variables

	Model 1		Model 2		Model 3		Model 4	
Variables	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Srat	0.6197	0.000	0.6300	0.000	0.6327	0.000	0.6308	0.000
	(0.0290)		(0.0277)		(0.0274)		(0.0272)	
ROE	-0.0242	0.019	-0.0239	0.021	-0.0227	0.026	-0.0220	0.029
	(0.0102)		(0.0102)		(0.0101)		(0.0100)	
NIM	-0.2522	0.026	-0.2764	0.014	-0.2865	0.010	-0.2626	0.011
	(0.1124)		(0.1107)		(0.1097)		(0.1025)	
T1RBC	0.1602	0.065	0.1644	0.059	0.1635	0.060	0.1845	0.021
	(0.0862)		(0.0863)		(0.0861)		(0.0790)	
PLLTL	-0.6508	0.057	-0.6495	0.058	-0.6305	0.065	-0.6102	0.072
	(0.3399)		(0.3404)		(0.3388)		(0.3366)	
NPLTL	0.1832	0.000	0.1681	0.000	0.1696	0.000	0.1700	0.000
	(0.0346)		(0.0322)		(0.0321)		(0.0321)	
TLTD	-0.0125	0.130	-0.0046	0.339	-0.0019	0.536		
	(0.0082)		(0.0048)		(0.0030)			
TLTA	0.0286	0.238						
	(0.0241)							
DA	-0.0357	0.167	-0.0111	0.464				
	(0.0257)		(0.0152)					
logassets	-1.3345	0.000	-1.3018	0.000	-1.3168	0.000	-1.3583	0.000
	(0.2205)		(0.2191)		(0.2178)		(0.2068)	
_cons	20.1873	0.000	19.5811	0.000	18.7444	0.000	18.8752	0.000
	(2.5394)		(2.4906)		(2.2109)		(2.1963)	

Standard errors in parentheses

Tab. 4.27: Moody's Confusion Matrix from Ordinary Least Squares Model with Variables

Predicted Rating	Actual Rating																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	**Predicted Rating**
1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
2	0	2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**5**
3	1	2	8	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**13**
4	0	0	4	7	3	2	0	0	0	0	0	0	0	0	0	0	0	0	**16**
5	0	0	0	6	3	3	1	0	0	0	0	0	0	0	0	0	0	0	**13**
6	0	0	0	4	4	6	3	0	0	0	0	0	0	0	0	0	0	0	**17**
7	0	0	0	0	3	9	7	0	0	0	0	0	0	0	0	0	0	0	**19**
8	0	0	0	0	0	1	4	2	4	4	0	0	0	0	0	0	0	0	**15**
9	0	0	0	0	0	0	2	1	7	3	1	0	0	0	0	0	0	0	**14**
10	0	0	0	0	0	0	0	0	2	2	3	0	0	0	0	0	0	0	**7**
11	0	0	0	0	0	0	0	0	0	2	9	2	1	0	0	0	0	0	**14**
12	0	0	0	0	0	0	0	0	0	0	1	0	4	1	1	0	0	0	**7**
13	0	0	0	0	0	0	0	0	0	0	0	1	5	0	0	0	0	0	**6**
14	0	0	0	0	0	0	0	0	0	0	0	0	4	1	1	0	0	0	**6**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	**3**
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**1**
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	**2**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	**4**
Actual Totals	**1**	**5**	**15**	**19**	**13**	**21**	**17**	**3**	**13**	**11**	**14**	**3**	**14**	**2**	**2**	**8**	**0**	**2**	**163**

Tab. 4.28: Moody's Correlation between Explanatory Variables and Principal Components for Ordinary Least Squares Model

Variable	Pc1	Pc2	Pc3	Pc4	Pc5	Pc6	Pc7
Srat	**-0.4180**	0.2655	0.1991	0.1554	-0.0156	**-0.6603**	**0.4798**
ROE	**0.3455**	**-0.3713**	**0.3279**	-0.2454	-0.0564	0.1250	**0.6988**
NIM	-0.1981	0.0539	**0.6908**	-0.1525	**0.6010**	0.1960	-0.1951
T1RBC	0.1256	**0.5034**	0.2905	**-0.3917**	**-0.3282**	-0.1686	-0.2311
PLLTL	**-0.3500**	0.1292	**0.3031**	**0.4622**	**-0.4916**	**0.5475**	0.1033
NPLTL	-0.2447	**0.4133**	**-0.4213**	-0.0620	**0.4403**	**0.3198**	**0.3383**
logassets	**0.4478**	0.2507	0.0620	**0.4107**	0.2229	0.0421	0.1470

Tab. 4.29: Moody's Ordinary Least Squares Model with Principal Components

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
pc1	-1.8155	0.000	-1.8155	0.000	-1.8155	0.000	-1.8155	0.000
	(0.0471)		(0.0470)		(0.0470)		(0.0470)	
pc2	0.9764	0.000	0.9764	0.000	0.9764	0.000	0.9764	0.000
	(0.0559)		(0.0558)		(0.0558)		(0.0558)	
pc3	0.0747	0.309	0.0747	0.308	0.0747	0.308		
	(0.0732)		(0.0730)		(0.0730)			
pc4	0.1947	0.023	0.1947	0.023	0.1947	0.023	0.1947	0.023
	(0.0849)		(0.0847)		(0.0847)		(0.0847)	
pc5	-0.0716	0.519						
	(0.1109)							
pc6	-2.2881	0.000	-2.2881	0.000	-2.2881	0.000	-2.2881	0.000
	(0.1338)		(0.1336)		(0.1335)		(0.1336)	
pc7	1.0739	0.000	1.0739	0.000	1.0739	0.000	1.0739	0.000
	(0.1787)		(0.1784)		(0.1783)		(0.1784)	
_cons	7.8957	0.000	7.8957	0.000	7.8957	0.000	7.8957	0.000
	(0.0830)		(0.0829)		(0.0829)		(0.0829)	

Standard errors in parentheses

Tab. 4.30: Moody's Confusion Matrix from Ordinary Least Squares Model with Principal Components

Predicted Rating	Actual Rating																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	**Predicted Total**
1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
2	1	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**7**
3	0	2	7	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**12**
4	0	0	4	6	3	2	0	0	0	0	0	0	0	0	0	0	0	0	**15**
5	0	0	0	6	2	1	1	0	0	0	0	0	0	0	0	0	0	0	**10**
6	0	0	0	4	6	8	3	0	0	0	0	0	0	0	0	0	0	0	**21**
7	0	0	0	0	2	8	6	0	0	0	0	0	0	0	0	0	0	0	**16**
8	0	0	0	0	0	2	5	2	4	5	0	0	0	0	0	0	0	0	**18**
9	0	0	0	0	0	0	2	1	7	2	1	0	0	0	0	0	0	0	**13**
10	0	0	0	0	0	0	0	0	2	2	6	0	0	0	0	0	0	0	**10**
11	0	0	0	0	0	0	0	0	0	2	6	1	1	0	0	0	0	0	**10**
12	0	0	0	0	0	0	0	0	0	0	1	1	5	1	1	0	0	0	**9**
13	0	0	0	0	0	0	0	0	0	0	0	1	5	0	0	0	0	0	**6**
14	0	0	0	0	0	0	0	0	0	0	0	0	3	1	1	0	0	0	**5**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	**3**
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**1**
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	**3**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	**3**
Actual Total	**1**	**5**	**15**	**19**	**13**	**21**	**17**	**3**	**13**	**11**	**14**	**3**	**14**	**2**	**2**	**8**	**0**	**2**	**163**

Standard and Poor's

The application of the OLS technique to the Standard and Poor's data is analysed in this section. Firstly we build the OLS model with variables and choose the model in which all variables are significant (Table 4.31). As we did in the previous analysis we compile the confusion matrix based on the model with variables we find that the model accurately classifies 45 per cent of the observations (64/142). This result is close to that of the ordered probit model with variables which was able to classify 47 per cent of the data (67/142). The rating categories that received accurate classifications of 50 per cent and above were 7, 10, 11, 12, 14 and 18.

Tab. 4.31: Standard and Poor's Ordinary Least Squares Model with Variables

	Model 1		Model 2	
Variables	Coefficient	P- value	Coefficient	P- value
Srat	0.6110	0.000	0.6058	0.000
	(0.0290)		(0.0270)	
ROE	-0.0562	0.005	-0.0559	0.005
	(0.0197)		(0.0196)	
NIM	-0.0507	0.618		
	(0.1013)			
T1RBC	0.3096	0.000	0.3070	0.000
	(0.0715)		(0.0711)	
NPLTL	0.1927	0.000	0.1909	0.000
	(0.0222)		(0.0219)	
TLTD	-0.0346	0.000	-0.0353	0.000
	(0.0086)		(0.0084)	
TLTA	0.0517	0.051	0.0538	0.039
	(0.0263)		(0.0259)	
DA	-0.1209	0.000	-0.1247	0.000
	(0.0320)		(0.0310)	
logassets	-0.8996	0.000	-0.9065	0.000
	(0.1093)		(0.1081)	
_cons	21.3490	0.000	21.4961	0.000
	(1.9259)		(1.8979)	

Standard errors in parentheses

Similar to the previous analysis we now apply the principal component method to further investigate whether or not the classifications are in anyway improved. We apply principal component analysis to model 2 from table 4.31. Table 4.33 shows the relationship between the principal components and the explanatory variables said to

Tab. 4.32: Standards and Poor's Confusion Matrix from Ordinary Least Squares Model with Variables

Predicted Rating	Actual Rating																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	**Predicted Totals**
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
4	0	0	4	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	**9**
5	0	0	0	3	4	5	0	0	0	0	0	0	0	0	0	0	0	0	**12**
6	0	0	0	0	3	3	1	0	0	0	0	0	0	0	0	0	0	0	**7**
7	0	0	0	0	0	3	8	1	1	0	0	0	0	0	0	0	0	0	**13**
8	0	0	0	0	0	1	3	7	2	0	0	0	0	0	0	0	0	0	**13**
9	0	0	0	0	0	0	2	7	7	4	1	0	0	0	0	0	0	0	**21**
10	0	0	0	0	0	0	0	1	10	9	2	1	0	0	0	0	0	0	**23**
11	0	0	0	0	0	0	0	0	1	0	6	3	0	0	0	0	0	0	**10**
12	0	0	0	0	0	0	0	0	0	0	2	10	4	1	1	0	0	0	**18**
13	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	**3**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	**3**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	**2**
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	**2**
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	**2**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	**2**
Actual Totals	**0**	**0**	**6**	**5**	**9**	**13**	**14**	**16**	**21**	**13**	**11**	**15**	**5**	**5**	**5**	**0**	**0**	**4**	**142**

explain credit ratings and table 4.34 give the results of the principal components in the OLS model. All the principal components are significant in the OLS model.

