AN EMPIRICAL INVESTIGATION OF THE DETERMINANTS AND IMPACT OF BANK CREDIT RATINGS

Bolanle Abubakar Karimu

A thesis submitted in partial fulfilment of the requirements of the University of the West of England, Bristol for the degree of Doctor of Philosophy

Bristol Business School

University of the West of England, Bristol

March 2015

DEDICATION

This thesis is dedicated to:

*My wife, **Toyin**, for her understanding, love and support, and above all, for taking care of our home and three lovely children during this process*

*My mother, **Mrs. Tinuke Karimu**,*
for her unflinching support and prayers over the years

The loving memory of my father,
***Pa (Hadji) Muftau Ayinla Karimu**,*
who I will always hold dearly in my heart.
May Allah, in His infinite mercy grant him Al janna Firdaus

"He grants wisdom to whom He pleases; and he to whom wisdom is granted receives indeed a benefit overflowing; but none will grasp the Message but men of understanding." (Q:2: 269)

ACKNOWLEDGEMENTS

In the name of Allah, the Most Beneficent, the Most Merciful.

First and foremost I give thanks to God for His enduring mercy and benevolence during this process. He has indeed blessed me and my entire family and I give all praises to Him.

Many people have contributed greatly to this thesis. Without their assistance, completing this work would not have been possible. To each of them, I owe my sincere thanks and gratitude.

I would like to thank my supervisory team of **Dr Iris Biefang-Frisancho Mariscal** and **Prof Jon Tucker** for their guidance and supervision these past years. I would like to say that I am deeply indebted to my second supervisor **Prof Jon Tucker**, for his encouragements, kind words, understanding and empathy. He is indeed a mentor and a source of motivation during the entire process. I will surely not be at here at this stage without the love he has shown me.

I am also deeply indebted to the **University of the West of England** for providing me with a four year bursary and full scholarship in acknowledgement of the importance of my work. I would not have been financially capable of bearing the burden of the cost of self-sponsorship. It is important that I mention the support from colleagues at the **Centre of Global Finance**, **UWE**. Although, there are too many names to mention, I would like to say a big thank you to **Dr Eleimon Gonis** for his enthusiasm in my research and the support he provided. I cannot forget to mention **Cherif, Ufuk, Robert, Osman, Nadine, Ismail, Debbie, Neil, Anthony, Aylwin** for their contributions and support. Special thanks go to **Hazel** and **Tamika** for helping to read through my work. I am sincerely grateful to **Gbenga** for helping with the formatting of my work. I thank **Prof Lukumon** and **Prof Olomolaiye** for their words of encouragement

I would like to thank my friends, **Temidayo (Jaiyeju), Ayo, Yinkus, Yemi Olar, Moses, Joe, Alaba, Jay, Jare, Mike, David, Apachi, Udonna, Emmunuel and Uncle Jimmy** for their prayers and support.

Finally, I wish to thank my family. To my lovely wife, **Olu**, my beautiful kids **Sofiyyah, Khalid** and **Amirah**, I love you all. Thank you for your patience and understanding. To my late dad (May he rest in peace) and my mum, I will be forever grateful to you. You are indeed my pillar. I would like to thank my sister, **Christine** and her husband, **Rob,** for always being there for us. I would like to thank my siblings **Tokunbo** and **Moshood** and their families. My thanks also go to my in-laws, the **Abijos**, for their love and support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

This thesis investigates three empirical issues in the field of bank credit rating in an international setting. First, it models the financial and non-financial determinants of bank credit ratings. Second, it examines the impact of news announcements concerning bank credit rating changes, that is, upgrades and downgrades, on the performance of bank stock. Lastly, the thesis examines the trends in bank credit rating over time by focusing on rating migration within the historical pattern of both ratings and rating changes.

The thesis reveals that the assignment of credit ratings to international banks is driven heavily by the *Capital Adequacy, Assets Quality, Management, Earnings, Liquidity and Sensitivity to the Market (CAMELS)*. The inclusion of non-financial variables, such as the *too-big-to-fail* and bank's corporate governance measures, adds to the explanatory power of the rating determinant models. In addition, the thesis reveals that there is asymmetry in the reaction of the market to rating actions. It finds significant positive market reactions to subsamples of bank upgrades. Downgrades generally elicit significant negative market reactions. Finally, the results provide evidence of downward momentum in the rating migration of banks over time and the importance of duration in a rating notch on the likelihood of a bank migrating to another state. Generally, the longer a rated bank stays in a particular rating notch, the lower its probability of transiting to another rating notch.

CHAPTER 1. INTRODUCTION

1.1 Introduction

This thesis investigates three empirical issues in the field of bank credit ratings in an international setting. First, it models the financial and non-financial determinants of bank credit ratings. The thesis presents a number of different specifications of the ordered probit model in the estimation of the bank rating determinant equation. The models aim to accurately predict the assignment of credit ratings to banks. It employs an out-of-sample approach in the test of prediction accuracy of credit rating agencies. This thesis is motivated by the intense spotlight on the credit rating agencies, particularly following the global financial crisis of 2007/08. The need to critically examine the credit rating industry and the accuracy of the ratings they assign warrant further investigation. In addition, the various regulatory changes concerning the global banking industry, particularly as it concerns structural reforms of banks, banking regulation and risk culture serve as important motives for this study.

Second, the thesis examines the impact of news announcements concerning bank credit rating changes, that is, upgrades and downgrades, on the performance of bank stocks. The aim of this event study analysis is to gauge the market reaction to bank rating changes. The premise for this is the claim by credit rating agencies that they possess private information not available to market. If this is the case, then the event study models should reveal significant abnormal returns around the time of news announcements. Finally, the thesis examines trends in bank credit ratings over time. This enables an investigation of bank credit rating dynamics, focusing on rating migration within the historical pattern of both ratings and ratings changes. The thesis tests for the effects of rating duration and drift (momentum) on bank credit rating migration.

The remainder of this chapter is structured as follows. Section 1.2 presents a brief overview of the background of, and motivation for, the study. Section 1.3 states the research questions and objectives that the thesis aims to address. Section 1.4 discusses the expected important contributions of the thesis. Section 1.5 presents the findings of the thesis. Finally, the summary of the chapter is presented in Section 1.6.

1.2 Overview and motivation

According to the US Securities and Exchange Commission, SEC (2003) in its report on the role and function of credit rating agencies in the operation of the securities market, ‘a credit rating reflects a rating agency’s opinion, as of a particular date, of the credit worthiness of a particular company, security or obligations’ (p. 5). Parker and Tarashev (2011) argue that rating reflects both quantitative assessments of credit risk (using models) and the expert opinion of a ratings committee. The external credit rating agencies such as Fitch, Moody’s, and Standard and Poor’s perform a major role in financial markets by bridging the information gap and providing valuable input to the assessment of credit risks of entities and their issues (Taylor 2013). Credit ratings are thus, an invaluable tool for investors when it comes to making decisions about transactions in bonds and other fixed income investments (Langohr and Langohr, 2008). However, credit rating agencies maintain that their ratings are only opinions on relative credit risk and therefore do not constitute investment advice in the same manner as buy, hold, or sell recommendations (Dodd-Frank Act, 2010). Thus, while forward-looking opinion is important to investors in their decision making processes, an investment grade rating does not guarantee that an investment will not default, nor is it a guarantee the future credit quality or credit risk if such rated entity or issue.

This thesis examines bank credit ratings within an international setting due to the unique features of the banking industry. Banks are generally considered as being opaque and difficult to assess due to the complexity of their structure, business models and the nature of their assets. The major credit rating agencies argue that the assessments of bank creditworthiness go beyond analysing and forecasting banks' performance. They maintain that there is need to account for the degree of external support, as well as an assessment of the degree of systemic risk and the inherent volatility of banks' performance (Fitch 2007). Banks are important in financial stability and their role as financial intermediaries and interconnectedness exerts considerable influence on the degree of external assistance they receive.

The findings from this thesis highlight the importance of the concept too "*too-big-to-fail*" (TBTF), or what the Financial Stability Board (FSB) in their 2013 report refers to as Systemically Important Financial Institutions (SIFIs), in the bank credit rating process. The TBTF problem arises when the threatened failure of an SIFI leaves national governments with no option but to bail it out using public funds to avoid financial instability and economic damage. The knowledge that this can happen encourages SIFIs to take excessive risks. According to the FSB (2013), SIFIs are institutions of such size, market importance and interconnectedness that their distress or failure would cause significant dislocation in the financial system and adverse economic consequence. Thus, in rating banks, a rating agency has to evaluate not only the ability of the parent or sovereign to honour this commitment but also their willingness to do so. This confers special treatment to banks in the assignment of their ratings. In addition, evidence exists to support the notion that the *too-big-to-fail* notion confers funding advantage to large financial institutions, particularly in the period before the enactment of the Dodd-Frank Act 2010 (Labonte, 2015). Part of the motive for this thesis is therefore linked to the argument that the decision by the major credit rating agencies to rate the largest financial firms more highly because of the additional government support they receive. This *too-big-to-fail* 'subsidy' may take the form of explicit direct payment, financial support, or guarantee (Cull, 2014).

The global financial crisis which resulted in global panic and economic slowdowns or severe recessions in many countries across the world reinforced the importance of external supports in times of crisis. The period witnessed the collapse of the subprime mortgage market in the US, and revealed the huge exposure of international banks to the securitization market. The failure or risk of failure of major global financial institutions such as Lehman Brothers and Washington Mutual, the takeover of the investment giant Bear Sterns, the nationalization of Northern Rock (now owned by Virgin Money), Lloyds TSB and the Royal Bank of Scotland, coupled with rescue packages of national governments across the world underscore the importance of a sound credit risk management system and the need for a holistic approach to bank risk assessments. Bank's rating is thus important because the creditworthiness of a bank depends on vulnerabilities that may build up in different parts of the financial system, as well as on interlinkages in this system. A bank's rating thus reflects the industrial, financial and economic context of the bank's business and not derived in isolation.

The role of credit rating agencies in the 2007/08 financial crisis has come under severe scrutiny, due to their claim *ab initio* of assigning true creditworthiness in the form of rating notches to financial institutions and their instruments. The over reliance of the market, and in particular of traders, investors and regulators, on external credit ratings contributed to the laxity and the herd behaviour of many of these market participants. This further aggravated the ineffective credit risk management system which characterised the industry. There has been significant criticism of the credit rating agencies, particularly with regards to their methodologies. The level of opacity in the rating methodology, particularly in the period leading up to the global financial crisis, has motivated international regulators such as the International Organisation of Securities, IOSCO (in Europe) and the SEC (in the US) to scrutinize, and recommend the changes in the credit rating methodologies and the level of disclosure within the industry. As a consequence, there is now increased demand for transparency in the rating process. The opacity of the rating methodology, as well as its perception as a 'black-box' approach, by market participants (Pender, 1992; Steeman, 2002), has attracted academics and researchers to explore the models, inputs and motivations underlying the rating methodology.

Overall, the motivation for this thesis relates to the implications of the 2007/08 financial crisis on the banking and credit ratings industries as well as the regulators and market participants. Some of the salient lessons from global financial crisis, the systemic nature of bank risk, weakened finances of some sovereign providers of support, and policy initiatives to reduce the over-reliance of banks on government support motivates this study. An empirical examination of the dynamics of the credit rating process has great policy implications because ratings that reflect changes to regulatory and support frameworks and accurately capture banks' vulnerabilities would help strengthen market discipline and align risk with funding costs. Further, the more transparent a rating is, the better it is at conveying explicit assessments of the external support available to banks (Packer and Tarashev, 2011).

In view of these motivations, and the growing interest in credit ratings, particularly from an academic stand point, including rating determinants and the influence of rating agencies on financial markets, this study aims to address three research questions. These are presented briefly in the next section.

1.3 Research questions and the objectives of the thesis

This thesis attempts to investigate three key areas of bank credit ratings: (i) the determinants of bank credit ratings; (ii) bank stock return reactions to bank credit rating news announcements; and (iii) bank credit rating dynamics through time. The thesis employs international bank data relating to stock prices and returns, credit ratings, market index data, as well as non-financial information relating to each bank. The thesis seeks to address the following questions:

1. What are the determinants of credit ratings for banks across the globe?

   The 2007/08 global financial crisis raises questions around the reliability of the credit ratings process. The assignment of credit ratings to banks is designed to capture their creditworthiness. This follows detailed evaluation of a wide range of factors, both financial and non-financial. This research question is motivated by the seeming failure of the credit rating agencies to accurately capture the credit risk of banks within their rating assignment process. The global financial crisis has further brought to the fore investors' limited understanding of the complexities of ratings and the underlying risks that the ratings of these instruments and entities entail. Thus, leading to an undue reliance placed on ratings by investors for their investment decisions. It is therefore imperative to examine the significant factors driving this bank credit rating process by modelling a number of different specifications of the ordered probit equation.

   The series of regulatory reforms and directives on CRAs after the global financial crisis, particularly in the EU and the US are expected to change the behaviour of the agencies. The key reform actions globally have centred around the overtly reliance on CRAs by financial institutions for their investment, the need for more transparency, more diversity and stricter independence of CRAs to address conflicts of interest, and to make CRAs accountable for the ratings they assign (ESMA, 2015).

This first research question is further motivated by the need to carry out detailed examination of banks' business models and their risk culture as these could potentially influence the determinants of their ratings. The IFC (2013) argues that CRAs struggle to correctly capture the risk exposure of banks due to their complexities and business models. Hence, for CRAs, the issue of transparency, disclosure and risk culture effectiveness in banks becomes important in their crating assignment process. In 2014, Christine Lagarde[1], Managing Director of the International Monetary Fund, asserts that "while some changes in behaviour are taking place [in banking], these are not deep or broad enough. The industry still prizes short-term profit over long-term prudence, today's bonus over tomorrow's relationship." Further, the Financial Stability Board (FSB) 2014 report argues that the weaknesses in risk culture are often considered a root cause of the global financial crisis. This thesis, provides significant contributions to the body of knowledge by investigating issues around corporate governance and how the notion of the "*too-big-to-fail*" have influence the way CRAs perceives risk in banks.

2. Do bank credit rating announcements result in abnormal returns behaviour around the announcement date?

   Rating agencies are important in the mitigation of information asymmetry problems in the capital market. They maintain that they possess private information which is not available to the market and thus, on average, there should be a significant abnormal equity returns reaction to rating news announcements. Evidence suggests

[1] Emily Cadman, "IMF's Lagarde attacks financial sector for blocking reform," Financial Times, May 27, 2014

that there are significant numbers of rating adjustments in the period following the financial crisis (FSB, 2009). The banks within the sample employed in this thesis show rating changes across the investment- and noninvestment-grades. There was considerable number of downgrades in the periods following the 2007/08 global financial crisis, partly due to the calibration of the CRAs' rating models (Jones and Mulet-Marquis, 2014). With the level of regulatory reforms in the US and EU, one would expect a change in behaviour by the CRAs after the crisis. In addition, part of the regulatory reforms involves reducing the influence of credit rating agencies in the market. It follows that the market reactions to news announcements concerning bank credit ratings will be different in the period following the 2007/08 financial crisis. Therefore, a thorough investigation of the behaviour of bank equity returns around the time of bank credit rating news announcements should provide further insight into the relevance of rating information to the market.

3. What are the dynamics of bank credit ratings changes through time? Do bank credit ratings demonstrate non-Markovian behaviour?

   This thesis seeks to investigate trends in bank credit quality over time by examining the movement of banks in each rating grade for each year across countries. The distribution of ratings changes plays a crucial role in many credit risk models (Nickell *et al*., 2001). These distributions may be argue to vary over time and across issuers and their issues. Guttler and Raupach (2007) maintain that rating downgrades are known to make subsequent downgrades more likely. This *rating momentum* implies that the probabilities of future transitions and defaults do not depend on the current rating only but also on previous transitions. This has become very important, particularly with the changes brought by the Basel III Accord to calculate the appropriate capital charge for banks. Further, a credit rating's importance to the predicted probability of default for long-term securities from short-term credit risk dynamics forms an important aspect of rating transition.

Evidence suggests that there are prevalence of rating momentum in cases of downgrades within a certain rating category, where ratings with previous downgrades are more prone to further downgrades and defaults than others (Jarrow *et al.*, 1997; Lando and Skodeberg, 2002; Christensen *et al.,* 2004). Other studies shows that the time (duration) an issuer spends on a particular rating class have impact on their transiting to the next rating class (Kavvathas, 2000; Altman and Kao (1992). An examination of the possible rating momentum and duration effects within a sample of international banks will enhance the understanding of bank rating behaviour. This inadvertently helps improve on how to manage portfolio credit risk.

Further, evidence suggests that rating agencies have become more conservative in assigning credit ratings (Baghai *et al.,* 2013). In the wake of the 2007/08 global financial crisis, credit rating agencies have come under increasing scrutiny, with reforms coming from regulators across the world. There are now increased requirements for transparency in rating methodology, adequate disclosure and accountability within the rating industry (ESMA, 2013). Thus, there is an increased likelihood that rating agencies will err on the part of caution in their (re)assignment of ratings, particularly to banks, as a wrong rating or reversal could further aggravate the mistrust of the markets in their rating actions.

Rating agencies maintain that their ratings are fairly stable as they rate 'through-the-cycle'. However, there is a trade-off between stability and timeliness of ratings (Blume *et al*., 1998). For the market to be efficient and for ratings to be relevant in investment decision making, rating actions must be timely. However, rating agencies claim to have a long-term view of the creditworthiness of their rated issuers and issues. Failure to establish a balance between stability and timeliness of rating actions may have significant impact on their reputation. To assess the stability of the distribution of rating changes, this thesis examines whether probabilities of moving between rating categories over one-year horizons vary either across different banks. If these ratings transition probabilities ware stable, then default probabilities at all possible future horizons would be stable. The cyclicality or otherwise of the rating process has been investigated by authors such as Cantor and Packer (1997), Blume *et al.* (1998), Amato and Furfine (2004), Altman and Rijken (2004) and their findings are mixed.

1.4 Contributions of this study

This thesis contributes to the existing literature in several ways: First, it is one of few studies that focus on the determinants of the long-term credit ratings of international banks. The use of an issuer long term rating confers the advantage of being able to examine the holistic effects of rating agency actions on an entity, rather than on its issues. Further, the thesis extends the current literature on bank credit rating determinants by incorporating the set of explanatory variables used in the extant literature, as well as qualitative non-financial variables in the empirical models. Much of the existing literature employs the more easily measurable variables drawn from the *CAMELS* framework alone. However, by incorporating data on the factors that capture *too-big-to-fail*, corporate governance, country-specific risk, as well as market information, this study makes a significant contribution.

The acronym "*CAMEL*" refers to the five components of a bank's condition that are typically assessed: *Capital adequacy, Asset quality, Management, Earnings, and Liquidity*. A sixth component, a bank's *S*ensitivity to market risk was added in 1997 by the Federal Deposit Insurance Corporation (FDIC); hence the new acronym *CAMELS* (FDIC, 1997). This latter component makes explicit reference to the quality of risk management processes in the management component. The *capital adequacy* refers to a financial institution's expected minimum capital requirement that serves as a buffer in times of shock. The effect of credit, market, and other risks on the institution's financial condition should be considered when evaluating the adequacy of capital. The *asset quality* rating reflects the quantity of existing and potential credit risk associated with the loan and investment portfolios, other real estate owned, and other assets, as well as off-balance sheet transactions. The *management* refers to the capability of the board of directors and management, in their respective roles, to identify, measure, monitors, and controls the risks of an institution's activities and to ensure a financial institution's safe, sound, and efficient operation in compliance with applicable laws and regulations is reflected in this rating. The *earnings* reflect not only the quantity and trend of earnings, but also factors that may affect the sustainability or quality of earnings. The quantity as well as the quality of earnings can be affected by excessive or inadequately managed credit risk that may result in loan losses. The *liquidity* refers to the current level and prospective sources of liquidity compared to funding needs, as well as to the adequacy of funds management practices relative to the institution's size, complexity, and risk profile. Finally, the *sensitivity to the market* risk component reflects the degree to which changes in interest rates, foreign exchange rates, commodity prices, or equity prices can adversely affect a financial institution's earnings or economic capital.

The origin of the *CAMELS* can be traced to the Uniform Financial Institutions Rating System (UFIRS) adopted by the Federal Financial Institutions Examination Council (FFIEC) in 1979. The UFIRS has proven to be an effective internal supervisory tool for evaluating the soundness of financial institutions on a uniform basis and for identifying those institutions requiring special attention or concern (FRBSF, 1999). Under the UFIRS, each financial institution is assigned a composite rating based on an evaluation and rating of six the essential components of an institution's financial condition and operations. Further, the evaluations of these components take into consideration the financial institution's size, the nature and complexity of its activities, and its risk profile.

The FDIC in their 1997 report on the UFIRS states that composite and component ratings are assigned based on a 1 to 5 numerical scale. A 1 indicates the highest rating, strongest performance and risk management practices, and least degree of supervisory concern, while a 5 indicates the lowest rating, weakest performance, inadequate risk management practices and, therefore, the highest degree of supervisory concern.

The thesis provides a detailed insight into the behaviour of bank stock returns around the period of bank credit rating news announcements. The thesis contributes in several respects to the existing literature. The general position in the extant literature is that rating upgrades are not associated with stock market reactions, while rating downgrades elicit significant negative reactions. This thesis employs several specifications in modelling bank stock behaviour by examining subsamples of bank upgrades and downgrades. More specifically, it examines bank credit rating changes within subsamples of bank stocks rated in the investment-grade, speculative-grade, across investment thresholds, as well as unanticipated rating actions. This study is among the first, to the author's knowledge, to test for bank stock reactions to credit rating change announcements. The reported results are insightful and indicate that market reactions vary significantly by rating category.

The thesis extends the bank credit rating literature by employing a robust news event testing technique using both parametric and non-parametric approaches. It adopts an extension of the traditional two-stage event-study parametric approach, by employing a one-stage dummy variable approach within the testing framework. In addition, the thesis accounts for changing variances of abnormal returns across the banks by employing two other variants of the traditional event study approach, that is, the Boehmer *et al.* (1991) specification and the GARCH (1,1) specification. To the author's best knowledge, this is the only study that does so for a sample of international banks.

By investigating the behaviour of international bank credit ratings over time, this thesis addresses two major issues: testing for the presence of non Markovian behaviour in bank credit rating transitions and issues around the evident downward trend in bank ratings, particularly following the 2007/08 financial crisis. These are important considerations because the major credit rating agencies adopt transition frameworks that make the strong assumption of the existence of Markovian behaviour in bank stock credit rating transition. In addition, the major credit rating agencies have reviewed their rating methodologies following the credit crisis due to pressure from regulators, particularly in the US and Euro zone. Thus, the thesis allows for a test of the level of impact this tightening has had on rating assignments for international banks.

1.5 Key findings

The discussion of the main findings of this thesis focuses on the three areas investigated. The study finds that across all the specifications employed, the *CAMELS* framework components, that is, capital adequacy, asset quality, earnings, liquidity and sensitivity to the market are all statistically significant determinants of international bank credit ratings. These findings reinforce the importance of a bank-specific, quantitative measure of balance sheet strength in the assigning of a credit rating to a bank. Langohr and Langohr (2008) argue that in the determination of a bank's probability of default, the financial strength rating evaluation comes first. The importance of financial strength ratings on banks further highlights the importance of the *CAMELS* system in the rating process.

This thesis makes a significant contribution to the body of knowledge in the area of bank credit rating determination, by employing variables that capture the *too-big-to-fail* notion as well as corporate governance factors related to this. It indicates that the variable *too-big-to-fail* is consistently significant across all model specifications. Credit rating agencies perceive the propensity to receive external support by banks as beneficial, and reward banks based on their size and connectedness within the financial system and economy at large. In addition to the *too-big-to-fail* impact on the rating framework, the results from the thesis confirm the importance of a range of corporate governance measures (directors' shareholdings, institutional ownership and the proportion of independent directors on the board of directors) as important factors in determining bank ratings, thereby supporting the hypotheses stated.

The results of the news events tests provide evidence of asymmetric reactions in bank stock returns to credit rating news announcements across announcement types. For the full sample of bank upgrades, the parametric approaches show significant (positive) news leakage and partial correction in the market following the date of a bank rating upgrade announcement. Overall, the results for the bank stock reactions for upgrades are consistent with the existing literature. This thesis adds to the body of knowledge by investigating subsets of rating announcements within both upgrade and downgrade settings. For upgrades within the investment grades, the results show significant positive event-day reactions for both the parametric and non-parametric approaches. This is an interesting finding considering that most of the existing studies on the effects of 'positive news' provide evidence of no significant market reactions.

In terms of the trends in credit rating transition for the sample of international banks, the bank credit rating migration matrices are more diagonally dominant in the cohort approach than in the duration approach. Generally, the probability of experiencing downgrades is higher for investment-grade banks than for speculative-grade banks. The results of the two non-Markovian behaviour tests, the rating drift and the waiting-time effect tests, show very strong evidence of downward momentum or drift in the top investment-grades (AAA to A-). In contrast, the hypothesis of no rating drift is accepted for banks in the lower investment-grade and speculative-grade ratings. This has considerable implication for portfolio manager in terms of assessing their asset portfolio constituents.

The results from this thesis reinforces the current policy debates around the reliability and over-reliance of credit ratings, the need for regulatory reforms and oversights of the credit rating industry and the need to hold credit ratings accountable for their rating actions. With regulatory reforms already initiated in the US (the Dodd-Frank Act, 2010) and the EU (with the emergence of the European Securities and Market Authority - ESMA in 2011) to tackle the issues of disclosure, transparency and conflicts of interest, this thesis presents empirical evidence of the continued importance of ratings in the financial market.

1.6 Summary

This chapter discusses the main research questions of the thesis which are (i) What are the determinants of credit ratings for banks across the globe?, (ii) Do bank credit rating announcements result in abnormal returns behaviour around the announcement date? and, (iii) What are the dynamics of bank credit ratings changes through time? Do bank credit ratings demonstrate non-Markovian behaviour? It further explains the contributions of the study to the existing body of knowledge in the bank credit ratings field. It presents the structure of the thesis and provides an overview and brief explanation of the approach of each chapter. Chapter 2 examines the credit rating industry and presents a review of the structure of the industry. The chapter examines the rating process and the criticism of the main credit rating agencies, before and after the financial crisis. It provides an insight into the regulatory role of credit ratings and the regulatory oversight within the industry

CHAPTER 2. CREDIT RATING FOUNDATION, ANALYSIS AND THE RATING PROCESS

2.1 Introduction

This thesis aims to investigate bank credit ratings by examining their determinants and the impact on the financial market. This chapter attempts to critically assess the credit rating industry and provides a better understanding of the dynamics of that industry, including the relevance, criticism and regulatory oversight of the credit rating agencies (CRAs) within financial markets. Further, the chapter examines developments in the industry following the 2007/08 global financial crisis. CRAs are an important part of the financial market and the relevance of a rating is typically measured by studying security prices. If such prices reflect ratings and rating changes, rather than the opposite causality, then the market pays close attention to ratings (Langohr and Langohr, 2008). However, the market may pay attention without any significant price movement if such rating announcements are fully anticipated.

A credit rating is a measure of the creditworthiness of an entity or its financial asset issue (e.g. a bond rating), and represents the opinion of a credit rating agency (Gonzalez *et al.,* 2004; Langohr and Langohr, 2008; Wappenschmidt, 2009). Rating agencies do not operate in isolation, but are subject to regulatory oversight, e.g. in the US, CRAs operate under Nationally Recognised Statistical Rating Organizations (NRSRO) governed by the Securities and Exchange Commission (SEC). Asmussen (2005) and Matthies (2013) maintain that the rating industry is an oligopoly in structure with the three leading rating agencies, *Fitch, Standards and Poor's (S&P)* and *Moody's*, controlling around 95% of the market.