We can now analyse pc1 in table 4.33 and table 4.34. The positive coefficient associated with pc1 in the OLS model means that any increase in pc1 will result in an increase in the numerical bank rating thereby signalling a worsening of the bank credit rating. As regards the variable Srat from table 4.33 we see that there is a positive relationship with pc1, if Srat increases then pc1 will increase. An increase in Srat means an increase in the numerical sovereign rating signifying a worsening of the rating assigned to the sovereign. As the sovereign rating worsens it is likely that the bank associated with that sovereign will see a worsening in there rating as sovereign ratings are said to influence bank ratings according to the rating agencies.

The next variables that pc1 is related to is ROE the inverse relationship means that any increase in ROE will result in a fall in pc1. If pc1 falls then we find that the numerical bank rating also falls implying an improved bank rating. This is in line with a priori expectations since we expect increasing asset and equity returns to improve the overall credit rating a bank receives.

Pc1 is positively correlated to NPLTL (non-performing loans to total loans), TLTD (total loans to total deposits) and TLTA (total loans to totals assets) any increase in these variables will increase pc1 and thereby worsen the bank credit rating. This finding for NPLTL is expected since an increasing ratio means that the non performing portfolio is rising or the total loans are falling all gesturing a weakening in the bank financials and therefore weakening the credit rating. The TLTD is a liquidity measure deposits are used by banks to give loans to customers, should there be a run on the bank a high loan to deposit ratio could signify a bank being illiquid. Despite this mismatch being how banks make profit the question of liquidity problems has plagued many banks with the recent financial crisis and regulators and rating agencies pay close attention to such ratios.

The last ratio of bank size which is negatively related to pc1 is loagassets. As total assets increase one would expect log assets to also increase. As this variable increases we find that pc1 would decrease. As seen form the OLS model any decrease in pc1 means a fall in the numerical bank rating pointing to an improvement in the overall bank credit rating by the rating agency. This result stands in line with expectations since on would expect increasing assets to strengthen the credit rating the bank receives.

As regards pc2 which also has a positive coefficient in the OLS model, we observe a positive relationship with ROE. This means that any increase in these variables will worsen the credit rating a bank receives, this is in contrast to the correlations seen with pc1. We observe that the correlations are stronger with pc1 but do not dispute that there maybe some banks that have increasing ROE but see worsened credit ratings due to other financial factors. As such it is important that financial ratios are not evaluated in isolation but as part of an entire picture.

The relationship between pc2 and TLTA and DA is positive, as these variables increase we find that pc2 increases and the numerical bank credit rating also increases. The analysis for logassets remains much the same between pc1 and pc2.

The third principal component (pc3) has a positive sign in the OLS model (table 4.34), not surprising the variable Srat is positively related and as mentioned previously any increase in the sovereign rating will therefore influence the bank credit rating adversely. In chapter 2 of this thesis I found that the sovereign rating always played an influential role in the bank credit rating where the variable (Srating) was always significant in the models assessing the numerical credit rating of the bank.

For pc3 and the variable T1RBC we see a positive relationship which means that any increase in these variables will worsen the bank credit rating. This seems questionable since we expect higher capital holdings to improve the credit rating of the banks since these can be used as a buffer against any impending financial problems the bank may face. The ratio deposits to assets (DA) is positively related to pc3 and any increase in DA is then said to worsen the bank credit rating.

As regards pc4 which has a negative coefficient in the OLS model we find that it is also negatively related to the variable Srat. Therefore any increase in Srat will decrease pc4 and thereby increase the numerical bank credit rating (a downgrade of the bank). The relationship to ROE is positive and therefore we conclude that increases in the variable will improve the bank credit rating.

Pc5 is positively related to both NPLTL and logassets. Since pc5 has a positive coefficient in the OLS model we conclude that any increase in pc5 will translate to a bank downgrade. While increases in NPLTL could lead to a bank downgrade as suggested by the model we also see that increases in logassets (which is in this case a measure of bank size) also suggests a bank downgrade. As relates to pc6 table 4.33 suggests a positive relationship with Srat and ROE but negative correlation with DA. The OLS model shows that pc6 has a positive leading to the conclusion that increases in pc6 trigger a bank downgrade.

The principal component pc7 which has a negative coefficient in the OLS model is inversely related to NPLTL . This means that as NPLTL rises then pc7 falls and the numerical bank rating rises, that is a bank downgrade occurs. On the other hand pc7 is positively related to TLTA and logassets and any in these variables will increase pc7 and lead to a bank upgrade. Pc8 carries a negative coefficient in the OLS model (Table 4.34). From the table 4.33 pc 8 is inversely related to T1RBC.

The main aim of the application of the principal component analysis is to investigate whether we can improve the classification of the model using principal components versus the model with variables under the ordinary least squares technique. The confusion matrix with principal components seen in table 4.35 shows that the principal component method gives the same classification of bank credit ratings as does the model with variables. Along the horizontal we have the actual bank credit rating categories and along the vertical gives the predicted categories. The model is able to accurately classify 45 per cent of the bank credit ratings accurately (64/142) the same as the model with variables which gave a 45 per cent accurate classification.

Tab. 4.33: Standard and Poor's Correlation between Explanatory Variables and Principal Components

Variable	Pc1	Pc2	Pc3	Pc4	Pc5	Pc6	Pc7	Pc8
Srat	**0.3184**	0.1392	**0.4506**	**-0.3221**	0.0906	**0.6888**	0.2261	0.1937
ROE	**-0.3890**	**0.3132**	-0.0963	**0.3074**	0.2155	**0.3382**	-0.1194	0.0831
T1RBC	-0.2100	-0.2856	**0.6092**	0.2421	-0.1490	0.0719	0.0034	**-0.6408**
NPLTL	**0.3961**	-0.2134	0.0304	0.0946	**0.7979**	-0.0604	**-0.3472**	-0.1619
TLTD	**0.3790**	-0.1591	-0.2811	**0.5116**	-0.1493	0.2408	0.2600	-0.0455
TLTA	**0.3573**	**0.3025**	0.0817	**0.4713**	-0.0263	-0.1819	**0.3646**	-0.0250
DA	0.0120	**0.4586**	**0.4322**	-0.0197	0.1781	**-0.4951**	0.1873	0.1248
logassets	**-0.3310**	**-0.3531**	-0.1303	-0.1282	**0.4100**	-0.0490	**0.7475**	0.0000

Tab. 4.34: Standard and Poor's Ordinary Least Squares Model with Principal Components

	Model 1	
	Coefficient	P-value
pc1	1.1951	0.000
	(0.0406)	
pc2	0.4014	0.000
	(0.0433)	
pc3	1.3791	0.000
	(0.0646)	
pc4	-0.9863	0.000
	(0.0716)	
pc5	0.4260	0.000
	(0.1091)	
pc6	1.7132	0.000
	(0.1136)	
pc7	-0.7382	0.000
	(0.1437)	
pc8	-0.7534	0.001
	(0.2195)	
_cons	9.0775	0.000
	(0.0740)	

Standard errors in parentheses

Tab. 4.35: Standard and Poor's Confusion Matrix from Ordinary Least Squares Model with Principal Components

Predicted Rating	Actual Rating																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	**Predicted Total**
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
4	0	0	4	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	**9**
5	0	0	0	3	4	5	0	0	0	0	0	0	0	0	0	0	0	0	**12**
6	0	0	0	0	3	3	1	0	0	0	0	0	0	0	0	0	0	0	**7**
7	0	0	0	0	0	3	8	1	1	0	0	0	0	0	0	0	0	0	**13**
8	0	0	0	0	0	1	3	7	2	0	0	0	0	0	0	0	0	0	**13**
9	0	0	0	0	0	0	2	7	7	4	1	0	0	0	0	0	0	0	**21**
10	0	0	0	0	0	0	0	1	10	9	2	1	0	0	0	0	0	0	**23**
11	0	0	0	0	0	0	0	0	1	0	6	3	0	0	0	0	0	0	**10**
12	0	0	0	0	0	0	0	0	0	0	2	10	4	1	1	0	0	0	**18**
13	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	**3**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	**3**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	**2**
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	**2**
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	**2**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	**2**
Actual Total	**0**	**0**	**6**	**5**	**9**	**13**	**14**	**16**	**21**	**13**	**11**	**15**	**5**	**5**	**5**	**0**	**0**	**4**	**142**

Fitch

This part of the analysis looks at the Fitch data set and the ability of an OLS model with variables versus one with principal components in accurately classifying bank credit ratings. Table 4.36 gives the output from the application of OLS to the Fitch data set with variables. The confusion matrix seen in table 4.37 gives the ratings that have been correctly classified along the main diagonals. The OLS model is able to accurately classify 46 per cent of the ratings by Fitch.

Upon closer observation of the confusion matrix from the model with variables it appears that the model struggles between the 6 to 9 rating categories. Ratings between this range are often misclassified in categories 1 notch higher or lower. The criticisms raised by Kaplan and Urwitz (1970) where they lament the inability of the OLS model to account for the ordinal nature of ratings may contribute to the poor performance of the model in comparison to other methodologies such as ordered probit and multiple discriminant analysis.

In an attempt to investigate whether we can improve the classification of ratings with an OLS model we use principal components. The principal components are computed based on the best OLS model in table 4.36 (Model 7). Table 4.38 shows the relationship between each principal component and the independent variables. The principal components are then placed in an OLS model seen in table 4.39.

In order to understand the impact of the principal components on the dependent variable (bank credit ratings) we must first assess the correlation between the principal components and the explanatory variables. Following this we evaluate the behaviour of the principal component in the OLS model. The first principal component (pc1) carries a negative sign in the OLS model and any increase in pc1 will result in a decline in the dependent variable meaning a bank upgrade (a fall in the numerical bank rating is synonymous with an upgrade). From table 4.38 we see that pc1 is positively related to the profitability variable. As ROE increases we find that pc1 will also increase and from the OLS model (Table 4.39) we see that any increase in pc1 results in a bank upgrade. Pc1 is inversely related to the variables ER, PLLTL and NPLTL (Table 4.38) and any increase in these variables result in a bank downgrade.