Credit ratings from the major rating agencies play a variety of roles in the financial market, and the meaning of agency ratings also varies depending on the analyst's perception of risk. Agencies insist that a rating is forward-looking as it assesses default risk over the life of an instrument or with regard to the issuer being rated. Further, they maintain that a rating is not a recommendation to buy, sell or hold, that is, it does not constitute an instrument pricing process. However, credit rating has become a standard benchmark for asset pricing and valuation in the financial markets, and market participants employ ratings as a benchmark for comparison with their own analysis and the internal ratings process (Erlenmaier, 2006).

The CRAs have been criticised for their role in the 2007/08 global financial crisis. In the aftermath of this crisis, the credit rating business and the rating process itself have come under intense scrutiny from regulatory authorities, market participants and the general public. The crisis highlights some salient issues around the role of CRAs in the market such as the timeliness of CRA ratings actions, the accuracy and the transparency of the rating process, the procyclicality of the assigned ratings and the ability of the CRAs to reduce information asymmetry. More importantly, the pertinent question of how rating agencies maintain objectivity when they are paid large fees (issuer-pay model) by the same companies they rate is a cause for concern. In particular, the failure of CRAs to provide accurate ratings for securitized products, e.g. the collateralized debt obligations (CDOs) and other asset-backed securities and sophisticated financial products in the run up to the global financial crisis of 2007/08, has cast doubt upon their value-adding role.

Moreover, some commentators (Levich *et al*., 2002; Darcy, 2009) argue that the CRAs knew very little about the fundamental creditworthiness of these products, hence making accurate ratings unlikely. Ciro (2013) argues that the inability of CRAs to account for the looming collapse in the housing market in the US also led to considerable mispricing of the inherent risk of these financial products. New regulations focusing on the credit rating industry and amendments to existing ones are bound to shape the dynamics of the industry and the way in which market participants view CRAs. There have been calls for greater disclosure from regulatory authorities, especially in the areas of fees received from issuers, the factors influencing rating actions, and the underlying assumptions of the CRA methodology. An understanding of these issues may better understanding of bank credit ratings process and provide some insight into this opaque industry. This thesis is thus very important as it is motivated by some of these criticisms, particularly the flawed business model, opaqueness of the rating methodologies, the conflict between timeliness and accuracy of ratings and the impact of new regulations of the credit rating industry. All these provide an opportunity to examine the determinants and relevance of bank credit rating in the financial market.

The remainder of this chapter is as follows. Section 2.2 examines the nature of credit ratings. Section 2.3 discusses credit rating classifications. Section 2.4 presents the credit rating system. Section 2.5 discusses the importance and criticism of CRAs, particularly following the 2007/08 global financial crisis. Section 2.6 examines the credit rating process and the dynamics of obtaining and maintaining a credit rating. Section 2.7 gives an insight into the regulatory role of credit ratings and the regulatory oversight existing in the industry. Section 2.8 summarises the chapter.

2.2 The nature of credit ratings

Credit rating plays an important role in the financial market as it to bridges the information gap between lenders and borrowers in the financial market. By providing information about the creditworthiness of an issuer or its issue, investors have better knowledge about their investment choices. Frost (2007) argues that almost all agencies base their rating on the relative, not absolute, probability of default. The relative aspect here relates to the use of ranked alphabet letters (with +/- signs) as shown in Table 2.1. These indicate the relative standing of the ratings within the major rating categories.

Table 2.1: Ratings classification system

AAA: Highest credit quality	'AAA' ratings denote the lowest expectation of default risk. They are assigned only in cases of exceptionally strong capacity for payment of financial commitments. This capacity is highly unlikely to be adversely affected by foreseeable events.
AA: Very high credit quality.	'AA' ratings denote expectations of very low default risk. They indicate very strong capacity for payment of financial commitments. This capacity is not significantly vulnerable to foreseeable events.
A: High credit quality.	'A' ratings denote expectations of low default risk. The capacity for payment of financial commitments is considered strong. This capacity may, nevertheless, be more vulnerable to adverse business or economic conditions than is the case for higher ratings.
BBB: Good credit quality.	'BBB' ratings indicate that expectations of default risk are currently low. The capacity for payment of financial commitments is considered adequate but adverse business or economic conditions are more likely to impair this capacity.
BB: Speculative.	'BB' ratings indicate an elevated vulnerability to default risk, particularly in the event of adverse changes in business or economic conditions over time; however, business or financial flexibility exists which supports the servicing of financial commitments.
B: Highly speculative.	'B' ratings indicate that material default risk is present, but a limited margin of safety remains. Financial commitments are currently being met; however, capacity for continued payment is vulnerable to deterioration in the business and economic environment.
CCC: Substantial credit risk	Default is a real possibility.
CC: Very high levels of credit risk	Default of some kind appears probable.
C: Exceptionally high levels of credit risk	Default is imminent or inevitable, or the issuer is in standstill. Conditions that are indicative of a 'C' category rating for an issuer include:
RD: Restricted default	'RD' ratings indicate an issuer that in Fitch Ratings' opinion has experienced an uncured payment default on a bond, loan or other material financial obligation but which has not entered into bankruptcy filings, administration, receivership, liquidation or other formal winding-up procedure, and which has not otherwise ceased operating.
D: Default	'D' ratings indicate an issuer that in Fitch Ratings' opinion has entered into bankruptcy filings, administration, receivership, liquidation or other formal winding-up procedure, or which has otherwise ceased business.

Sources: Fitch Ratings – Definitions of Ratings and Other Forms of Opinion (2014) *Used with permission of the publisher

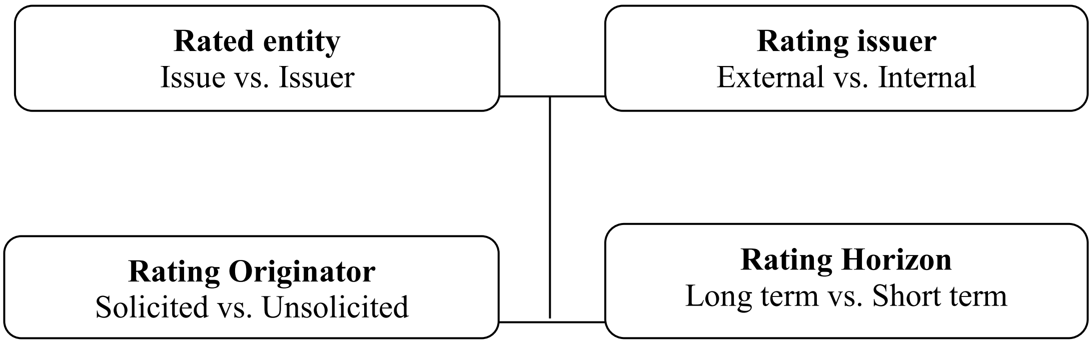
In the 1970s, the US introduced the Nationally Recognised Statistical Rating Organizations (NRSRO) requirement which sought to recognise rating agencies and allow the use of ratings by financial institutions for regulatory purposes. The creation of the NRSRO allows for a lowering of the barrier to entry into the rating industry as new CRAs only need to meet the requirements for registration to qualify as members.

2.3 Credit rating classifications

The rating classification may be based on: the rated entity (this can be the rating of an specific issue/instrument or the issuer/counterparty itself); the issuer of the rating (those that carry out the rating process, and this can be external or internal); the originator of the rating (focusing on who initiated that rating, i.e. solicited at the request of the issuer, or unsolicited); and finally, the rating horizon (that is, whether it is a long-term or short-term rating).

Generally, in an issue-specific rating, agencies primarily assess the likely amount that debt holders would be able to recover in the event of default (Trueck and Rachev, 2009). It deals with the performance of a specific instrument, e.g. a bond. Further, the issue-specific rating combines the risk of default and the expected loss-given-default. The risk of default is the possibility that the issuer of an instrument or issue (for example, a bond) will default, by failing to repay the outstanding commitments (Standard and Poor's, 2007).

Figure 2.1: Categorization of ratings



Default may not always lead to losses as recovery may be possible even in the event of default. The expected loss-given-default (LGD) is the magnitude of likely loss on exposure (exposure being the amount that may be lost on an investment) (HBIK, 2012). A debt instrument can experience a loss only if there is default, at or before maturity (Schuermann, 2004). A Standard & Poor's issue-specific credit rating for example, is 'an opinion of the creditworthiness of an obligor with respect to a specific financial obligation, a specific class of financial obligations, or a specific financial programme; this may be a bank loan or a debt issue' (Standard and Poor's 2005: 8).

The issuer credit rating, also called the counterparty risk rating, rates the issuer as a whole, regardless of a particular debt instrument. Counterparty risk is the risk that the counterparty to a financial contract will not meet the terms of the contract. According to the Corporate Ratings Criteria for Standard and Poor's (2005: 9) an issuer credit rating is 'not specific to any particular financial obligation, because it does not take into account any particular obligation'; rather it 'provides an overall assessment of a company's credit worthiness'.

Ratings may also be classified on the basis of the provider. When a rating is provided by a rating agency, the type of rating is referred to as an external credit rating as opposed to the case where ratings are produced by the internal rating systems of banks and other corporate entities and involve the establishment of an internal rating model to classify the credit risk exposure of a bank's activities and its counterparties. The new Basel III Accord proposes a shift from the over-reliance on external credit rating agencies measuring credit risk, to a more risk sensitive internal rating based approach. The Financial Stability Board (FSB) in 2010 issued a set of principles for reducing reliance on external credit assessments in standards, laws and regulations. The FSB maintains that this aims to reduce the cliff effects and herding behaviour that threaten financial stability and were seen to arise from external credit assessment thresholds being hard-wired into laws, regulations and market practices.

Credit ratings ascribed by CRAs can also be divided into either solicited or unsolicited credit ratings. For solicited ratings, borrowers request a rating, provide private information, pay for, and obtain the rating. One can argue that solicited ratings provide CRAs access to private information which normally will not be available to investors, as the entity being rated has the incentive to provide qualitative, detailed information that will aid in its rating. Solicited ratings provide more detailed information to the market since they communicate previously unknown information which has been held by the top management of companies soliciting such ratings. However, the issuer-pay model practiced by the credit rating industry presents a conflict of interest between the rater and the company being rated. A bank seeking a better rating may '*go shopping*' to find the rating agency that is willing to assign the best rating for their instruments.

The length of rating horizon presents another way of categorising credit ratings. Here, ratings can be classified as either long-term or short-term. Long-term ratings provide an opinion of the creditworthiness of an issue or an instrument over a time horizon that extends three to five years in the future (Langohr and Langohr, 2008). It is argued that long-term ratings give an indication of the rating quality of a company without any procyclicality, and this thesis employs this long-term view in its approach. The need for stability in a rating is another motive for developing a long term credit rating devoid of any short term business cycle effects. Rosch (2005) argues that long-term ratings are free of any short term bias that might cause temporary change in a firm's credit quality. A short-term rating deals primarily with the coming year and provides an opinion on the ability of an issuer to make timely payments on short-term financial commitments.

Apart from the above categorization of ratings in the corporate sector, ratings can also be given to governments (or States). This type of rating is called a sovereign rating. Sovereign ratings give an opinion of the ability and willingness of a government to service its debt in full and on time. The current sovereign debt crises that affects countries such as the US, the UK, Greece and Italy which have all seen their sovereign ratings downgraded (and some by more than one notch), have a direct impact on the ratings of companies operating within those countries.

2.4 The credit rating system

A rating expresses the opinion of the CRA on the relative credit strength of an issuer in general or of an instrument over its lifetime. Credit rating agencies summarize their opinions about obligors (contractual partners) in ratings with graded symbols, such as AA-, BBB+, and Caa3. The distinctive characteristic of this credit rating scale is its ordinality. The ordinality implies that all ratings along this scale or rank are comparable. Each symbol represents a group within which the credit risk characteristics are broadly the same across entities. One of the main challenges for major CRAs is maintaining consistency across all classes of issuers, industries, instruments, and regions.

This thesis examines the market impact of bank credit rating announcements by employing different specifications of rating actions, one of which is rating anticipation. Rating anticipation may come in the form of rating outlooks or placements of a Watchlist. Rating outlooks indicate the potential direction of a rating over the intermediate term (usually six months to two years) (Langohr and Langohr, 2008). An outlook signal does not necessarily result in a rating change; however it provides an element of stability to long-term ratings. The rating outlook can be *positive, negative, stable* or *developing*, i.e. the rating could be raised, lowered, not likely to change, or may be either raised or lowered respectively. The motive for the direction assigned to an outlook depends on the perception of the analyst about issues such as the firm's risks, the political situation and the firm's earnings growth forecast.

Watchlists give a high probability that the issuer rating will change, even though the direction of change may be uncertain. Johnson (2003) maintains that by placing a rating on their Watchlists, CRAs effectively send a signal to the market that they are reviewing the underlying creditworthiness of the company. However, Cantwell (2000) argues that the concept of the Watchlist is out-of-date, as financial markets have become more efficient and the sheer quantity and quality of information available in an online real-time environment makes them of limited added value.

Investors and the users of ratings information often have unrealistic expectations regarding what ratings actually mean (SEC, 2003). Hence, a careful interpretation of ratings is important. The credit rating agencies (especially the major ones) often maintain that ratings address benchmark probabilities of default and that their ratings are not absolute default probabilities. This implies that rating opinions are not meant to be guarantees of credit quality or exact measures of the probability that a particular issuer or debt issue will default. However, a rating expresses an opinion about the credit quality of an issuer or a debt issue within a scale, from the strongest to the weakest, relative to others on that scale. It may be argued that since future events cannot be foreseen, the assignment of credit ratings is not an *exact science*.

Ratings also tend not to be procyclical, but rather aim to be ‘cycle neutral’, so that they are not systematically adjusted in times of boom or bust (Carey and Stulz, 2006). Ratings thus do not typically change through the business cycle. If ratings were cyclical then a security could be rated low because of poor performance in the short-term, pending its expected recovery and good performance in the near future. Any cyclicality in ratings on the part of CRAs would lead to volatile ratings.

Langohr and Langohr (2008) argue that ratings are also descriptive, and not prescriptive of the debt situation. The optimal credit rating for a company’s debt at any given point in time may range from speculative (worst) to investment grade (safest). Shareholders attempt to increase the amount that their firm should borrow so that shareholders’ wealth can be maximized. Shareholders often trade-off the cost of lower credit ratings against the benefit of additional debt. However, there is an optimal debt-to-asset ratio that maximizes shareholders’ wealth, and minimises the over cost of capital (Kisgen, 2006). A rating does not prescribe such an optimal ratio as reporting it could lead to an error of judgement on the part of investors.

Ratings do not put a value on an instrument, rather they only measure and grade credit risks. Credit risk is just one of the factors that drive an instrument's risk: market risk, operational risk, liquidity risk are some of the other drivers. However, CRAs do not report directly on these other risks. The change in credit ratings occurs discretely whereas bond yields may be observed to move continuously. Credit ratings hence do not price instruments; rather they give an opinion on whether an issuer will be able to make payments in a timely manner.

This study recognises the issue of reverse causality in the modelling of the determinants of international bank credit ratings. Reverse causality is particularly plausible from the level of ratings to some bank characteristics such as profitability or funding structure. For example, banks with low ratings may face higher financing costs, seek shorter maturities on the liability side of their balance sheet or experience lower profitability. Ratha *et al*. (2007) suggest the use of lagged variables rather than contemporaneous ones to account for any reverse causality. This thesis employs three time specifications to account for possible reverse causality within the modelling process for the bank credit rating determinants.

2.5 The importance and criticism of credit ratings

This section discusses the role and criticism of credit ratings in the financial market and how ratings have evolved over the last couple of decades. CRAs maintain that they add value to the financial market by helping to reduce information asymmetry, providing more access to the market and reducing the overall cost of funds. However, the global financial crisis exposed some of the shortcomings of the rating process including potential conflicts of interest, a lack of understanding of the nature of rated instruments, and alleged unfair practices.

2.5.1 Credit ratings and the financial market

Credit ratings from the major rating agencies play a variety of roles in financial markets. This section focuses on the various ways in which credit rating brings value to market participants. By providing independent opinions on the creditworthiness of both obligors (issuing companies) and of individual securities, CRAs help investors to allocate risk and to make decisions about the value and pricing of securities (Keenan and Sobehart, 2000). The financial market provides an avenue that aims to bring together the buyers and sellers of financial instruments. Investors need information on the nature of the investments and wish to invest their funds, and issuers need access to those funds. Hence, credit ratings help to *shorten* the distance between lenders and borrowers. As a result, there is a reduction in the cost of information and a reduction in the cost of market access. Credit ratings present an important source of information for potential investors and other market participants to assess the riskiness of investments.

In sum, ratings aim to achieve the somewhat conflicting objectives of accuracy, comparability of rating information, timeliness, and stability of the rating action. However, there exists credit rating inconsistency, especially among the big three rating agencies. Laere *et al.* (2012) argue that the major CRAs set different standards for particular rating grades. They maintain that both S&P and Moody's bank ratings reflect different indicators and dimensions of a bank's financial health and this contributes to disparity in some instances. Ratings may be said to function as a measure of credit risk, a means of comparison between issues, and a common standard against which to refer to credit risk. These functions are often difficult to disentangle and are complementary in the sense that the demand for one of the functions of ratings is enhanced by the fact that ratings fulfil all three functions.

Over time, CRAs have also assumed a so-called ‘certification’ role, whereby ratings act as a credit-quality threshold in financial contracts (Deb *et al*., 2011). For instance, when referenced in an investment mandate or performance benchmark, ratings help investors to discipline fund managers by restricting investments to assets with certain characteristics. Johnson and Kriz (2002) argue that the availability of credit ratings prevents the buyers of financial securities from grouping all financial products in the market into one category without distinguishing the superior credit quality of some over others. The absence of credit ratings, they add, drives rational buyers into believing that the sellers of financial securities have an incentive to market poor-quality financial products as high-quality products.

The availability of CRA ratings as convenient composite measures of credit quality has led to a broadening and deepening of their role over time. Table 2.2 highlights a number of areas in which CRA ratings are now ‘hardwired’ into contracts and market practices (Deb *et al*., 2011). In their certification role, ratings can help to resolve moral hazard problems between individual investors (principals) and the institutions (agents) they appoint to manage their portfolios.

Further, Thompson and Vaz (1990) argue that credit rating agencies, via their certification function, convey the true credit quality of companies, which is in turn determined on the basis of constant monitoring and evaluation of a company’s financial and non-financial performance. Information barriers are lifted with the publication of credit ratings, hence market participants benefit and the whole market improves in its efficiency.

Table 2.2: Examples of the certification role of the CRA ratings

Purpose	Comment
Investment mandates/Policies/Criteria for index inclusion	Ratings are often hardwired into the investment mandates of life insurers, pension funds, mutual funds, etc. They also determine eligibility criteria for inclusion in bond indices that track a certain segment of the credit market (e.g. investment-grade bonds; sub-investment grade bonds) and act as performance benchmarks for fund managers.
Access to capital markets	The cost and availability of funding in capital markets is often linked directly to a borrower's credit rating. Indeed, access to some financial markets is restricted to issuers with ratings above a particular threshold For example, access to wholesale funding markets is typically restricted to entities with a sufficiently high short-term credit rating.
Secured funding and repo markets	Similarly, secured funding and repo markets rely heavily on CRA ratings. Metrick and Gorton (2010) observe that, pre-crisis, banks' increasing demand for secured funding from the parallel banking system (e.g. money market mutual funds, structured investment vehicles, CDOs) led to a commensurate increase in the demand for high-quality collateral, typically identified by its credit rating.
Collateral agreements	Many financial contracts include references to credit loan contracts ratings. For instance, the Credit Support Annex (CSA) of a standard International Swaps and Derivatives Association (ISDA) Master Agreement in the OTC derivatives market specifies the terms on which collateral calls will be made. CSAs often state that additional collateral will be called in the event of a credit rating downgrade.

Source: Deb *et al.* (2011), Bank of England Financial Stability Paper (March 2011) *A non-inclusive permission to reproduce the material for the purpose outlined, subject to the acknowledgement of the source (Bank of England)

However, adverse selection arises because borrowers possess more accurate information about the true state of their company than lenders. Particularly as a company will generally have an option to finance projects internally through retained earnings, any attempt to source external financing from capital markets may face a standard 'lemons problem' (Akerlof, 1970). The lemon problem describes the information asymmetry which occurs when the seller knows more about a product than the buyer

2.5.2 Credit ratings and information asymmetry in financial markets

Investors are much less informed about what is going on within a firm than the managers which run them. Seyhun (1998) argues that general shareholders know less than insiders. Hence, one of the most critical impediments to investor rights is their ignorance of what goes on in a company, that is, the information asymmetry between outside investors and the insiders who control company operations. Steeman (2002) posits that this information gap can lead investors to investing in the wrong firm because of limited or costly information. The niche that credit rating agencies occupy within the financial market is thus that of dealing with information asymmetry as they try to bridge the information gap, whilst assisting companies in attracting investor funds and helping them signal their credit quality to the public. Mauboussin (2006) argues that information asymmetry will persist in the market because one can never fully move from the outside to the inside. Insiders will always be 'ahead of the crowd', and will always know more than outsiders. It may however be argued that market participants will only pay attention to the information contained in ratings if they offer something unique (Levich *et al*., 2002).

CRAs argue that the information they provide is very relevant to the market and this argument is supported by the literature which focuses on CRA access to non-public information, the associated economies of scale, and the nature of CRA certification. With respect to information asymmetry, Frost (2006) argues that CRAs play a validation role by disseminating information to market participants. In this role they further argue that CRAs gather and analyse information widely available to investors, portfolio managers, buy-side firms, sell-side firms and others. Similarly, Boot *et al.* (2006) argue that credit ratings act as information equalisers as most of the investors in the financial markets are faced with a shortage of information on the company's credit profile, while other major actors in these markets (including banks and CRAs) have access to more detailed information, which is embodied in a credit rating. Hence, investors can then use this information to make reasonable investment decisions. Other authors (Galil, 2003; Gonzalez *et al.*, 2004; Partnoy, 2009) argue that credit ratings reduce information asymmetries between investors and companies, prospective and existing issuers of debt, and thus become the driving force behind the development of financial markets. The issue of access to private and confidential information is further highlighted by Holthausen and Leftwich (1986) who contends that CRA decisions convey valuable information to the capital market based on their access to this private information about the company's health and prospects alike. Furthermore, Griffin and Sanvicente (1982) maintain that this information advantage of credit ratings emanates from the agencies giving an incentive to company managers to reveal non-public information to them 'about production, investment and financial plans' (p. 104) in an attempt to obtain a favourable rating. They further argue that to the extent that such new data provide rating agencies with valuable information, the whole rating process becomes a 'vehicle for communication of private knowledge to investors and creditors' (p. 104).

In economic terms, the rationale for using ratings may stem from their ability to provide informational economies of scale and from their contribution to solving the principal-agent problem. Gonzalez *et al*. (2004) argue that creditors and investors have found it efficient to use rating opinions in initiating and monitoring their transactions because of the economies of scale achieved in gathering and analysing information. This, they argue has in turn facilitated the access of borrowers to debt markets, by widening the investor pool and reducing the adverse selection problems resulting from information asymmetries between investors and issuers of debt, and has provided a good basis for the development of financial markets. In addition, ratings are used to solve the principal-agent problem, that is, equity holders can use the information to determine what is going on within a company. Consistent with Gonzalez *et al.*, Baker and Mansi (2002) argue that rating agencies are competent in gathering and analysing information and that they can bear the cost of collecting this kind of information better than individual investors due to the sheer volume of companies they rate. More importantly, Holthausen and Leftwich (1986) highlights the need for special skills and training associated with information gathering and processing which gives rating agencies a distinct advantage over other information providers, hence increasing the importance of credit ratings as an investment aid.

Despite the role of the CRAs in bridging the information gap in the financial market, there has been some heavy criticism of their informational value. Weinstein (1977) notes that unless bonds are continuously rated, ‘a rating change will always lag the information that led to the change’ (p. 331). He further maintains that bond ratings are not *informationally* efficient since they only reflect a reaction by rating agencies to information that the market already possesses. Goh and Ederington (1999) also show that credit rating changes and their information content do not have any effect on market prices nor do they produce any significant abnormal returns. However, the whole certification process is based on standardised quality categories with a view to overcoming information asymmetries between both sides of the market. Therefore, rating agencies act as information intermediaries and cannot be expected to provide reliable warning signals in the event of deterioration in a company’s credit (Li *et al*., 2006).

2.5.3 Credit ratings, market access and the cost of funds

Credit ratings impact on the market access of firms as well the cost of funds. Kaplan and Urwitz (1979) argue that the credit rating that has been allocated to a given company can determine the risk premium that markets and investors require, as well as determining the marketability of a debt issue. Kisgen (2006) shows that credit ratings exert a considerable impact on a company’s cost of capital, and that as long as the capital market regards ratings as being informative, ‘firms will be pooled together by ratings and thus a ratings change would result in discrete changes in a firm’s cost of capital’ (p. 1036). Credit ratings determine the interest rate that businesses have to pay investors in order to persuade them to part with their funds (Liu and Thakor, 1984;

Creighton *et al.*, 2007). Firms with strong credit ratings tend to offer a lower promised yield than those of lower credit quality. This is because companies with high credit ratings especially those in the investment-grade category are not considered to be very likely to default, and the likelihood of default tends to decrease as one goes up the rating scale.

Steeman (2002) argues that credit ratings are important because they not only give an indication of a company's funding costs, they also provide access to the capital market since they are a publicly available measure of inherent credit risk linked to a specific corporate entity. However, not every market participant agrees that credit ratings are the major factor that differentiates which companies are creditworthy and which are not; credit ratings are there to resolve the issue of information asymmetry and offer each market participant an equal amount of information in order to make an investment decision (Duff and Einig, 2009).

2.5.4 Credit ratings and procyclicality

One of the major goals of CRAs is to assign ratings that are uncorrelated with the cyclical nature of business and other macroeconomic trends. This goal could potentially benefit investors with buy-to-hold strategies as opposed to trading in instruments. The rating process may thus be said to be *through-the-cycle* as the assigned ratings are immune to short term volatility and variation in the market. Amato and Furfine (2004) posit that a rating *through-the-cycle* is a rating process that is 'independent of the state of the business cycle, conditional on its underlying financial and business characteristics' (p. 2642). However, Loffler (2003) argues that it is plausible to expect the long-term creditworthiness of firms and hence their credit ratings to covary positively with the business cycle. The author maintains that in many instances a *long-lived* fundamental shock in the market drives both the financial and business performance of firms and hence may induce business cycle fluctuations. However, credit rating agencies claim to rate *through-the-cycle*, and not take changes in business cycle into account.

Prior studies present evidence about the cyclical nature of credit ratings and the financial system as a whole (Blume *et al*., 1998; Nickell *et al*., 2000; Bangia *et al*., 2002; Altman *et al*., 2002; Cantor and Mann, 2003). The financial system tends to be procyclical, with the volume of bank lending at its peak during an economic boom and at its lowest point trough during a recession or financial crisis. However, within the financial system, the perception of risk by market participants is countercyclical, i.e. it is at its highest during a financial crisis or *bust.* Both the regulatory authorities and lenders tend to be more lax and less vigilant during times of economic boom and this contributes to the countercyclical behaviour of the market (Lown *et al.,* 2000). Credit rating is not designed to vary in a procyclical manner. However, Nickell *et al.* (2000) find that transition matrices tend to exhibit a higher frequency of downgrades during a recession and a higher occurrence of upgrades during boom times. Similarly, Altman and Kao (1992) find that credit ratings tend to exhibit serial correlation, i.e. an upgrade is more likely to be followed by a subsequent upgrade than a downgrade. Generally, empirical evidence shows that even though credit ratings move with the business cycle, the cyclicality is driven more by the changes to business and financial risks, rather than to rating standards.