Pc2 carries a positive sign in the OLS model (Table 4.39) and so any increase in pc2 will result in a bank downgrade. From the correlations seen in table 4.38 pc2 is positively related to Srat, DA and DF this means that as these variables increase we find that pc2 increases and from table 4.39 we have established that an increase in pc2 leads to a bank downgrade. We have already established how an increase in the sovereign rating translates to a bank downgrade, now we discuss the deposits to assets (DA) and deposits to funding (DF) ratios. An increase in deposits while beneficial in terms of broadening the banks lending base can also present some liquidity strain if banks can adequately cover a run on these deposits. The ratio may also increase if the denominator of the ratios fall in this case falling assets and funding all impact the bank negatively.

Pc4, pc5, pc6 and pc8 all carry negative signs in the OLS model (Table 4.39) and an increase in these principal components will trigger a bank upgrade. Pc4 is inversely related to Srat and higher sovereign ratings in this case will trigger a bank downgrade. Conversely pc4 is positively related to DF and increases in this variable will then result in a bank upgrade. Pc5 is inversely related to Srat but positively related to ER. As regards pc6 we see an inverse relationship to ER and T1RBC but a positive relationship to PLLTL and NPLTL (Table 4.38). Pc8 is positively related to PLLTL but inversely related to NPLTL.

Pc7 carries a positive sign in the OLS model (Table 4.39) this means that an increase in this principal components translate to an increase in the dependent variable that is a bank downgrade. Pc7 is positively related to Srat, and ER.

The confusion matrix seen in table 4.40 gives the classification of ratings based on the OLS model with principal components. The correct classifications are seen along the diagonals of the matrix. From the table we observe that 58/122 (48 per cent) of the ratings are accurately classified. The principal component OLS model with Fitch data gives a surprising result since its classification is higher than the model with variables, a result not seen in any other rating agency or methodology. Despite the weak classification it is still surprising that in this case the model with principal components can outperform the model with variables.

Tab. 4.36: Fitch Ordinary Least Squares Model with Variables

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Variables	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Srat	0.6066	0.000	0.6058	0.000	0.6060	0.000	0.6121	0.000	0.6155	0.000	0.6197	0.000	0.6114	0.000
	(0.0318)		(0.0296)		(0.0294)		(0.0255)		(0.0250)		(0.0242)		(0.0221)	
ROE	0.0203	0.164	0.0204	0.160	0.0208	0.146	0.0200	0.157	0.0214	0.126	0.0195	0.153	0.0216	0.101
	(0.0145)		(0.0144)		(0.0142)		(0.0140)		(0.0139)		(0.0136)		(0.0131)	
NIM	0.0468	0.654	0.0468	0.653	0.0433	0.674								
	(0.1043)		(0.1038)		(0.1027)									
ER	-0.0108	0.021	-0.0106	0.010	-0.0107	0.009	-0.0108	0.008	-0.0108	0.008	-0.0111	0.006	-0.0111	0.006
	(0.0046)		(0.0041)		(0.0040)		(0.0040)		(0.0040)		(0.0040)		(0.0039)	
T1RBC	-0.1013	0.180	-0.0965	0.013	-0.0981	0.011	-0.0981	0.010	-0.1072	0.003	-0.1049	0.003	-0.1113	0.001
	(0.0751)		(0.0382)		(0.0377)		(0.0375)		(0.0350)		(0.0347)		(0.0338)	
PLLTL	-0.4911	0.019	-0.4948	0.014	-0.5076	0.010	-0.5045	0.010	-0.4859	0.012	-0.4395	0.015	-0.4281	0.015
	(0.2059)		(0.1990)		(0.1938)		(0.1929)		(0.1905)		(0.1771)		(0.1734)	
RLLTL	-0.0077	0.347	-0.0076	0.333	-0.0074	0.340	-0.0074	0.341	-0.0073	0.347	-0.0072	0.349		
	(0.0082)		(0.0078)		(0.0077)		(0.0077)		(0.0077)		(0.0077)			
NPLTL	0.1059	0.000	0.1063	0.000	0.1075	0.000	0.1058	0.000	0.1035	0.000	0.1000	0.000	0.0976	0.000
	(0.0218)		(0.0208)		(0.0204)		(0.0199)		(0.0196)		(0.0188)		(0.0181)	
TLTD	-0.0063	0.450	-0.0062	0.450	-0.0062	0.451	-0.0055	0.492	-0.0053	0.503				
	(0.0083)		(0.0082)		(0.0081)		(0.0079)		(0.0079)					
TLTA	0.0183	0.460	0.0178	0.450	0.0174	0.456	0.0148	0.509	0.0162	0.467	0.0073	0.683		
	(0.0247)		(0.0234)		(0.0233)		(0.0224)		(0.0222)		(0.0178)			
DA	0.0470	0.291	0.0476	0.276	0.0466	0.283	0.0525	0.200	0.0557	0.170	0.0716	0.030	0.0735	0.018
	(0.0443)		(0.0435)		(0.0432)		(0.0407)		(0.0403)		(0.0325)		(0.0306)	
DF	-0.0715	0.021	-0.0720	0.017	-0.0708	0.018	-0.0734	0.012	-0.0734	0.012	-0.0747	0.010	-0.0768	0.005
	(0.0305)		(0.0297)		(0.0294)		(0.0287)		(0.0286)		(0.0284)		(0.0270)	
EA	0.0000	0.760												
	(0.0000)													
logassets	-0.4138	0.462	-0.4195	0.449	-0.3887	0.474	-0.3605	0.502						
	(0.5601)		(0.5523)		(0.5410)		(0.5348)							
_cons	8.9369	0.019	9.0156	0.013	8.9002	0.014	8.7691	0.014	6.8137	0.001	5.9031	0.000	6.5428	0.000
	(3.7531)		(3.5858)		(3.5512)		(3.5240)		(1.9956)		(1.4611)		(0.6066)	

Standard errors in parentheses

Tab. 4.37: Fitch Confusion Matrix from Ordinary Least Squares Model with Variables

Predicted Rating	Actual Rating															
	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	**Predicted Totals**
2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	**2**
3	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	**4**
4	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	**3**
5	0	0	2	1	2	0	0	0	0	0	0	0	0	0	0	**5**
6	0	0	0	2	7	6	1	0	0	0	0	0	0	0	0	**16**
7	0	0	0	0	6	4	8	1	0	0	0	0	0	0	0	**19**
8	0	0	0	0	0	6	5	1	0	0	0	0	0	0	0	**12**
9	0	0	0	0	0	0	7	14	1	0	0	0	0	0	0	**22**
10	0	0	0	0	0	0	0	3	12	3	0	0	0	0	0	**18**
11	0	0	0	0	0	0	0	0	4	6	0	0	0	0	0	**10**
12	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	**2**
13	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	**4**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	**4**
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
Actual Totals	**2**	**3**	**6**	**3**	**15**	**16**	**21**	**19**	**17**	**10**	**1**	**0**	**4**	**0**	**5**	**122**

Tab. 4.38: Fitch Correlation Between Variables and Principal Components for Ordinary Least Squares Model

Variable	Pc1	Pc2	Pc3	Pc4	Pc5	Pc6	Pc7	Pc8
Srat	-0.1208	**0.4019**	0.1377	**-0.4275**	**-0.6435**	-0.2599	**0.3220**	0.1919
ROE	**0.4566**	-0.0981	0.2286	-0.2844	0.1401	0.2243	0.2432	0.0720
ER	**-0.3898**	-0.1774	-0.0462	-0.0254	**0.4909**	**-0.3523**	**0.6382**	0.1999
T1RBC	0.0248	0.0010	**0.7914**	0.0192	0.1707	**-0.4928**	-0.2953	-0.1119
PLLTL	**-0.4240**	0.1583	0.2568	0.0681	0.0978	**0.4142**	-0.2484	**0.6793**
NPLTL	**-0.4092**	0.0936	**0.3264**	-0.1610	0.0413	**0.5166**	0.2295	**-0.5968**
DA	0.1743	**0.5798**	-0.0280	0.2391	0.2106	0.0156	0.0639	0.0472
DF	0.1841	**0.5449**	0.0444	**0.3737**	0.1496	0.0097	0.2423	-0.0974

Tab. 4.39: Fitch Ordinary Least Squares Model with Principal Components

	Model 1		Model 2		Model 3	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
pc1	-0.3659	0.000	-0.3659	0.000	-0.3659	0.000
	(0.0350)		(0.0349)		(0.0348)	
pc2	1.1577	0.000	1.1577	0.000	1.1577	0.000
	(0.0438)		(0.0437)		(0.0436)	
pc3	0.0509	0.380	0.0509	0.378		
	(0.0577)		(0.0575)			
pc4	-1.6007	0.000	-1.6007	0.000	-1.6007	0.000
	(0.0695)		(0.0693)		(0.0692)	
pc5	-1.4047	0.000	-1.4047	0.000	-1.4047	0.000
	(0.0783)		(0.0781)		(0.0780)	
pc6	-0.2210	0.039	-0.2210	0.038	-0.2210	0.038
	(0.1057)		(0.1054)		(0.1053)	
pc7	0.5538	0.000	0.5538	0.000	0.5538	0.000
	(0.1191)		(0.1188)		(0.1187)	
pc8	-0.2563	0.094	-0.2563	0.093	-0.2563	0.093
	(0.1517)		(0.1512)		(0.1511)	
_cons	8.3689	0.000	8.3689	0.000	8.3689	0.000
	(0.0668)		(0.0666)		(0.0666)	

Standard errors in parentheses

Tab. 4.40: Fitch Confusion Matrix from Ordinary Least Squares Model with Principal Components

Predicted Rating	Actual Rating														
	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	**Predicted Totals**
2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	**3**
3	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	**3**
4	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	**3**
5	0	0	2	1	3	0	0	0	0	0	0	0	0	0	0	**6**
6	0	0	0	2	6	5	1	0	0	0	0	0	0	0	0	**14**
7	0	0	0	0	6	6	8	1	0	0	0	0	0	0	0	**21**
8	0	0	0	0	0	5	6	1	0	0	0	0	0	0	0	**12**
9	0	0	0	0	0	0	6	15	1	0	0	0	0	0	0	**22**
10	0	0	0	0	0	0	0	2	11	3	0	0	0	0	0	**16**
11	0	0	0	0	0	0	0	0	5	5	0	0	0	0	0	**10**
12	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	**3**
13	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	**4**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	**4**
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
Actual Totals	**2**	**3**	**6**	**3**	**15**	**16**	**21**	**19**	**17**	**10**	**1**	**0**	**4**	**0**	**5**	**122**

4.5.4 *Artificial Neural Networks*

This section of the results gives the classification of ratings from the artificial neural network methodology. This computer learning method has been praised in the literature as having the ability to learn from the data and apply the necessary mathematical conditions needed to accurately estimate relationships between the independent and dependent variables. The analysis develops the ANN models on the same foundation as the previous models, using both variables and principal components to investigate which approach is better at classifying bank ratings.