2.5.5 Credit ratings and moral hazard

Mukhopadhyay (2004) argues that CRAs suffer from a possible moral hazard problem. The 2007/08 global financial crisis exposes the flaws in the structure of the market of CRAs leading to serious moral hazard problems that are not easy to resolve. The business model of the credit rating agencies, that is the issuer-pay model, implies majority of the users of the rating information, investors and regulators do not pay for such information. This current practice where issuers pay for ratings raises serious concerns about conflict of interest. CRAs may be tempted to inflate the rating they assign in order to maximize their profit, however, they argue that there is a reputational issue at stake that in assigning ratings despite being paid for the process by the issuer. However, Cantor and Packer (1994) argue that the fear of losing reputation, that is, that desire to prevent long-term loses, seems to be more important than a desire to make short-term gains by inflating ratings. There are also concerns whether or not issuers shop for better ratings. An issuer may decides on which company it wants to be rated by based on the expected rating level they are going to get. With the structure of the market and the increase competition, issues might be tempted to shop around for the best rating, thus leading to a compromise in rating standards and an inflation in ratings.

There have been calls to introduce a government-backed agency in the rating industry following the series of downgrades of Greece, Portugal and Spain by the major CRAs in 2010. The call for an ‘independent’ European rating agency (Tait, 2010) was suggested to be a way forward in mitigating the moral hazard problems faced by the major CRA. Further, an EU-based rating agency may act as a balance from negative influences that CRAs currently have on financial markets in Europe.

2.5.6 Credit ratings and objectivity

The quality of the rating process is very important in entrenching confidence in the market place on the accuracy of ratings. A CRA has in principle no incentive to present biased and inaccurate data as if it was unbiased and inaccurate (Langohr and Langohr, 2008). Objectivity or independence of opinion is thus a cornerstone of the value that CRAs have in making predictive assessments about an issuer’s creditworthiness. CRAs maintain that their independence of opinion is very key in their business. In addition, Deb *et al*. (2011) argue that rating agencies emerge to assist dispersed investors in the monitoring of issuers in debt capital markets. By assigning an objective measure of credit quality to debt issues, based on independent analysis of issuer-supplied financial information, CRAs can help to reduce information asymmetry between investors and borrowers. This allows for wider market participation and provides deeper and more liquid markets.

With the fiasco of the 2007/08 global financial crisis and the culpability of the CRAs, there are concerns about the independence and objectivity of the opinion of CRAs on the ratings they issue. These in turn have significant impact on the reputation of the CRAs. Again, this objectivity ties in with timeliness of the rating action, as a delay in say, a downgrade may have serious consequences for investors. A related issue is that of due-diligence in the rating process, and CRAs have been accused of paying inadequate attention to details (US SEC, 2003). CRAs however, maintains their position against the charges of inaccuracy, rating delays, and inadequate due diligence. Following the 2007/08 global financial crisis, there are evidence to suggest that the three main CRAs have taking steps towards improving their objectivity, timeliness and due-diligence (Corbet, 2013). These actions includes appointment of forensic accounting expertise by S&P to very issuer information, appointment of analysts by Moody's to deal with off-balance-sheet exposures and analyst training (SEC, 2013). There are also discussion around the transparency of the rating assignment process which deals with adequacy, fairness and confidentiality of rating-related information (ESMA, 2012).

2.5.7 Credit ratings, business model and accuracy of ratings

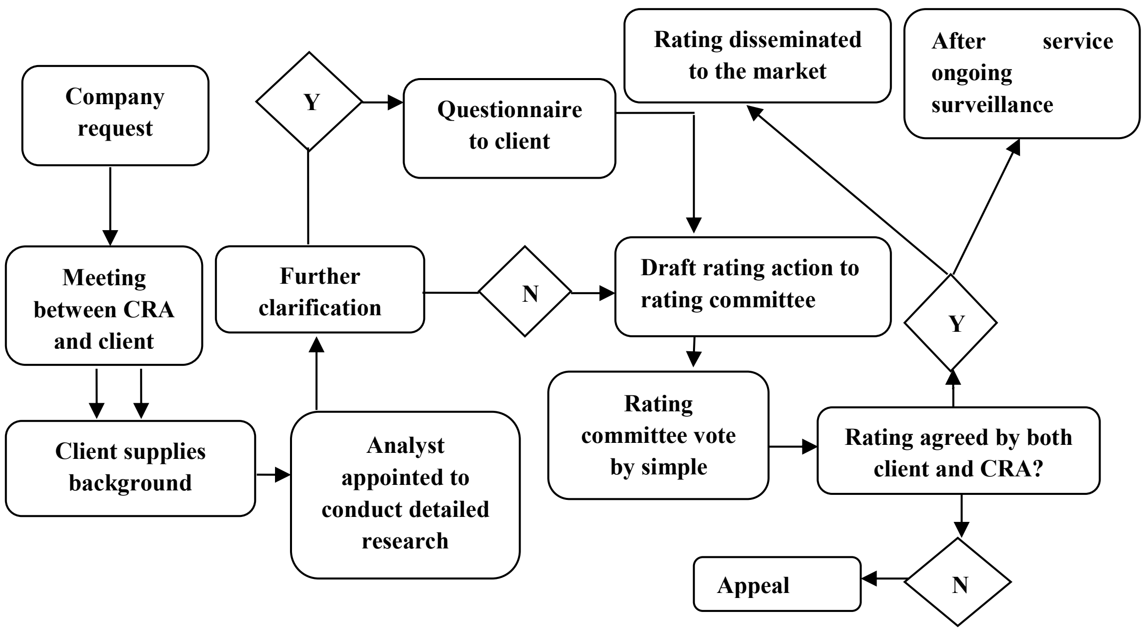
The demand for ratings comes from both investors and issuers, and both are willing to pay for them (Langohr and Langohr, 2008). The CRAs aim to provide investors with valuable information about firms in need of financing. Due to asymmetric information between the firms and the investors, credit ratings often have a significant impact on the firms' financing outcomes. The current business model in the credit rating industry, the issuer-pay model, has raised several questions on rating inflation, flawed ratings and conflict of interest between the parties involved. Despite being held culpable in the 2007/08 global financial crisis the CRAs claim that this conflict is unlikely to bias their ratings out of concern for their reputation is not true. Deb and Murphy (2009) argue that there are two justifications for charging issuers: firstly, issuers receive substantial value through the publication of independent ratings that gives them access to public funds; and secondly, the CRAs need these revenues to be able to sustain the costs of their activities. They further provide an analysis of the annual reports of the big-three rating agencies and suggest that the issuer-pay rating revenues account for roughly 84% of Moody's total revenues (average of last 5 years), while the corresponding amount for S&P and Fitch is 72% and 85% respectively.

Rochet *et al.* (2008) argue that reputational concerns are not enough to solve the conflict of interest problem and that in equilibrium, rating agencies are likely to behave laxly, that is, rate bad banks as good and are prone to reputation cycles. Further, Camanho *et al.* (2011) suggest that moving from a monopolistic to a duopolistic setting within the credit rating industry will increase ratings inflation and aggravate the lax behaviour of rating agencies. The new regulatory regime in the EU (by the European Securities and Market Authority) and the US (the Securities and Exchange Commission) are shifting the paradigm of credit ratings being considered as `opinions' and to a situation where CRAs are going to be made liable for the quality of their ratings. This has the potential of resolving the conflict of interest and reduces the flawed, inaccurate or inflated ratings.

2.6 The credit rating process – obtaining and maintaining a credit rating

The processes and methods used to establish credit ratings vary widely across CRAs, though the largest international CRAs tend to follow similar procedures for similar types of instrument. An overview of the credit rating process is provided below in Figure 2.2. The first stage in the process of obtaining a credit rating involves a meeting between the CRA and the management of the client company. The meeting provides an avenue for the client to provide detailed background information about their company (usually the information spans at least five years). This information is required to assist the rating team in making a more informed decision regarding the creditworthiness of the firm. In-depth interviews with company management are an integral part of the rating process.

Figure 2.2: A conceptual framework of the rating process



Source: Conceptual framework developed by the author

The lead analyst tends to direct extensive research which is aimed at finding a conditional, unbiased and efficient estimate of the client's default probability. Following this, a rating recommendation is made in a draft report submitted to the rating committee, where the lead analyst defends his/her proposal. The primary objective of the rating committee is to ensure the validity and accuracy of the rating, whilst also ensuring that consistent standards are being applied in its determination.

The issuer and adviser are immediately informed of the rating action. However, the issuer has the opportunity to review the draft press release before it is made public. This allows the issuer to raise any concerns and if necessary submit an appeal to express their disagreement with the accuracy of the assigned rating. Rating agencies argue that they are willing to correct any mistakes in their ratings, but categorically do not allow firms to dictate their rating assessment and opinion (Fitch, 2007b). The final part of the credit rating process is the communication of the rating to the market after the issuer agrees with the recommendation. There may also be an *after-sales service* to the client issuer which may come in the form of an advisory role or continuing professional relationship, which enables the client and the credit rating agency to work together in order to get periodic feedback about the company's relative standing and how it is evolving. Hence rating analysts need to be up-to-date regarding developments in the company.

2.7 Credit ratings and regulatory oversight

The general position of the market is that flawed credit rating contributed to the global financial crisis of 2007/08. The use of rating processes that were deemed unsuitable for highly sophisticated financial products, and the failure of credit rating agencies to properly assess the risks of complex financial securities, have brought such ratings under intense scrutiny. A key question which resulted from this crisis was whether CRA operating practices and/or the lack of adequate regulatory oversight contributed to investor losses during the crises. This has led to the proposal and implementation of several radical reforms within the CRA industry. These reforms have resulted in new developments in the general governance of the industry, with resulting effects for both the major CRAs and the global financial institutions. For example, in 2014, the US SEC adopted new requirements for credit rating agencies to resolve issues around the areas of governance, conflicts of interest, transparency and disclosure in order to improve the quality of credit ratings and increase credit rating agency accountability. The new rules fall under the requirements of the Dodd-Frank Wall Street Reform and Consumer Protection Act (2010) and apply to credit rating agencies registered with the Commission as nationally recognized statistical rating organizations (NRSROs). In the EU, the European Securities and Market Authority, ESMA, has been created to contribute to safeguarding the stability of the European Union's financial system by enhancing the protection of investors and promoting stable and orderly financial markets. The ESMA carries out policy work in the area of CRAs in its role as the single supervisor of CRAs within the European Union. The latest of their reform on the credit rating industry is the Regulation (EU) No 462/2013 on Credit Rating Agencies. This focuses in reducing the reliance on CRAs and their ratings.

Thus, this section discusses new developments in the credit rating industry, mostly triggered by the regulatory reforms following the failings of the rating agencies in the period leading up to the 2007/08 global financial crisis. These developments form part of the core motivation for this thesis in light of the efforts by the US SEC and European Securities and Markets Authority (ESMA) to improve the quality and consistency of CRA supervision. The regulatory reforms within the credit rating industry have implications for the structure and the way the CRAs do their business. For example, banks are now being encourage to adopt a more internal rating based model, and reduce the over-reliance on external credit rating agencies in measuring the risk of their credit portfolios. CRAs are required to increase their disclosure, particularly in terms of their methodology and models. By modelling the determinants of these bank ratings, it would be possible to better understand the dynamics of the rating process and better align these with those of the industry.

2.7.1 The regulatory use of credit ratings

Credit ratings play a crucial regulatory role in the financial market. The sheer success of credit rating products and services may have contributed to regulators deciding to use ratings for their own prudential regulatory purposes, amongst others. Credit rating is featured prominently in the current Basel II standardized approach to calculating credit risk. The new Basel III Accord takes a fresh approach to the use of credit ratings within a bank's risk management process by proposing a significant reduction in the use and reliance of ratings issued by CRAs (BCBS, 2014). According to Gonzalez *et al.* (2004) the importance of rating-based regulations can be traced as far back as the 1930s where it was particularly visible in the United States. In the European Union (EU), as in the case of the US, the regulatory use of credit ratings is a part of the capital adequacy requirements of financial institutions, especially the Committee of European Securities Regulators (CESR/10-945, 2010) guidance. The directive holds that the European legislation makes use of ratings as a regulatory instrument.

Table 2.3 shows a summary categorization of the uses of credit ratings – prudence, market access, and investor protection. The prudential regulatory role of credit ratings relates to their use in maintaining market confidence. The most significant part of this prudential regulatory role relates to the minimum regulatory capital requirements imposed upon financial institutions.

Table 2.3: The regulatory use of ratings

Key purpose	Summary
Prudence	The regulatory use focuses on ensuring the stability of a financial institution in order to maintain market confidence; deciding the credit risk class of assets.
Market access	It is used here as a criteria for issuers that want to gain access to the capital market. Ratings are used to differentiate the information requirements that the issuer must fulfil to be granted access to the market.
Investor protection	This is the ultimate goal of financial regulation and across the globe credit ratings have been used to achieve it.

Source: Author's conceptualization of the regulatory use of ratings

In 2012, the Financial Stability Board (FSB) reports an accelerated route towards the implementation of the FSB Principles to reduce reliance on CRA's ratings. In the EU, this reform is driven by the ESMA which was designated as the single supervisor of credit rating agencies within the region in accordance with the provisions of Regulation 1060/2009 on credit rating agencies. Further, there are efforts within the EU to increase the harmonisation of the supervision of CRAs at international level through its work with the International Organisation of Securities Commissions (IOSCO).

In response to the regulatory developments in the US and Europe, many Asia-Pacific economies have already taken action to strengthen the regulatory framework governing the use of credit rating (Van Laere, 2010). In November 2009, the Australian Federal Government passed new regulations regarding CRAs in an effort to limit investors' over reliance on ratings. Part of the new regulation proposed by the Australian Securities and Investment Commission (ASIC) removes the exemption that protected CRAs from liabilities that may arise from having their ratings published in prospectuses, disclosure statements and take-over documents. Further, for CRAs to keep their licences, they will have to manage conflicts of interest, have resources that match the 'scale and complexity' of their business, and have in place risk management systems.

CRAs in India are regulated by the Security and Exchange Board of India (SEBI), and their duties cover the disclosure, transparency and integrity of rating agencies. On May 3, 2010, the SEBI released further CRA guidelines on matters including transparency and disclosure, conflict management and documentation, which reinforce the existing CRA regulatory framework in India. In addition, attempts are now being made to tackle 'rating shopping' which has arisen from the issuer-pay business model. Bolton *et al.* (2009) show that with multiple ratings, issuers have more opportunity to rate-shop. Skreta and Veldkamp (2008) explore the interaction between rate-shopping, complexity of the security and competition and show that the intensity for rate-shopping increases with the complexity of the security and competition between rating agencies amplifies this problem.

Similarly, in Japan, CRAs are required to secure personnel who have sufficient expert knowledge and skills, to ensure the quality of information used in credit rating activities. Further to this, on June 1, 2011 there was an agreement for collaboration in terms of supervision and information exchange sharing between the Financial Services Agency of Japan (FSA) and the European regulatory body ESMA. This was to facilitate cross border cooperation on CRAs.

The major External Credit Assessment Institutions (ECAIs) play a significant role in the standardised approach and securitisation framework of prudential regulation through the mapping of each of their credit assessments to the corresponding risk weights. However, the global financial crisis of 2007/08 highlighted the risks of over-reliance on ECAIs which are dominated by a small pool of credit rating agencies. With the implementation of Basel III, several changes to asset risk measurement approach place more responsibility on financial institutions to strengthen their own credit risk assessment and not to rely solely and mechanistically on external credit ratings (Credit Rating Agencies Regulation, CRA III, 2013). These reforms also have implications for regulators (and regulatory regimes) and central banks who were overly dependent on CRA's credit ratings. The wider consequence of this is that regulators and central banks will need to start using their own judgement when determining what financial instruments they will accept for regulatory purposes. With the directives to banks to strengthen their internal credit risk assessment processes (based on the Capital Requirements Directives, CRD IV) in the EU, banks are positioning themselves to further strengthen their own risk analysis of the assets that they hold. CRD IV requires banks with material credit risk exposures to shift from the use of ratings by external rating agencies to an internal risk based (IRB) models. According to a report by PWC

(2014), the European Banking Authority (EBA) monitors banks' progress against parameters, such as the probability of default (PD, loss given default (LGD) generated by the IRB models, and discloses, on an annual basis, information on the steps taken by institutions to reduce their over-reliance on external credit ratings and on the degree of supervisory convergence in Europe.

Further, the new Basel III Accord in its design makes provisions for the counter-cyclical buffer (CCB), which requires banks to raise capital requirements in the build-up to a credit boom as buffer against the outcome of the credit boom. Alongside this CCB, the proposed buffer for systemically important financial institutions (SIFIs), could potentially have significant implications for the credit rating process and the way CRAs (re)assign bank credit ratings.

These reforms help to motivate this research. The thesis examines the level of market reliance on the information content of credit rating actions as well as investigating the trends in the rating dynamics. In so doing, it provides a better understanding of the workings of the credit rating agencies. For example, ESMA (2014) argue that downgrades usually lag behind market sentiment, in part because the CRAs need more time to carry out their detailed analysis. This motivates part of this thesis on the impact of credit rating news announcements. Another illustration of the apparent lag in credit rating agency's reaction is the case of the yields on Greece and Irish government debts, which rose long before credit rating agencies downgraded their debt (Mnyanda and Meakin 2012). Further, the CRA III directives stipulate the adoption of specific and rigorous methodologies (capturing all relevant variables) for rating sovereign debt. The accurate capture of the sovereign rating is important for banks. In most cases, sovereign ratings serve as a ceiling for bank ratings within a particular country and the results of this thesis show that it impacts on the final rating assigned to banks.

2.7.2 Regulatory oversight of the credit rating industry

In order to avoid conflicts of interest between the CRAs and the firms they rate, the various national and global regulators provide oversight that ensures good practice in the industry. The scandals that resulted from the financial crises of early 2000 and 2007-08 (relating specifically to the structured finance market) highlight the fact that CRAs have to be competent, diligent, transparent, independent and trustworthy to ensure a stable and functioning capital market. However, Ustig (2010) argues that any approach to regulating the CRAs must address the question of what should be regulated and with what tools - in other words, how should CRAs be regulated? There is quite extension regulation of the credit rating industry. At one end, the CRAs may regulate themselves while at the other end of the spectrum there is the government as the regulatory authority. For self-regulation to work, that is, allowing CRAs to set their own codes of conduct, there is a need for an effective supervision that would reveal if there are breaches in these codes and more importantly there must be identifiable sanctions for any breach.

The regulatory oversight of the credit rating industry may be viewed from three major perspectives: global, the US and the EU. Table 2.4 illustrates the regulation of the credit rating industry before and after the global financial crisis. Prior to the crisis of 2007/08, IOSCO maintained that credit rating agencies could voluntarily comply with its code of conduct. More importantly, CRAs were expected to incorporate the IOSCO code into their own codes of conduct or explain in clear terms why certain aspects had not been adopted, that is, 'comply or explain'. This voluntary compliance focuses on the areas of: the quality and integrity of the entire rating process; the issue of conflicts of interest; CRA responsibilities to the investing public and issuers; and the public disclosure of the CRA's own code of conduct. There were no mechanisms in place to force the CRAs to comply, nor was there any reference to government regulation of the credit rating industry.

However, most CRAs, and especially the major agencies, already had their own codes of conduct incorporated into their objectives. Hence, there was an internationally accepted framework of self-regulation. After the financial crises, however, IOSCO revised its code of conduct and strengthened its position. Some of its demands were for the CRAs to increase their public disclosure, improve the quality of their rating processes, and ensure that there is constant monitoring and timeliness of ratings. All of these measures aimed to ensure that credit rating agencies function in the way that they were intended to.

Table 2.4: Summary of the regulatory oversight of credit rating agencies

	Before the Crisis	After the Crisis
IOSCO	Voluntary compliance by the CRAs ('comply or explain basis'). No enforcement mechanism / government regulations. Agencies develop own code of conduct	Revised its code of conduct framework. Increased public disclosure. Differentiated structured finance products from other non-structured assets
US(SEC)	Informal recognition of CRAs by US SEC (NRSROs). No regulation of credit rating process including procedures and methodologies. Credit Rating Reform Act 2006.	Enhanced disclosure of performance statistics and rating methodologies.
EU(ESMA)	Relied heavily on voluntary adherence to the IOSCO codes. External credit rating assessment only to be provided by credit rating agencies recognised by national authorities.	Application to ESMA for registration if CRAs want their ratings to be used in the EU. Constant supervision by the EU (ESMA) of registered CRAs.

Source: Author's interpretation of the various regulatory oversights of the CRAs

Further, the IOSCO (2008) report suggests that CRAs are too slow to review existing ratings and make downgrades as appropriate, and highlights the possible conflict of interest arising from CRAs advising issuers on how to design structured financial products. In addition, the IOSCO (2012) survey report provides a comprehensive description of the key risk controls implemented by the CRAs to promote the integrity of the credit rating process and the procedures put in place to manage conflicts of interest. This provides a better understanding of the workings of the CRAs and allows CRAs to compare their internal controls and procedures with those of their peers. Further, the IOSCO (2015) presents changes to the definition of *credit rating*[2], to provide more clarity by replacing "opinion" with "assessment". The modification reflects the fact that under the provisions of the IOSCO CRA Code (2015), CRAs should strive to determine credit ratings: (1) using methodologies that are rigorous, (2) that reflect all information known and are believed to be relevant at the time when the credit rating is determined; (3) using analysts that have appropriate knowledge and expertise; and (4) that are free of bias and not influenced by conflicts.

Regulation of the credit rating industry in the US prior to the financial crisis could be traced back to 1975 when there was an informal recognition of the CRAs through the designation of *Nationally Recognised Statistical Rating Organisations* (NRSROs). This allowed the use of ratings by financial institutions to satisfy part of their regulatory requirements. The regulation at this stage was minimal, with very little oversight, as the role of ratings was dependent on market acceptance rather than on regulatory rules. However in 2006, the Credit Rating Agency Reform Act was passed in the US which gave the SEC legal authority over CRAs. Some of the legal oversight is in line with IOSCO and includes greater disclosure of information on internal standards and policies, as well as the rating methodologies used by the CRAs. In addition, the regulatory authorities could also conduct on-site inspections of CRAs and impose disciplinary action if there is a violation of the law. After the global financial crisis of 2007/08, there was an amendment of the Act (Amendments to Rules for NRSRO, Exchange Act Release 34-59342, 2009) and the Dodd-Frank Wall Street Reform and Consumer Protection Act (2010), which now stipulates that there should be even greater

[2] The term "credit rating" is defined in the 2008 Code as "an opinion regarding the creditworthiness of an entity, a credit commitment, a debt or debt-like security or an issuer of such obligations, expressed using an established and defined ranking system" (IOSCO 2008: 5).

and enhanced disclosure of performance statistics and rating methodologies. Other requirements include enhanced record keeping and practice that minimizes conflicts of interest, especially between CRAs and clients. In August 2014, the US SEC adopted rules regarding NRSRO reports of internal controls over the ratings process and the transparency of NRSRO ratings performance. This includes steps to be followed when adopting or revising credit ratings procedures and methodologies and adopt standards for NRSRO analysts including rules regarding ratings symbols.

The EU relies heavily on voluntary adherence to the IOSCO code. For credit rating agencies to act as external credit assessment institutions under the standardized approach of the Basel III framework, they need to be recognised by the authorities and satisfy criteria set by supervisors concerning objectivity, independence, continuous monitoring, and transparency. The global financial crisis of 2007/8 led to more stringent requirements. One resulting effect of the crisis is that all rating agencies that wanted their credit ratings to be used in the EU need to apply for registration with CESR, and to be subjected to regular supervision. Some of the other stringent rules imposed by the EU also include: 'prohibition from advisory services – which could limit conflicts of interest; enhanced disclosure and transparency requirements; differentiation of complex products and stronger internal governance mechanisms' (Katz *et al.,* 2009: 5). The reforms within the EU are driven by the ESMA. In 2014, the ESMA publish a report on the *Use of Credit Ratings by Financial Intermediaries Article 5(a) of the CRA Regulation*. This report states that "the European Banking Authority (EBA), the European Insurance and Occupational Pensions Authority (EIOPA) and ESMA shall not refer to credit ratings in their guidelines, recommendations and draft technical standards where such references have the potential to trigger sole or mechanistic reliance on credit ratings by the competent authorities, the sectoral competent authorities" (p. 7). They argue that the goal of this principle is to reduce the *cliff effects* from CRA ratings that can amplify procyclicality and cause systemic disruption (i.e. mitigate risks over credit cycles and not allow say a downgrade to spread to other part of the financial system). However, the use of external ratings is also driven by investors who often refer to external credit ratings before buying shares of a fund, or when guiding investment managers on the basis of a tailored investment mandate.

The IOSCO Consultation Report (2015) stresses the importance for asset managers to have the appropriate expertise and processes in place to be able to assess the credit quality of a financial instrument or counterparty. The report further emphasises that in performing such an assessment, asset managers may choose to use external credit ratings, however these should only be used as one element among others of the internal credit assessment process.

2.8 Summary

This chapter reviews the credit rating industry with a view to understanding its dynamics and trends over the sample period. The credit rating industry has grown significantly since the 1970s when the US established the NRSRO. Evidence shows that credit rating agencies are an important component of the financial market. Even though the ratings they produce do not price instruments, their information content has become highly valuable in the decision making process of market participants. The chapter examines the credit rating industry from four main perspectives: the nature of the credit ratings and the rating system; the role and criticism of credit ratings; the rating process; the regulatory use of ratings; and the regulatory oversight of credit ratings.

Credit rating is a reflection of the creditworthiness of an issue or issuer and is usually measured on an ordinal scale. The major credit rating agencies employ letters to indicate the relative standing of the ratings within the major rating categories. The industry has experienced a shift in the business model, from an initial subscriber-pay model to an issue-pay model. Despite concerns about conflicts of interest that this generates, the model has been maintained over the last few decades. It has also led to the generation of huge revenue for the CRAs. In order to break into new markets and maintain competition, the CRAs introduced unsolicited ratings. This involves assigning ratings to firms and issues based on publicly available information. Credit rating agencies have become an integral part of the financial market, performing salient roles ranging from reducing the cost of information and market access to regulatory roles in the calculation of risk-weighted assets. The use of credit rating as a measure of credit risk within a bank's portfolio is changing under the new Basel III Accord.

There are unrealistic expectations by users and market participants regarding what ratings actually mean. The over-reliance on the information contents of ratings may have contributed to the global financial crisis where grossly inaccurate ratings of exotic instruments resulted in huge financial losses for investors. Similarly Goh and Ederington (1999) maintain that credit rating changes and their information content do not add value to the market. Basel III presents new challenges for the users of credit rating in measuring credit risk, with the new regulation being driven towards reduced reliance on ECAIs via the standardized approached. Banks are now being encouraged to develop their own internal rating based models for credit risk assessments. The Basel III requirements are consistent with the several changes to US asset risk weightings driven by the Dodd-Frank Act requirement to remove from US regulations reliance on external credit ratings (e.g., in the context of investments in securitized assets or sovereign debt). Within the EU, institutions with a material number of exposures in a given portfolio will be required to develop internal ratings for that portfolio and to use external ratings to benchmark the resulting capital requirements to their internal credit opinions.

The pro-cyclical nature of ratings has also come under scrutiny, with evidence showing that the claim of *through-the-cycle* rating may not be realistic as rating agencies are confronted with the trade-off between rating stability and timely response. CRAs are sometimes accused of being too lax in rating securities that they are familiar with. Similarly a conflict of interest arguably exists between the CRAs and the companies they rate. The issuer-pay model creates an avenue for *credit rating shopping*, where an issuer can shop around for a better rating. The global financial crisis also highlights laxity in the regulation and oversight of the credit rating industry. There is an over reliance on ratings by the regulatory authority, especially within the context of Basel II Accord, which Basel III Accord hope to reduce.

The regulatory reforms within the credit rating industry are driven by regulatory institutions such as (IOSCO), US (SEC) and EU (ESMA). Their reforms introduced since the global financial crisis focus on the need for a revised code of conduct within the credit rating industry including, but not limited to enhanced disclosure, reduction in the over-reliance of ratings by market participants, and addressing conflicts of interest. These reforms should result in increased competition, enhanced internal control, disclosure of greater statistical information, as well as a more consistent application of rating symbols and definitions.