Moody's

This section gives the results from the artificial neural network method for Moody's. We again use a model with variables and the results from this model are seen in table 4.41. The appendix figure C.1 shows the explanatory variables used in the model, all of which have been used in the previous methodologies. While the ANN method uses all 163 bank ratings for Moody's we find that the data set is split into a training data set and a testing data set. We allowed the program SPSS to choose the testing and training data set randomly in all cases. In this instance the model uses 73 per cent of the data as training data and 28 per cent as testing data. There is one hidden layer with three units in that layer (Appendix figure C.1). The activation function applied to the hidden layer is hyperbolic tangent and the activation function applied to the output layer is softmax.

From the classification structure in table 4.41 we see that the model accurately classifies approximately 64 per cent of the testing data after the classification on the training data results in a 53 per cent classification accuracy. Despite the attraction of ANN being computer learning technique we find that the multiple discriminant analysis model with variables still performs better. Nonetheless the ANN with variables model outperforms both the ordered probit and OLS approaches.

In an attempt to investigate whether we can improve the classification accuracy we utilise principal components in the ANN model. However we find the model with 8 principal components gave the best results (Appendix figure C.1). The classification structure seen in table 4.42 shows that the model with principal components only accurately classifies 60 per cent of the ratings. This model used 70 per cent of the data to train and 20 per cent to test. Again there was one hidden layer with four units. The same activation functions were applied to the hidden layer and output layer, hyperbolic tangent and softmax respectively.

Standard and Poor's

The application of ANN to the Sandard and Poor's data is discussed in this section. The model with variables has one hidden layer with two units. The hidden layer uses the hyperbolic tangent as the activation function and the output layer uses softmax. In this instance the model uses 79 per cent of the data to train on and the remainder as the testing data set.

The results from the application of ANN is seen in table 4.43 where 63 per cent of the training data was accurately classified. In this instance the training process only rendered a classification accuracy rate of 38 per cent. The model with variables from ANN performed better than the ordered probit and ordinary least squares method for Standard and Poor' s since these techniques were only able to accurately classify 47 and 45 per cent of the data. On the other hand the multiple discriminant method was able to classify 64 per cent of the data and marginally outperformed the ANN approach.

For Standard and Poor's the application of ANN to the model with principal components did not improve the classification of ratings. Using principal components we only classified 59 per cent of the ratings (Table 4.44). Despite the principal component method performing worse than the model with variables it was still able to classify more ratings than the multiple discriminant analysis approach with principal components (58 per cent classification).

Fitch

Here we analyse the results from the artificial neural network technique applied to the Fitch data set. Similar to the previous analysis we use all the ratings assigned by Fitch which comprised of 122 ratings in our data set. Table 4.45 gives the results from the model using variables. The model uses 8 explanatory variables all of a financial nature with the exception of the sovereign rating. This time the ANN method saw 67 per cent

Tab. 4.41: Moody's Classification Structure from Artificial Neural Networks with Variables

Sample		Predicted															
		2	3	4	5	6	7	8	9	10	11	12	13	14	16	18	% Correct
Training	2	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	3	0	8	2	0	0	0	0	0	0	0	0	0	0	0	0	80.0
	4	0	3	10	1	2	0	0	0	0	0	0	0	0	0	0	62.5
	5	0	0	3	1	5	0	0	0	0	0	0	0	0	0	0	11.1
	6	0	0	2	1	6	5	0	0	0	0	0	0	0	0	0	42.9
	7	0	0	0	0	2	8	0	2	0	0	0	0	0	0	0	66.7
	8	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0.0
	9	0	0	0	0	0	1	0	3	5	0	0	0	0	0	0	33.3
	10	0	0	0	0	0	1	0	2	3	2	0	0	0	0	0	37.5
	11	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	100.0
	12	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	33.3
	13	0	0	0	0	0	0	0	0	0	2	0	7	0	0	0	77.8
	14	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0.0
	16	0	0	0	0	0	0	0	0	0	0	0	1	0	5	0	83.3
	18	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0.0
	Overall %	0.0	12.9	14.7	2.6	12.9	13.8	0.0	6.9	6.9	12.9	.9	9.5	0.0	6.0	0.0	53.4
Testing	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	3	0	4	1	0	0	0	0	0	0	0	0	0	0	0	0	80.0
	4	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	66.7
	5	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	25.0
	6	0	0	0	0	5	2	0	0	0	0	0	0	0	0	0	71.4
	7	0	0	1	0	1	3	0	0	0	0	0	0	0	0	0	60.0
	8	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0.0
	9	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	50.0
	10	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	33.3
	11	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	100.0
	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	13	0	0	0	0	0	0	0	0	0	1	0	4	0	0	0	80.0
	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	16	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	100.0
	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	Overall %	0.0	13.6	9.1	2.3	20.5	18.2	0.0	6.8	2.3	13.6	0.0	9.1	0.0	4.5	0.0	63.6

Tab. 4.42: Moody's Classification Structure from Artificial Neural Networks with Principal Components

Sample		Predicted																
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	% Correct
Training	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	2	0	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	25.0
	3	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	100.0
	4	0	0	3	9	0	2	0	0	0	0	0	0	0	0	0	0	64.3
	5	0	0	0	1	8	2	0	0	0	0	0	0	0	0	0	0	72.7
	6	0	0	0	2	2	8	2	0	0	0	0	0	0	0	0	0	57.1
	7	0	0	0	1	2	3	2	0	0	2	0	0	0	0	0	0	20.0
	8	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0.0
	9	0	0	0	0	0	0	2	0	3	3	0	0	0	0	0	0	37.5
	10	0	0	0	0	0	0	1	0	1	6	1	0	0	0	0	0	66.7
	11	0	0	0	0	0	0	0	0	0	0	8	0	2	0	0	0	80.0
	12	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	100.0
	13	0	0	0	0	0	0	0	0	0	0	1	0	6	0	0	1	75.0
	14	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0.0
	15	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0.0
	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	100.0
	Overall %	0.0	.9	14.2	12.4	10.6	13.3	7.1	0.0	3.5	11.5	9.7	2.7	8.0	0.0	0.0	6.2	61.9
Testing	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	3	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	100.0
	4	0	0	2	2	1	0	0	0	0	0	0	0	0	0	0	0	40.0
	5	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	50.0
	6	0	0	0	0	1	6	0	0	0	0	0	0	0	0	0	0	85.7
	7	0	0	0	1	1	2	3	0	0	0	0	0	0	0	0	0	42.9
	8	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0.0
	9	0	0	0	0	0	0	2	0	0	1	1	0	1	0	0	0	0.0
	10	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	50.0
	11	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	100.0
	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	13	0	0	0	0	0	0	0	0	0	0	1	0	5	0	0	0	83.3
	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	15	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0.0
	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	100.0
	Overall %	0.0	0.0	16.7	6.3	8.3	18.8	12.5	0.0	2.1	4.2	12.5	2.1	12.5	0.0	0.0	4.2	60.4

Tab. 4.43: Standard and Poor's Classification Structure from Artificial Neural Networks with Variables

Sample		Predicted														
		3	4	5	6	7	8	9	10	11	12	13	14	15	18	% Correct
Training	3	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0.0
	4	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0.0
	5	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0.0
	6	0	0	0	8	3	0	0	0	0	0	0	0	0	0	72.7
	7	0	0	0	0	4	4	0	0	0	0	0	0	0	0	50.0
	8	0	0	0	0	1	3	7	0	0	0	0	0	0	0	27.3
	9	0	0	0	0	1	2	14	0	0	0	0	0	0	0	82.4
	10	0	0	0	0	0	1	10	0	0	0	0	0	0	0	0.0
	11	0	0	0	0	0	0	6	0	0	3	0	0	0	0	0.0
	12	0	0	0	0	0	0	1	0	0	9	0	1	0	0	81.8
	13	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0.0
	14	0	0	0	0	0	0	0	0	0	0	0	5	0	0	100.0
	15	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0.0
	18	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0.0
	Overall %	0.0	0.0	0.0	23.2	8.0	8.9	33.9	0.0	0.0	10.7	0.0	15.2	0.0	0.0	38.4
Testing	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0.0
	4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0.0
	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	6	0	0	0	2	0	0	0	0	0	0	0	0	0	0	100.0
	7	0	0	0	0	5	1	0	0	0	0	0	0	0	0	83.3
	8	0	0	0	0	1	4	0	0	0	0	0	0	0	0	80.0
	9	0	0	0	0	0	0	4	0	0	0	0	0	0	0	100.0
	10	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0.0
	11	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0.0
	12	0	0	0	0	0	0	0	0	0	4	0	0	0	0	100.0
	13	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0.0
	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	15	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0.0
	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	Overall %	0.0	0.0	0.0	13.3	20.0	16.7	30.0	0.0	0.0	20.0	0.0	0.0	0.0	0.0	63.3

Tab. 4.44: Standard and Poor's Classification Structure from Artificial Neural Networks with Principal Components

Sample		Predicted														
		3	4	5	6	7	8	9	10	11	12	13	14	15	18	% Correct
Training	3	6	0	0	0	0	0	0	0	0	0	0	0	0	0	100.0
	4	3	0	2	0	0	0	0	0	0	0	0	0	0	0	0.0
	5	1	0	4	2	0	0	0	0	0	0	0	0	0	0	57.1
	6	0	0	1	7	2	0	0	0	0	0	0	0	0	0	70.0
	7	0	0	0	2	4	5	0	0	0	0	0	0	0	0	36.4
	8	0	0	0	0	4	4	1	2	0	0	0	0	0	0	36.4
	9	0	0	0	1	1	5	9	4	0	0	0	0	0	0	45.0
	10	0	0	0	0	0	0	3	5	2	0	0	0	0	0	50.0
	11	0	0	0	0	0	0	0	2	4	0	1	0	1	0	50.0
	12	0	0	0	0	0	0	0	0	0	9	0	1	0	0	90.0
	13	0	0	0	0	0	0	0	0	0	2	1	1	0	0	25.0
	14	0	0	0	0	0	0	0	0	0	1	0	3	0	0	75.0
	15	0	0	0	0	0	0	0	0	0	0	0	1	1	1	33.3
	18	0	0	0	0	0	0	0	0	0	0	0	0	0	4	100.0
	Overall %	8.8	0.0	6.2	10.6	9.7	12.4	11.5	11.5	5.3	10.6	1.8	5.3	1.8	4.4	54.0
Testing	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	5	0	0	1	1	0	0	0	0	0	0	0	0	0	0	50.0
	6	0	0	1	2	0	0	0	0	0	0	0	0	0	0	66.7
	7	0	0	0	0	2	0	1	0	0	0	0	0	0	0	66.7
	8	0	0	0	1	0	3	1	0	0	0	0	0	0	0	60.0
	9	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0.0
	10	0	0	0	0	0	0	0	3	0	0	0	0	0	0	100.0
	11	0	0	0	0	0	0	0	1	1	0	1	0	0	0	33.3
	12	0	0	0	0	0	0	0	1	1	3	0	0	0	0	60.0
	13	0	0	0	0	0	0	0	0	0	0	1	0	0	0	100.0
	14	0	0	0	0	0	0	0	0	0	0	0	1	0	0	100.0
	15	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0.0
	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	Overall %	0.0	0.0	6.9	13.8	6.9	13.8	6.9	17.2	6.9	10.3	6.9	6.9	0.0	3.4	58.6

of the data used as training data and 33 per cent used as testing data. There is one hidden layer with 5 units in this model, the hidden layers uses the hyperbolic tangent activation function while the output layer uses a softmax activation function.