CHAPTER 3. REVIEW OF BANK CREDIT RISK EXPOSURE

3.1 Introduction

Credit risk is the possibility of incurring a loss as the result of a borrower or counterparty failing to meet its financial obligations or as a result of the deterioration in the credit quality of the borrower or counterparty (Bessis, 2010). In the event of a customer default, the loss incurred by a bank is expressed as the outstanding amount owed by the debtor, less any recoveries, e.g. from liquidation of collateral. A change in the credit quality of the counterparty has an impact on the valuation of assets eligible for fair value measurement. Switzer and Wang (2013) maintain that the credit risk of banks is recognised as one of the key features of the liquidity panic in the US financial system and the global financial crisis of 2007/08. The crisis underscores the importance of adequate risk management, efficient regulation and supervisory oversight for banking institutions around the world. Thus these two issues (risk culture in banks and banking regulatory reforms) present a couple of the key motivations for thesis, because they both have significant impact on the way international banks are perceived not just the CRAs, but also the global financial market.

The 2007/08 global financial crisis renewed interests in the risk culture of banks and their effects on the way banks are run and managed. There is no doubt that the failures of risk culture, which permitted excessive and uncontrolled risk-taking were at the heart of the financial crisis (Jackson, 2014). This view is supported by Ernst and Young (2014) who maintain that risk culture in banks is driven by continuing high-profile conduct failings and growing pressure from regulators to tighten controls on risk behaviour in banks. This is further reinforced by McKinsey and Company (2013), who argues that the risk culture in failed banks can be traced to the failings of corporate governance in these banks. Boards and senior management are facing growing scrutiny and pressure from stakeholders to tighten internal controls and reduce high-risk behaviour. The impact of rising litigation costs, steep fines and reputational damage has been a catalyst for banks to re-evaluate and strengthen their risk governance frameworks (FCA, 2015). Stulz (2014) notes that across international banks, boards are adding new committees to more closely monitor business ethics and conducts. All these create interesting issues for the CRAs in their assessments of an international bank's credit rating. This thesis provides an opportunity to contribute to literature by incorporating measures of corporate governance within its bank credit rating determinant equation.

In addition, this thesis introduces another important issue in its examination of bank ratings. This relates to the subsidy a bank gets by being *too-big-to-fail*. This notion has not only aggravated the risk culture, complacency and moral hazard issues in banks, it forms an important consideration for the largest CRAs in their assessment of bank ratings. For example, Fitch publishes a support rating floor (SRF) that reflects its view about the likelihood of government support for a bank or its holding company. Further, one may argue that when market participants expect financial institutions to receive support, they under-price their risk, and this results in excessive risk-taking (moral hazard) and pressures competing firms to do likewise. However, the sweeping reforms in the financial industry particularly in the US and in the EU (e.g. Walker, 2009; Dodd-Frank Act, 2010; Vickers Report, 2012; Liikanen report, 2012) all aim to reduce the influence of this notion on risk assessments of banks. The investigation of the determinants of international bank credit rating presents an opportunity to examine the impact of banks' changing risk culture, business model and corporate governance in the wake of the global financial crisis.

The rest of this chapter is structured as follows. Section 3.2 discusses the importance of bank credit ratings. Section 3.3 discusses the influence of other bank related risks on credit rating assignment. Section 3.4 discusses how rating has been influenced by global regulations, particularly the new Basel III Accord and the regulatory reforms at all levels across the world. Section 3.5 explores the relationship between credit risk and the corporate governance structure of banks. This section reviews the extensive literature that has emerged, focusing on the effects of corporate governance on bank risk-taking attitude. Section 3.6 examines how financial innovations impacts on the perception of CRAs in the assessments of bank credit rating. The impact of the financial crisis on banks is reviewed in Section 3.7. The chapter summary is presented in Section 3.8.

3.2 Importance of understanding the determinants of bank credit ratings

External credit ratings can be regarded as comprehensive measures of risk, because they incorporate all of the risk factors that are perceived to be relevant by rating agencies. However, following the 2007/08 global financial crisis, the role of the major credit rating agencies and the ratings they assign to banks have come under increased search light, with CRAs recalibrating their rating scales and providing greater disclosure about their methodologies (Fitch, 2015). The difficulty of the CRAs to assign the appropriate ratings to banks in a timely manner is evidenced by the series of downgrades in the global banking industry following the 2007/08 global financial crisis. Parker and Tarashev (2011) argue that prior to the 2007/08 global financial crisis, credit ratings were not particularly successful in recognising the build-up of pervasive risk exposures in the financial system or in identifying which banks were most exposed to them. The crisis highlights important lessons about systemic risk and the volatility of banks' performance, weakened finances of some sovereign providers of support, and policy initiatives to discourage banks from seeking external support (Kenny and Morgan, 2011). The financial crisis has given rise to policy initiatives that aim to weaken the reliance of regulators and investors on rating agencies.

The risk assessments of banks for the purpose of evaluating their credit risk exposure (and the assigned credit ratings) are quite unique and different from those of other firms. The nature of banks' business as financial intermediaries, and their interconnectedness to other sectors of the economy shape the risk factors they are exposed to. The assessment of a bank's creditworthiness involves not just an examination of the strength of its balance sheet; it includes an evaluation of the degree of liquidity risk, systemic risk, access to government support, the level of internal credit risk control, as well as issues concerning corporate governance. Banks differ from other firms not just in size, but also in their asset and liability structure, capital and liquidity requirements, and funding structure. The investigation of the determinants of international bank credit rating present an opportunity to examine the impact of banks' changing risk culture, business model and corporate governance in the wake of the global financial crisis.

It is thus important to investigate the determinants of a bank credit rating due the failure of the CRAs to adequately capture the true ratings of international banks in the build-up to the 2007/08 global financial crisis. In addition, following this crisis, and in light of the current regulatory reforms within the banking and credit rating industries, this thesis investigates how the CRAs methodologies have changed in response to the crisis. Bank credit rating methodologies are changing in response to regulatory pressure and the volatile nature of the banking industry following the 2007/08 global financial crisis. This is evident in many of the credit rating documentations and reports. Packer and Tarashev (2011) argue that major credit ratings agencies are implementing significant changes to their bank rating methodologies, seeking public comments. Further, there are recalibrations in the relative importance attached to rating factors.

The issue of bank capital and bank liquidity position are fundamental to the understanding of the role of banks, their risk appetite, and how these risks are managed. In the traditional banking business model, banks transform many small deposits of a short-term maturity into fewer longer-term loans. This 'maturity transformation' is an inherent part of a bank's traditional business model. Banks' business models have changed significantly, in particular, during the period leading up to the global financial crisis. This has been motivated by the development of financial instruments for transferring credit risk from on- to off-balance sheet. This further complicates an accurate assessment of overall bank risk exposure.

In addition, Nijsken and Wagner (2011) suggest that the business model of some banks relies on excessive leverage and short-term financing over time. An Institute of International Finance (2008) report argues that the inability of banks to withstand market shock is due to series of factors including risk governance weaknesses, misaligned incentives, incomplete risk capture in management reports, and ineffective market discipline. It is notable that market stress following the 2007/08 global financial crisis affected many major financial institutions. According to the Credit Risk Management Policy Group III (2008) report, a number of banks had weak controls over balance sheet growth and off-balance sheet risks, as well as inadequate communication and aggregation across business lines and functions.

A bank's capital may be viewed as a potential mitigating factor in the transmission of shocks through bank lending (Kapan and Minoui, 2013). However, the proposals for new regulations (in particular, Basel III Accord) have been spurred by the fact that banks which required government support during the crisis actually met thresholds of capital adequacy before the crisis (Frag *et al.*, 2013). Not only did capital ratios fail to raise concerns ahead of the crisis, they also failed to accurately predict the institutions that incurred the highest losses or ultimately failed (IMF, 2009; Mayes and Wood, 2009; Haldane and Madouros, 2012).

The run up to the 2007/08 global financial crisis highlights weaknesses in the credit risk management and internal controls of banks. A report by the Senior Supervisors Group (SSG, 2009) argues that the global financial crisis highlighted significant vulnerabilities of banks whose business models rely heavily on uninterrupted access to secured financing markets. Excessive reliance on short-term wholesale funding of long-term illiquid assets by banks, in particular, cross-border financing further impeded the ability of banks to withstand market shocks. Studies (e.g. Poghosyan and Chiak, 2011; Rosengren, 2013) suggest that banks that are less affected by changes in the market had conservative and well-structured internal control processes in place prior to the global financial crisis. International banks that had significant size and diversification were able to draw on other funding sources including a reliance on central bank lending facilities. All these mitigated against market stress and shock in the period of the global financial crisis.

Ciro (2013) maintains that during the run up to the 2007/08 global financial crisis there were failures on the part of some boards of directors and senior managers of large financial institutions to establish, measure, and adhere to a level of risk acceptable to the firm. The SSG (2009) report further links the internal control weaknesses of banks to compensation programs that conflict with the control objectives of those banks, as well as inadequate technological infrastructure that hindered effective risk identification and measurement. The Financial Stability Forum (2008) report argues that the standard risk management tools used by financial firms in the run up to the 2007/08 global financial crisis are not suited for estimating the scale of potential losses in the adverse tail of risk distributions for structured credit products.

Hence, the issues raised thus far around the changing bank business model, flawed ratings, bank risk culture and the push towards an improved methodological approach in the rating process motivates this study. It is thus important to investigate the determinants of a bank credit rating due the failure of the CRAs to adequately capture the true ratings of international banks in the build-up to the 2007/08 global financial crisis.

3.3 Other bank related risks and bank credit rating

There is a strong link between liquidity risk and credit risk, which has implications for bank stability and creditworthiness. The global financial crisis of 2007/08 resulted in huge credit risk within the portfolio of bank assets, and this potentially caused a freeze in the interbank liquidity market. Imbierowicz and Rauch (2014) argue that each risk category has a significant impact on bank default probability and suggest a joint management of liquidity risk in conjunction with asset quality and credit risk in a bank. Liquidity risk is particularly synonymous with banks, and banks are inherently vulnerable especially in their fundamental role in the maturity transformation. A bank can thus experience liquidity problems on both sides of the balance sheet, that is, if there are significant unexpected loan defaults and, say, large unexpected withdrawals from depositors (e.g. bank-run). Cai and Thakor (2008) argue that a bank may be motivated to take on excessive credit risk in order to manage its liquidity risk in loan markets that have limited competition.

Studies on financial crises, such as that in 2007/08 (e.g. Diamond and Rajan, 2005; Acharya and Viswanathan, 2011; Gorton and Metrick, 2011; He and Xiong, 2012a), suggest a positive relationship between liquidity risk and credit risk. The credit rating process involves an evaluation of the bank asset quality and the risk associated with the deterioration of these assets. Bank failure is linked with either insolvency or an aggregate shortage of liquidity in the system. Diamond and Rajan (2005) argue that liquidity problems and insolvency problems interact, and can each cause the other; bank failures can themselves cause liquidity shortages.

In a similar study, Imbierowicz and Rauch (2014) investigate the relationship between these two major sources of bank default: liquidity and credit risk employing a sample of US commercial banks during the period 1998-2000. They argue that the financial crisis of 2007/08 was driven by large credit risk in banks' portfolios, and this caused a freeze of the market for liquidity. The ultimate risk a bank is exposed to is the risk of going out of business. There is therefore the need to examine the effects of the interaction of liquidity risk and credit risk on a bank's probability of default (PD). Acharya and Mora (2013) analyse the liquidity provision roles of banks at the individual bank level during the global financial crisis of 2007/08. They find that the aggregate liquidity shock at the start of the crisis impacted greatly on banks with exposure to drawdowns of commitments and credit lines. They argue that these banks, especially those that failed, suffered from liquidity shortages just before the actual default. They provide evidence to support the argument that the joint occurrence of liquidity risk and credit risk pushed banks into default during the global financial crisis. Distressed banks faced liquidity issues which resulted in an aggressive drive for deposits that saw them offering high commercial deposit (CD) rates. In another related study, He and Xiong (2012b) provide explanations on how liquidity and credit risk jointly cause default.

Risk concentrations is another area of weakness in banks and it played a key role in the financial instability of the banking sector, particularly in the crisis of 2007/8 (Reynolds, 2009). Bandyopadhyay (2010) argues that concentration risk has direct impact on a bank's portfolio loss and hence its core capital and solvency position. Bonti *et al*. (2006) argue that the term 'concentration risk' within the context of banking generally refers to risk occurring in credit portfolios, and arises from an uneven distribution of bank loans to individual borrowers (single-name concentration) or in industry and service sectors or geographical regions (sectoral concentration). Existing studies in the area of bank credit risk exposure focus on credit risk concentration and this is motivated by the global banking regulation that stipulates the increasing use of external and internal credit ratings (BCBS, 2006). The Basel Committee has identified the treatment of credit concentration risk as one of the main factors which need to be covered by the supervisory review process in the implementation of the Basel III Accord.

The events leading to the 2007/08 collapse of the subprime market in US, where bank risk exposure to the housing market created joint concentration in a particular sector, exemplifies systematic concentration risk. The economic disruption which affected the group of joint borrowers jeopardised the solvency of the entire group of banks involved and put the financial stability of the global banking system at risk. The focus of most banks' internal risk management, as well as supervisory and regulatory view, is on concentration credit risk at the level of individual institutions. However, this risk is not limited to the credit portfolio, and may involve other forms of risks such as market risk (trading activities) and liquidity risk (e.g. concentration in liabilities such as the concentration of depositors). The most significant concentration risk with implications for the solvency of banks is the concentration in credit portfolio at the micro level (BCBS, 2005).

The impact of credit concentration risk depends on the extent of correlation among borrowers under various economic conditions. The amount of portfolio credit risk may change with macroeconomic conditions. During economic booms, losses may be seen as being 'stored' and tend not to create any noticeable adverse effects on performance or credit quality. However, correlations amongst borrowers in a bank loan portfolio usually become very apparent when there is an economic downturn. Banks may hold enough risk capital to mitigate against higher level of unexpected losses due to high concentration risk in their portfolios. Nickell *et al*. (2000) show that the probability of default depends on the stage in the business cycle, and that transition matrices tend to exhibit a higher frequency of downgrades during recessions and a higher occurrence of upgrades during booms.