The model is able to accurately classify 58 per cent of the Fitch rating data. It is important to note that the training data was able to classify 61.3 per cent of the data. With the training data set we find that the rating categories 3, 5, 10, 14 and 16 are all classified with 100 per cent accuracy. As regards the testing data set the categories 10, 14 and 16 are classified with 100 per cent accuracy. For Fitch both the multiple discriminant analysis and the ordered probit models outperform the ANN methodology classifying approximately 62 and 60 per cent respectively.

In the next step we run the model with principal components in an attempt to improve the classification. The model with principal components is split into testing and training data sets with 26 per cent being testing data and 74 per cent being training data. The same activation functions are applied and the results show that the model only classifies 53 per cent of the testing data accurately. Only the rating category 10 is classified with 100 accuracy.

Tab. 4.45: Fitch Classification Structure from Artificial Neural Networks with Variables

Sample		Predicted												
		3	4	5	6	7	8	9	10	11	12	14	16	% Correct
Training	3	3	0	0	0	0	0	0	0	0	0	0	0	100.0
	4	1	2	0	1	0	0	0	0	0	0	0	0	50.0
	5	0	0	1	0	0	0	0	0	0	0	0	0	100.0
	6	0	0	0	5	5	0	0	0	0	0	0	0	50.0
	7	0	0	0	4	3	4	0	0	0	0	0	0	27.3
	8	0	0	0	1	3	5	3	0	0	0	0	0	41.7
	9	0	0	0	0	0	4	8	0	0	0	0	0	66.7
	10	0	0	0	0	0	0	0	12	0	0	0	0	100.0
	11	0	0	0	0	0	0	1	3	3	0	0	0	42.9
	12	0	0	0	0	0	0	0	0	1	0	0	0	0.0
	14	0	0	0	0	0	0	0	0	0	0	3	0	100.0
	16	0	0	0	0	0	0	0	0	0	0	0	4	100.0
	Overall %	5.0	2.5	1.3	13.8	13.8	16.3	15.0	18.8	5.0	0.0	3.8	5.0	61.3
Testing	3	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	4	2	0	0	0	0	0	0	0	0	0	0	0	0.0
	5	0	0	0	2	0	0	0	0	0	0	0	0	0.0
	6	0	1	0	1	3	0	0	0	0	0	0	0	20.0
	7	0	0	0	0	3	2	0	0	0	0	0	0	60.0
	8	0	0	0	0	3	5	0	1	0	0	0	0	55.6
	9	0	0	0	0	0	0	6	1	0	0	0	0	85.7
	10	0	0	0	0	0	0	0	5	0	0	0	0	100.0
	11	0	0	0	0	0	0	1	1	1	0	0	0	33.3
	12	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	14	0	0	0	0	0	0	0	0	0	0	1	0	100.0
	16	0	0	0	0	0	0	0	0	0	0	0	1	100.0
	Overall %	5.0	2.5	0.0	7.5	22.5	17.5	17.5	20.0	2.5	0.0	2.5	2.5	57.5

Tab. 4.46: Fitch Classification Structure from Artificial Neural Networks with Principal Components

Sample		Predicted													
		2	3	4	5	6	7	8	9	10	11	12	14	16	% Correct
Training	2	0	0	0	0	0	2	0	0	0	0	0	0	0	0.0
	3	0	0	0	0	1	1	0	0	0	0	0	0	0	0.0
	4	0	0	0	0	5	1	0	0	0	0	0	0	0	0.0
	5	0	0	0	0	2	0	0	1	0	0	0	0	0	0.0
	6	0	0	0	0	8	1	0	2	0	0	0	0	0	72.7
	7	0	0	0	0	4	2	2	1	0	0	0	0	0	22.2
	8	0	0	0	0	3	2	7	3	2	0	0	0	0	41.2
	9	0	0	0	0	0	0	3	11	1	0	0	0	0	73.3
	10	0	0	0	0	0	0	0	0	11	0	0	0	0	100.0
	11	0	0	0	0	0	0	0	0	6	0	0	0	0	0.0
	12	0	0	0	0	0	0	0	0	1	0	0	0	0	0.0
	14	0	0	0	0	0	0	0	0	4	0	0	0	0	0.0
	16	0	0	0	0	0	0	0	0	3	0	0	0	0	0.0
	Overall %	0.0	0.0	0.0	0.0	25.6	10.0	13.3	20.0	31.1	0.0	0.0	0.0	0.0	43.3
Testing	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0.0
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	6	0	0	0	0	3	1	0	0	0	0	0	0	0	75.0
	7	0	0	0	0	2	3	0	1	1	0	0	0	0	42.9
	8	0	0	0	0	1	0	2	1	0	0	0	0	0	50.0
	9	0	0	0	0	0	0	1	3	0	0	0	0	0	75.0
	10	0	0	0	0	0	0	0	0	6	0	0	0	0	100.0
	11	0	0	0	0	0	0	0	1	3	0	0	0	0	0.0
	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	16	0	0	0	0	0	0	0	0	2	0	0	0	0	0.0
	Overall %	0.0	0.0	0.0	0.0	18.8	15.6	9.4	18.8	37.5	0.0	0.0	0.0	0.0	53.1

4.6 Conclusion

This chapter tests the ability of four statistical techniques to accurately classify ratings assigned by three rating agents (Moody's, Standard and Poor's and Fitch). Not only does the chapter test the ability of the statistical techniques (ordered probit, multiple discriminant analysis, ordinary least squares and artificial neural networks) but also tests two types of models. One model is built with variables while the other is constructed with principal components. Much of the literature has used and criticised many of the multi variate and univariate models used in this analysis but within recent time we have found the computer learning techniques to be quite popular. The main argument in favour of computer learning techniques such as artificial neural networks is the removal of many limiting assumptions and mathematical restrictions placed on other techniques.

An analysis of the four statistical techniques gives some interesting results. Thus far we find that the multiple discriminant analysis technique out performs all others, for the Moody's, Standard and Poor's and Fitch this method is able to accurately classify 66, 64 and 62 per cent of the ratings respectively. While there has been an eruption in the praise of computer leaning techniques it would appear that the artificial neural network approach is sub par when compared to multiple discriminant analysis. Additionally the models with variables in all techniques outperformed the models with the principal components. We can then conclude that the principal component method applied in no way strengthened any of the models (Table 4.47).

Tab. 4.47: Summary Table of Classification Accuracy

	Moody's	Standard and Poor's	Fitch
		per cent	
Ordered Probit Model			
Variables	52	47	60
Principal Components	51	47	53
Multiple Discriminant Analysis			
Variables	66	64	62
Principal Components	57	58	60
Ordinary Least Squares			
Variables	38	45	46
Principal Components	36	45	48
Artificial Neural Networks			
Variables	64	63	58
Principal Components	60	59	53

5. GENERAL CONCLUSION

In the final chapter of this dissertation I summarise the findings and implications of the empirical analysis undertaken. An overview is given of the study and the findings presented followed by a section on the policy implications of the empirical analysis in each chapter.

5.1 Overview and Findings of Study

This dissertation has the events of the 2008 financial crisis at the heart of the study and evaluates prediction and classification models with this event in mind. It seeks to answer three fundamental questions (i) which default model, structural or accounting is better at predicting bank default? (ii) is there transmission from sovereign credit ratings to bank credit ratings in the Euro zone? (iii) does the use of a particular statistical approach improve the classification of bank ratings?

In paper I we focus on the central question of the default prediction ability of accounting versus structural models. The study is developed on 536 defaulted US banks taken from the Federal Deposit Corporation database between 1993-2012, the pre crisis defaulted banks were included in an attempt to extend the model to pre-crisis periods so that we can test and validate its predictive abilities.

While notable works have developed accounting and structural models to predict default, this paper adds to the existing literature by investigating the non-normality of the financial variables to observe whether transformation of non-normal variables would improve default detection. While the improvements were minimal we did find that both the accounting and structural models adequately determined default with the accounting model performing slightly better.

In the paper II we investigate the transmission of sovereign rating to bank credit ratings, an area with limited studies in the literature. This chapter sought to trace the transmission following the approach of the papers by Williams et al (2013) and Alsakka et al (2014). Their methodology saw the data set including bank ratings that were granted 3 months post the rating of the sovereign. The main arguments was that any ratings taken after this period could have other influences.

In an attempt to deepen their study we opted to include accounting variables in the model since it was felt that eliminating such vital information meant we would draw conclusions based solely on the geographic location of the bank. To state clearly arriving at a conclusion based only on sovereign data and bank rating data would suggest that banks were downgraded due only to the sovereign rating and not based on their own accounting and financial positions.

In particular we found that the sovereign downgraded exerted great influence on the amount of notches the bank was downgraded by. Multiple notch sovereign downgrades in every case seemed to exert great pressure on the amount of notches banks were downgraded by. We also found that the financial fundamentals did play a role in the determining the overall rating a bank received that is A, AA or AAA etc. We also investigated the interdependence of ratings and found that there exists interdependency among the rating agents.

In paper III we examined the classification of bank credit ratings. We tested four statistical approaches namely, ordered probit, multiple discriminant analysis, ordinary least squares and artificial neural networks. For each statistical model we used two approaches, one model with financial variables and the other with principal components.

In every case the model with variables was able to outperform that with principal components. In the end we found that the multiple discriminant analysis approach was better able to classify the rating of banks, accurately classifying 66, 64 and 62 per cent for Moody's, Standard and Poor's and Fitch. Despite the growing popularity of artificial neural networks we found that multiple discriminant analysis and the ordered probit model to be the better classification models in terms of classifying bank credit ratings.

The dissertation focuses on the models that can be used to give more in depth information surrounding the stability of the banking sector. It provides a basic framework for policy makers and regulators alike to analyse on a basic level the possible ramifications of changes to a bank accounting portfolio or alterations in sovereign ratings. These all give some alert as to possible problems banks may face.

5.2 Policy Implications

This work and much of its implications centre around the events of the recent financial crisis that has plagued both the developed and developing world. There has been a widespread initiative to focus policy measures on the prevention of the events that led up to the crisis. The focus of institutions like the International Monetary Fund (IMF), World Bank, BIS and other such regulatory agents have all seen the importance in promoting financial stability and engaging Central Banks and other agents in understanding, anticipating and dealing with financial threats. The policy recommendations that stem from this analysis fall in line with those which have been highlighted by many of the stability reports.

In the first instance this research suggests that included in the monitoring tool kit for the banking system should be a combination of the structural and accounting default approaches. Many times as has been seen we evolve to technical and challenging models that limit our ability to interpret and analyse the findings on any real basis. The application of the accounting and structural approaches on its most basic level can be added to the monitoring tool kit to give a basic idea of the operations of the banking institutions under the purview of the regulators.

Apart from the technical models used to influence the approach regulators take in dealing with banks there also needs to be a better understanding of the transmission effects of ratings. In many cases the transmission from sovereign to banks has been left unanalysed since pre crisis it was seen that there was limited transmission from a change in rating to the sovereign to the bank. Now that we have established the transmission exists particularly in critical events this should become part of the evaluation package that regulators use. Closer evaluation of the ratings sovereigns receive and how those may influence the financial entities in an economy.

The importance of the financial sector and in particular the banking sector has been highlighted in recent years. The fact that a crisis which originated in the financial sector transcended to an economic crisis speaks volumes to the importance of how this sector needs to be monitored and managed. While many of the policy recommendations suggest improvements in monitoring through empirical tools it is also important for supervisors to understand the banks internal mechanisms and ask the hard questions to ensure that the profit motive is not driving the banks to endanger the stability of the sector.

APPENDIX

A. BANK DEFAULT PREDICTION USING PRINCIPAL COMPONENT ANALYSIS

A.1 Transformed variables

Tab. A.1: Estimation results : Log transformed variables

Variable	**Coefficient**	**(Std. Err.)**
lta	2.549	(0.507)***
logtbe	0.023	(0.230)
lognoncurrentll	-2.603	(0.502)***
logniea	0.761	(0.179)***
loger	-0.197	(0.133)
loglancl	0.294	(0.148)**
ncaoreta	0.657	(0.160)***
lognlltcd	0.816	(0.288)***
logtier1rbc	-2.377	(0.244)***
logncll	2.982	(0.517)***
gdp	-0.017	(0.024)
tbills	0.326	(0.055)***
Intercept	-5.291	(1.018)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. A.2: Log Model Classification Accuracy

Classified	Defaulted	Non-Defaulted
Defaulted	64%	2%
Non-Defaulted	36%	98%
Total	**100%**	**100%**

Tab. A.3: Estimation results : Box Cox transformed bounded ratios and log transformed unbounded ratios

Variable	**Coefficient**	**(Std. Err.)**
lta	0.995	(0.503)**
logtbe	-0.123	(0.226)
bnoncurrentll	-0.599	(0.326)**
bniea	0.574	(0.131)***
loger	-0.130	(0.132)**
blancl	0.122	(0.113)
bncaoreta	0.715	(0.227)***
lognlltcd	0.190	(0.278)
logtier1rbc	-2.190	(0.236)***
logncll	1.161	(0.471)**
gdp	-0.017	(0.024)
tbills	0.324	(0.054)***
Intercept	-6.968	(1.309)

Tab. A.4: Box Cox and Log transformed Model Classification Accuracy

Classified	Defaulted	Non-Defaulted
Defaulted	65	2%
Non-Defaulted	35%	98%
Total	**100%**	**100%**

Tab. A.5: Estimation results : Principal component analysis of normalised accounting/financial variables

Variable	**Coefficient**	**(Std. Err.)**
pc1	0.601	(0.042)***
pc2	-0.244	(0.037)***
pc3	-0.217	(0.073)***
pc4	0.898	(0.066)***
Intercept	-5.162	(0.121)***

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. A.6: Principal Component Analysis Model Classification Accuracy

Classified	Defaulted	Non-Defaulted
Defaulted	56	2%
Non-Defaulted	44%	98%
Total	**100%**	**100%**

B. DO SOVEREIGN CREDIT RATINGS INFLUENCE BANK CREDIT RATINGS?

Tab. B.1: Estimation results : Bank downgrade model with lagged independent variables

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : bankdowngrade		
lSov $\uparrow_1$	1.039	(0.530)**
lSov $\uparrow_2$	0.000	(0.000)
lSov $\downarrow_1$	0.397	(0.141)***
lSov $\downarrow_2$	0.162	(0.129)
lnegativewatch	0.249	(0.111)**
lsovereignrating	0.045	(0.010)***
Equation 2 : cut1		
Intercept	-0.013	(0.070)
Equation 3 : cut2		
Intercept	1.271	(0.080)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. B.2: Estimation results :Bank downgrade model with lagged financial variables

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : bankdowngrade		
lSov $\uparrow_1$	1.003	(0.568)*
lSov $\uparrow_2$	0.000	(0.000)
lSov $\downarrow_1$	0.440	(0.184)**
lSov $\downarrow_2$	0.160	(0.163)
lnegativewatch	0.155	(0.142)
lsovereignrating	0.063	(0.017)***
lroa	-0.002	(0.018)
ltier1rbc	0.005	(0.031)
lplltl	0.170	(0.155)
lnpltl	-0.019	(0.015)
ltltd	0.001	(0.002)
Equation 2 : cut1		
Intercept	0.269	(0.475)
Equation 3 : cut2		
Intercept	1.442	(0.479)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. B.3: Estimation results : Bank upgrade model with lagged indepedent variables

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : bankupgrade		
lSov $\uparrow_1$	0.695	(1.097)
lSov $\uparrow_2$	0.000	(0.000)
lSov $\downarrow_1$	-0.228	(0.712)
lSov $\downarrow_2$	-0.240	(0.543)
lnegativewatch	-0.276	(0.343)
lsovereignrating	-0.063	(0.027)**
Equation 2 : cut1		
Intercept	-0.280	(0.127)
Equation 3 : cut2		
Intercept	1.164	(0.149)
Equation 4 : cut3		
Intercept	1.963	(0.240)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. B.4: Estimation results : Bank upgrade model with lagged financial variables

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : bankupgrade		
lSov $\uparrow_1$	0.000	(0.000)
lSov $\uparrow_2$	0.000	(0.000)
lSov $\downarrow_1$	4.060	(8.068)
lSov $\downarrow_2$	-1.405	(0.849)*
lnegativewatch	-4.341	(8.055)
lsovereignrating	0.160	(0.085)*
lroa	0.966	(0.292)***
ltier1rbc	-0.358	(0.140)**
lplltl	0.529	(0.941)
lnpltl	-0.121	(0.056)**
ltltd	-0.005	(0.005)
Equation 2 : cut1		
Intercept	-3.721	(1.562)
Equation 3 : cut2		
Intercept	-2.059	(1.534)
Equation 4 : cut3		
Intercept	-0.792	(1.549)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. B.5: Estimation results : Bank level model with lagged independent variables

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : banklevel		
lSov $\uparrow_1$	1.178	(0.421)**
lSov $\uparrow_2$	0.000	(0.000)
lSov $\downarrow_1$	-0.305	(0.122)**
lSov $\downarrow_2$	-0.587	(0.110)***
lnegativewatch	0.023	(0.094)
lsovereignrating	0.291	(0.011)***
Equation 2 : cut1		
Intercept	-1.412	(0.111)
Equation 3 : cut2		
Intercept	-0.944	(0.082)
Equation 4 : cut3		
Intercept	-0.456	(0.067)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

Tab. B.6: Estimation results : Bank level model with lagged financial variables

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : banklevel		
lSov $\uparrow_1$	1.822	(0.599)***
lSov $\uparrow_2$	0.000	(0.000)
lSov $\downarrow_1$	-0.212	(0.159)
lSov $\downarrow_2$	-0.639	(0.143)***
lnegativewatch	0.140	(0.125)
lsovereignrating	0.370	(0.019***)
lroa	-0.005	(0.017)
ltier1rbc	-0.046	(0.026)**
lplltl	0.006	(0.133)
lnpltl	0.037	(0.012)***
ltltd	-0.001	(0.001)
Equation 2 : cut1		
Intercept	-2.368	(0.558)
Equation 3 : cut2		
Intercept	-1.314	(0.417)

*,**,*** statistical significance at the 10%, 5% and 1% levels.

C. A COMPARISON OF BANK CREDIT RATING MODELS

C.1 Artificial Neural Network Structure

Fig. C.1: Moody's Artificial Neural Network Structure with Variables

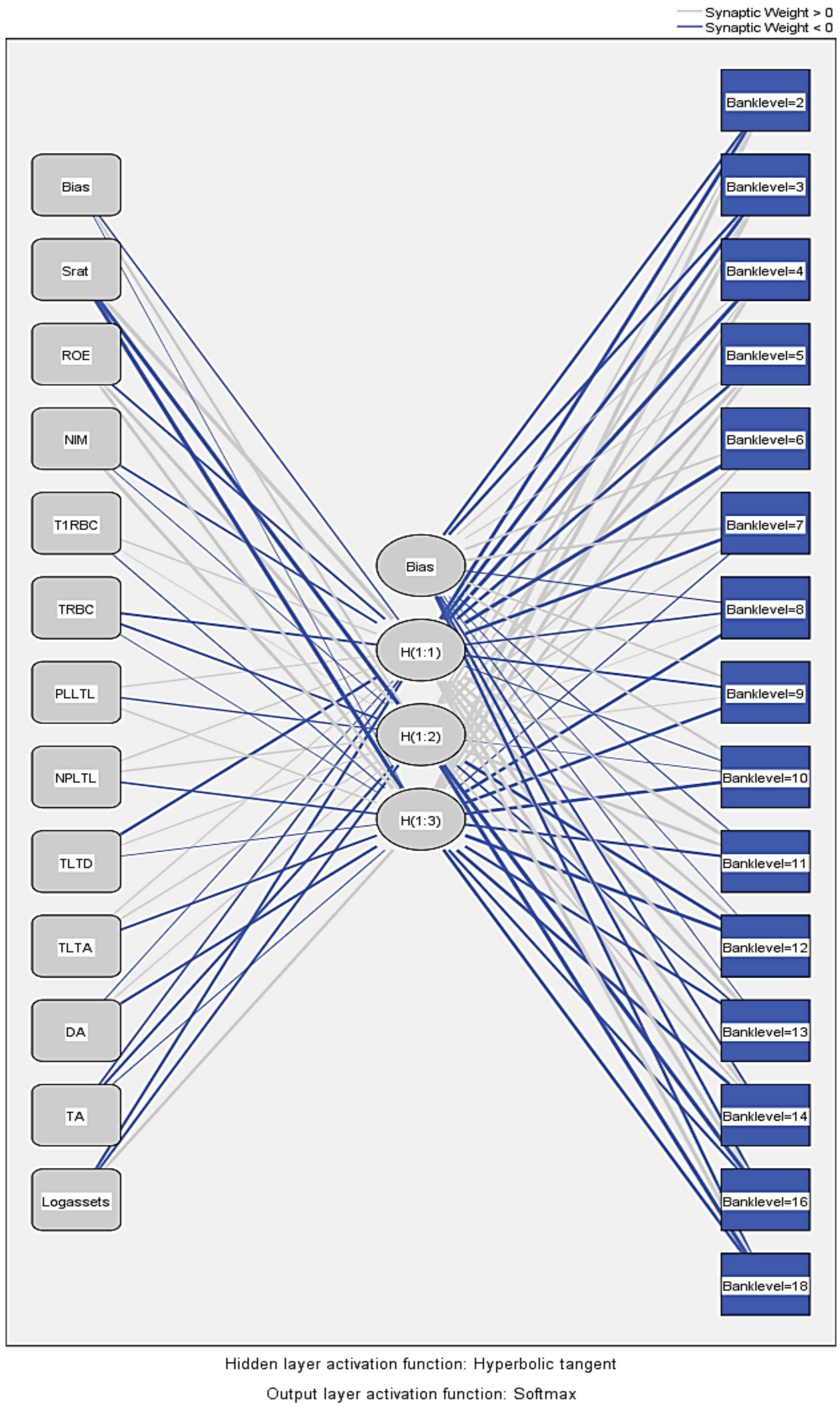


Fig. C.2: Moody's Artificial Neural Network Structure with Principal Components

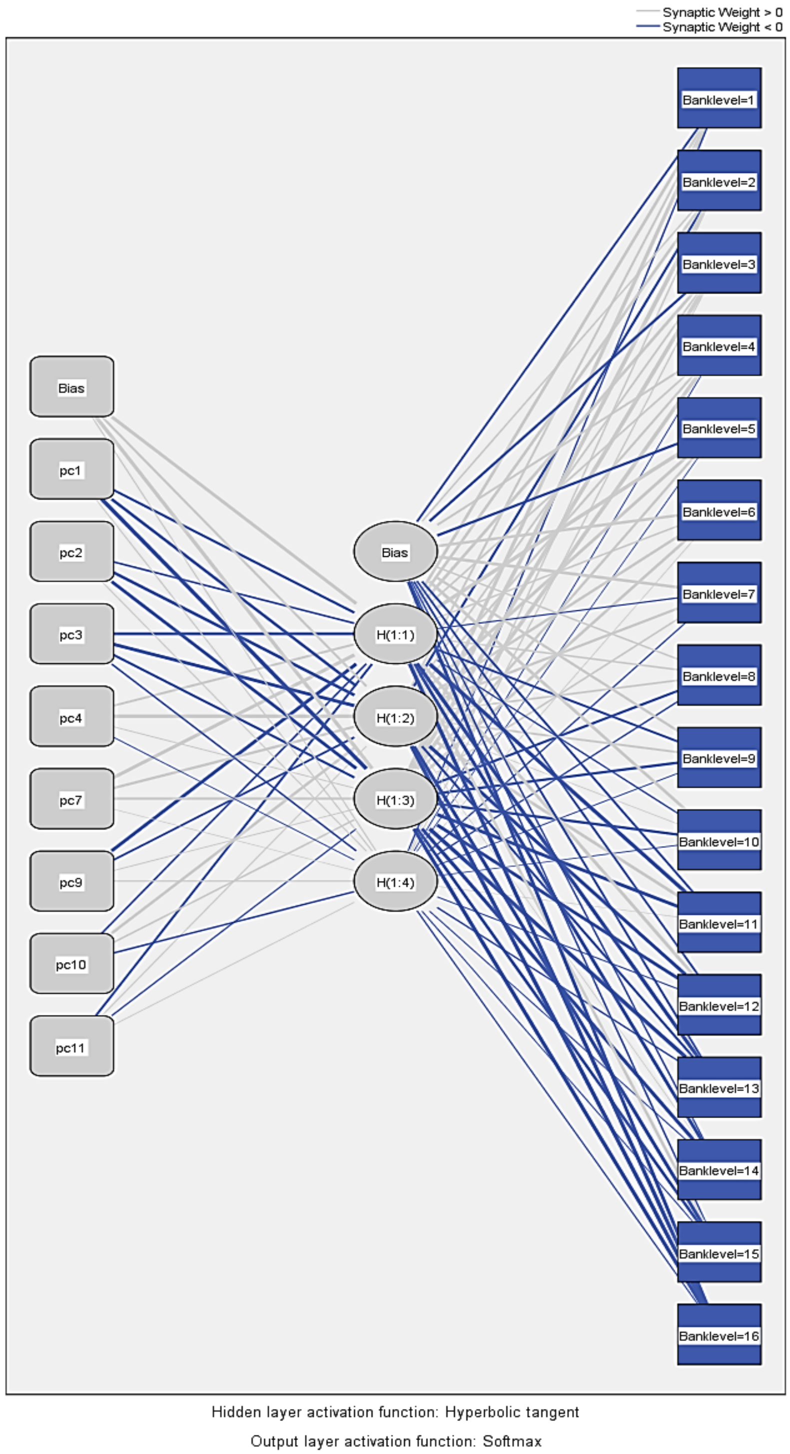


Fig. C.3: Standard and Poor's Artificial Neural Network Structure with Variables

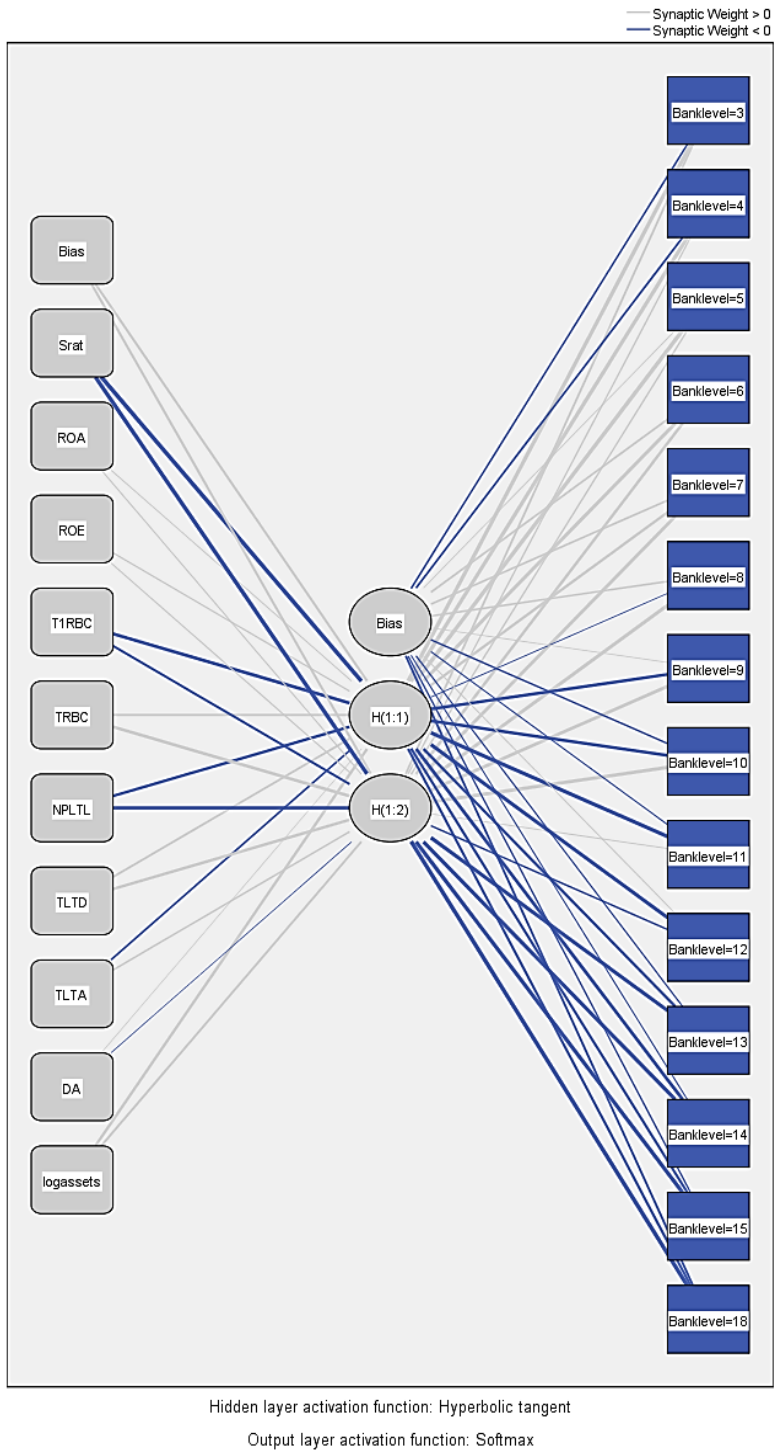


Fig. C.4: Standard and Poor's Artificial Neural Network Structure with Principal Components

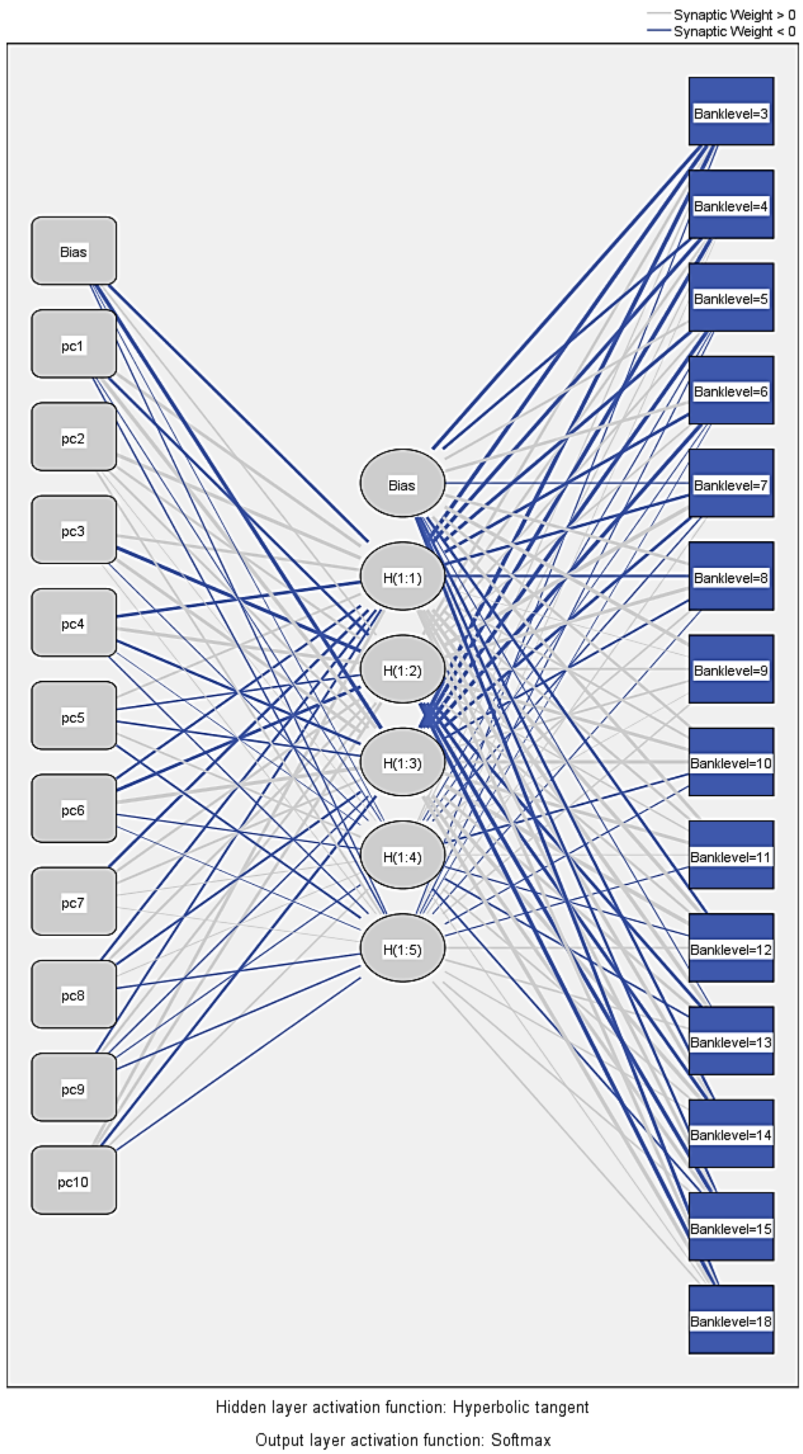


Fig. C.5: Fitch Artificial Neural Network Structure with Variables

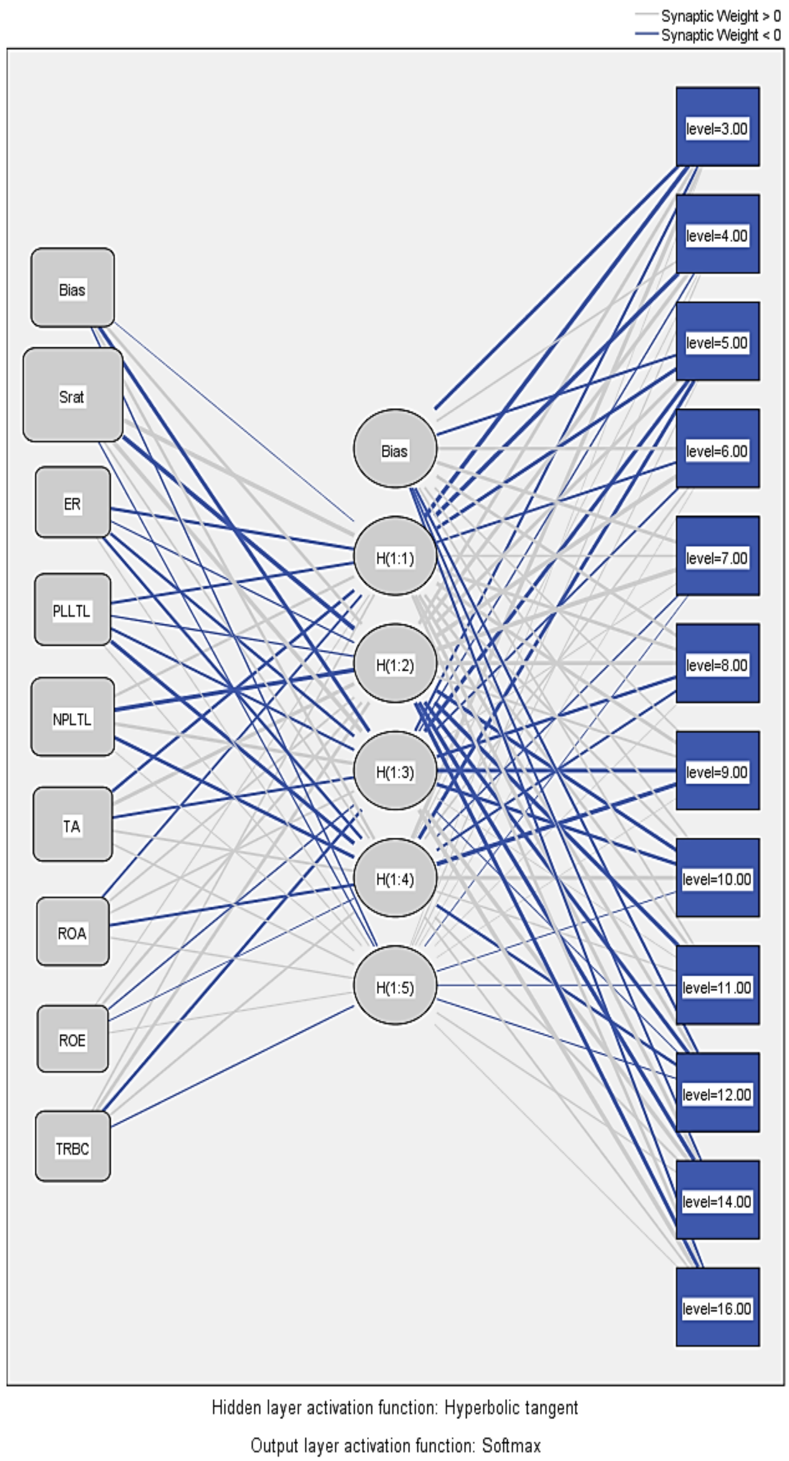
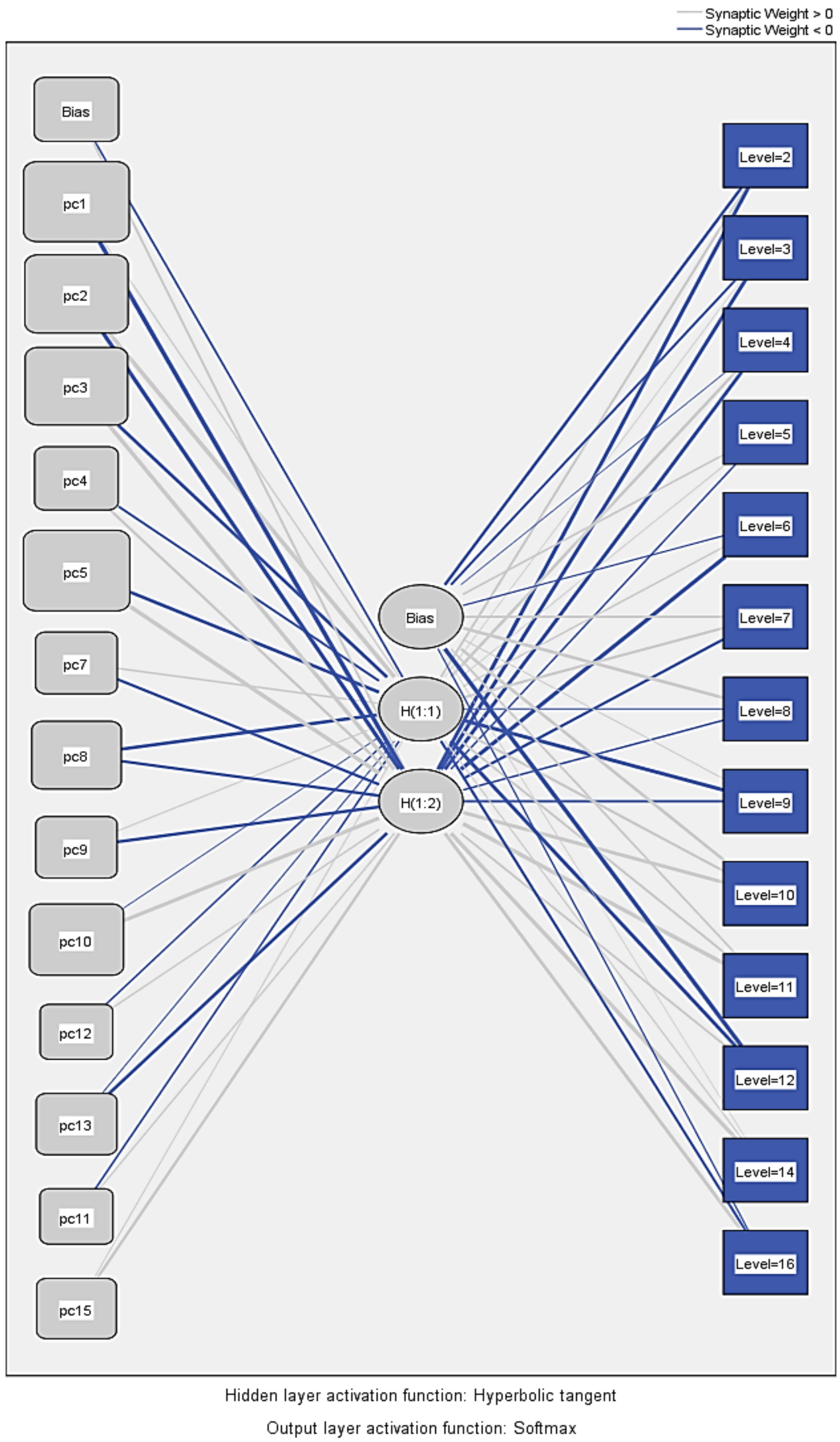


Fig. C.6: Fitch Artificial Neural Network Structure with Principal Components



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