The concern about issues related to concentration in bank portfolios is particularly important now because of the downgrades to several countries, such as US, Greece, UK, Italy, in the period following the financial crisis of 2007/08. Avila *et al*. (2013) argue that concentration of credit exposure constitutes one of the most important causes of large losses in banks portfolios, hence the need for proper monitoring and evaluation by supervisory authorities. The CRAs' assessment of the credit quality of banks' asset portfolios pay particular attention to the diversification and the level of correlation existing amongst them.

It is important to understand the determinants of bank credit ratings in light of these failings and the crisis that resulted from them. In providing clarity on the issue of bank credit rating assignments, this thesis models bank credit rating determinants by employing variables that capture the main drivers of bank credit risk. In doing so, the thesis investigates the impact of the 2007/08 global financial crisis on bank ratings, whilst also testing for any indication of increased stringency in the rating methodologies over the sample period. An important consideration in modelling bank credit rating determinants is the inclusion of variable(s) that capture external support by banks to be able to support their operations. The 2007/08 crisis shows that access to external government support (capital injections, asset purchases or liquidity provisions) is significant and impacts on a bank's assigned rating. This thesis employs relevant proxies for this variable in the various model specifications (e.g. the *too-big-to-fail* variable). Further, the introduction of other proxies for credit risk and liquidity risk measures, couple with an appreciation of the effects of risk concentration build up within a bank's asset portfolio provides an opportunity for an holistic approach to modelling an international bank's rating determinants.

3.4 Global banking regulation

The financial industry is perhaps the most heavily regulated industry within the economy and the banking sector represents the most regulated sector within that industry. Events in the last couple of decades indicate that the financial industry is prone to crisis and instability. Banking is a very sensitive industry due to the level of interconnectivity between institutions, as well as the nature of the core business of the industry, i.e. maturity transformation. The significant tendency for contagion, coupled with the problem of systemic risk, that is, the risk that problems in one banking institution may spread to others, increases bank exposure and makes the industry as a whole very vulnerable. Lindquist (2004) argues that as other industries are deregulated, capital adequacy regulation becomes more important for banks, and this has resulted in an increased focus on banks' capital to assets ratios. The focus on capital requirements as a key instrument of banking regulation is on providing both a cushion during adverse economic conditions and a mechanism for preventing risk-taking *ex ante* (Jokipii and Milne, 2010). The Basel Committee on Bank Supervision (BCBS) performs the role of an international advisory authority on bank regulation and has been at the forefront of promulgating guidance in ensuring healthy banking across global banking systems

The 2007/08 global financial crisis provided an opportunity for the BCBS to implement fundamental restructuring of the ways risk management and regulations are carried out in the financial industry. These reforms (contained in Basel III Accord) aim to strengthen global capital and liquidity rules, as well as promoting a more resilient banking industry. The framework of the proposed Basel III now includes bank stress testing and market liquidity risks, in addition to the regulation of bank capital adequacy.

This section examines the effects of the evolving regulatory framework on bank credit risk assessments under the Basel Accord. It focuses on the Basel III Accord, while discussing the issues and implications of the changes leading up to its implementation.

3.4.1 Basel III Accord and its implications for credit risk assessment

Credit ratings measure the creditworthiness of an entity and as such, measure an aspect of credit risk relating to the amount of regulatory capital that should be set aside to cover the risky assets in a bank's books. The global financial crisis has shown several weaknesses in the global regulatory framework and in banks' risk management practices. In response to the crisis, the BCBS began consultation to address the deficiencies in financial regulation and strengthen bank capital requirements by increasing liquidity and decreasing bank leverage. This gave rise to the Basel III Accord in 2010 whose full implementation is currently proposed for March 2019.

Table 3.1 presents some of the reforms to the Basel II framework by the BCBS in 2009. These include enhanced risk coverage and counterparty credit risk disclosure. There is now an increased capital requirement for the trading book and complex securitization positions. The new regulation, Basel III, now adds the following reforms: the calculation of capital requirements for counterparty credit risk (CCR) based on stressed outputs; the introduction of a capital charge for potential mark-to-market losses, that is, credit valuation risk; and strengthening standards for collateral management and raising CCR management standards (Accenture, 2013). These are underpinned by a leverage ratio that serves to constrain excess leverage in the banking system and provide an extra layer of protection against model risk and measurement error. Finally, the Committee introduces a number of macroprudential elements into the capital framework to help contain systemic risks arising from procyclicality and from the interconnectedness of financial institutions. Paul Tucker[3] maintains that one of the implications of the new macroprudential guidelines as contained in the UK's proposed banking reform to address the *too-big-to-fail* notion (which at the moment, effectively subsidised longer-term bond finance for banks). This notion presents an important element for this thesis as the Basel III deferred implementation on how to deal with SIFIs (systemically important financial institutions, i.e. TBTF, "Too-Big-To-Fail" institutions). By including a proxy for the measure of the TBTF, this thesis makes a significant contribution and adds policy implication findings to the existing studies.

Table 3.1: Summary of the key amendments to Basel II Accord (the new Basel III)

Basel Committee on Banking Supervision reforms - Basel III

Strengthens microprudential regulation and supervision, and adds a macroprudential overlay that includes capital buffers.

	Capital					Liquidity
	Pillar 1			Pillar 2	Pillar 3	
	Capital	Risk coverage	Containing leverage	Risk management and supervision	Market discipline	Global liquidity standard and supervisory monitoring
All Banks	**Quality and level of capital** Greater focus on common equity. The minimum will be raised to 4.5% of risk-weighted assets, after deductions. **Capital loss absorption at the point of non-viability** Contractual terms of capital instruments will include a clause that allows – at the discretion of the relevant authority – write-off or conversion to common shares if the bank is judged to be non-viable. This principle increases the contribution of the private sector to resolving future banking crises and thereby reduces moral hazard. **Capital conservation buffer** Comprising common equity of 2.5% of risk-weighted assets, bringing the total common equity standard to 7%. Constraint on a bank's discretionary distributions will be imposed when banks fall into the buffer range. **Countercyclical buffer** Imposed within a range of 0-2.5% comprising common equity, when authorities judge credit growth is resulting in an unacceptable build up of systematic risk.	**Securitisations** Strengthens the capital treatment for certain complex securitisations. Requires banks to conduct more rigorous credit analyses of externally rated securitisation exposures. **Trading book** Significantly higher capital for trading and derivatives activities, as well as complex securitisations held in the trading book. Introduction of a stressed value-at-risk framework to help mitigate procyclicality. A capital charge for incremental risk that estimates the default and migration risks of unsecuritised credit products and takes liquidity into account. **Counterparty credit risk** Substantial strengthening of the counterparty credit risk framework. Includes: more stringent requirements for measuring exposure; capital incentives for banks to use central counterparties for derivatives; and higher capital for inter-financial sector exposures. **Bank exposures to central counterparties (CCPs)** The Committee has proposed that trade exposures to a qualifying CCP will receive a 2% risk weight and default fund exposures to a qualifying CCP will be capitalised according to a risk-based method that consistently and simply estimates risk arising from such default fund.	**Leverage ratio** A non-risk-based leverage ratio that includes off-balance sheet exposures will serve as a backstop to the risk-based capital requirement. Also helps contain system wide build up of leverage.	**Supplemental Pillar 2 requirements.** Address firm-wide governance and risk management; capturing the risk of off-balance sheet exposures and securitisation activities; managing risk concentrations; providing incentives for banks to better manage risk and returns over the long term; sound compensation practices; valuation practices; stress testing; accounting standards for financial instruments; corporate governance; and supervisory colleges.	**Revised Pillar 3 disclosures requirements** The requirements introduced relate to securitisation exposures and sponsorship of off-balance sheet vehicles. Enhanced disclosures on the detail of the components of regulatory capital and their reconciliation to the reported accounts will be required, including a comprehensive explanation of how a bank calculates its regulatory capital ratios.	**Liquidity coverage ratio** The liquidity coverage ratio (LCR) will require banks to have sufficient high-quality liquid assets to withstand a 30-day stressed funding scenario that is specified by supervisors. **Net stable funding ratio** The net stable funding ratio (NSFR) is a longer-term structural ratio designed to address liquidity mismatches. It covers the entire balance sheet and provides incentives for banks to use stable sources of funding. **Principles for Sound Liquidity Risk Management and Supervision** The Committee's 2008 guidance *Principles for Sound Liquidity Risk Management and Supervision* takes account of lessons learned during the crisis and is based on a fundamental review of sound practices for managing liquidity risk in banking organisations. **Supervisory monitoring** The liquidity framework includes a common set of monitoring metrics to assist supervisors in identifying and analysing liquidity risk trends at both the bank and system-wide level.
SIFIs	In addition to meeting the Basel III requirements, global systemically important financial institutions (SIFIs) must have higher loss absorbency capacity to reflect the greater risks that they pose to the financial system. The Committee has developed a methodology that includes both quantitative indicators and qualitative elements to identify global systemically important banks (SIBs). The additional loss absorbency requirements are to be met with a progressive Common Equity Tier 1 (CET1) capital requirement ranging from 1% to 2.5%, depending on a bank's systemic importance. For banks facing the highest SIB surcharge, an additional loss absorbency of 1% could be applied as a disincentive to increase materially their global systemic importance in the future. A consultative document was published in cooperation with the Financial Stability Board, which is coordinating the overall set of measures to reduce the moral hazard posed by global SIFIs.					

Source: Bank for International Settlement (2014) *Used with permission of the publisher

[3] 'Banking reform and macroprudential regulation: implications for banks' capital structure and credit conditions', speech given by Paul Tucker, Deputy Governor Financial Stability, at the SUERF/Bank of Finland Conference 2013, 'Banking after regulatory reform – business as usual', Helsinki Regulation Authority Board

For a bank to be assigned a particular rating, CRAs take into consideration the impact of changing capital regulation on banks' credit risk exposure. However, Berger *et al.* (2008) maintain that most banks prior to the 2007/08 global financial crisis held capital in excess of the regulatory minimum requirement. They suggest that this could have been motivated by the advantages linked with high economic capital and external pressure from regulators and/or financial markets. Despite the high levels of capital adequacy in banks in the pre-crisis period, the onset of the crisis raised serious concerns about the practical role capital plays in strengthening banks and the impact it has on banks' credit ratings.

The proposed Basel III reforms raise both the quality and size of the regulatory capital base and enhance the risk coverage of the capital framework. The aim of Basel III is to put in place structures that enable banks to improve their loss-absorption capacity in both going concern and liquidation scenarios (PWC, 2011). In terms of the quality of capital, common equity and retained earnings are required to be the predominant components of Tier 1. The direct implication of this for banks is the raising of significant capital along with the retention of profits and reduced dividends. This may impact positively on the assessments of banks by credit rating agencies due to the availability of a more reliable capital buffer to cushion banks in times of shock. The level of capital capacity results in an increase in the minimum common equity Tier 1 from 2.0 percent to 4.5 percent. Further, the capital conservation buffer of 2.5 percent will now be required under the Basel III, bringing the total common equity requirement to 7.0 percent. This implies that banks will face additional capital requirements (common equity).

Basel III develops a counter-cyclical buffer which will be implemented by increases to the capital conservation buffer during periods of excessive credit growth. The internal rating based (IRB) approach in Basel II has the tendency to encourage procyclical behaviour on the part of banks, i.e. maintaining lower amounts of capital in good times, and banks adopting the IRB methodology may have had lower estimates of risk for their assets. In a recession or time of economic downturns, banks are forced to have capital reflecting higher risk levels. This may have resulted in banks, lending less to the economy, which might inhibit growth and economic recovery (Cummins and Phillips, 2009). This can impact on the credit rating of a bank due to it taking more risky actions either to shore up its deposits or to increase its capital. Hence the main objectives of the countercyclical buffer are to: reduce any excess cyclicality of the minimum capital requirement; promote more forward-looking provisions; conserve capital to build buffers at individual banks and in the banking sector that can be used in periods of stress-testing. The exact amount of the countercyclical buffer is determined by national regulators (BIS, 2010) and will generally be determined by the state and amount of credit in a given economy. The more the credit lending, the higher is the buffer.

An underlying cause of the global financial crisis was the build-up of excessive on- and off-balance sheet leverage in the banking system. The Basel III framework introduced a simple, transparent, non-risk based leverage ratio to act as a credible supplementary measure to the risk-based capital requirements (BCBS, 2014). The leverage ratio acts as a non-risk-sensitive backstop measure to reduce the risk of built-up of excessive leverage in the financial institution and in the financial system as a whole (PwC 2011). The potential implication of the introduction of the leverage ratio in Basel III Accord is that it could reduce lending and presents a clear incentive to banks to strengthen their capital position. Banks may thus be required by the market and the rating agencies to maintain a higher leverage ratio than requested by the regulators.

Another regulatory response to the global financial crisis is the application of comprehensive stress testing techniques by central banks and supervisory authorities to assess the vulnerabilities of the financial systems to credit risk. The stress test focuses on linking macroeconomic drivers of stress with bank-specific measures of credit risk (Foglia, 2009). Schuermann (2013) argues that the reason for the increasing use of stress testing is because existing techniques such as regulatory capital ratios are no longer informative and are heavily discounted by the market. The regulatory focus on stress testing is driven by need for regulators to be pre-emptive about the possible loss by banks and to help mitigate moral hazard.

Prior to the 2007/08 global financial crisis, the bank stress testing approach in some banks was executed as an isolated exercise within the risk function with little interaction with other business areas. The first use of the regulatory stress testing approach was in the US in 2009, and it allowed for the disclosure of information on the financial sector's potential losses under exceptional but plausible shocks. Other countries and regions, particularly in those countries where the crisis impacts were severe, such as the UK and the EU zone, have followed the US by introducing regular, comprehensive stress testing regimes. A survey by the PwC (2014) shows that most banks expect to develop their existing stress testing frameworks over the next three years (up to 2017). This is in recognition of the fact that this regulatory development will place increasing demands on bank stress testing capabilities.

This potentially helps regulators to assess the significance of the financial systems' vulnerabilities. Apart from applying a forward-looking macroeconomic perspective, it allows for the assessment of risk exposure across institutions (World Economic and Financial Surveys, 2014). The European Banking Authority, EBA (2014) maintains that banks within the EU zone should undergo formal stress testing of their banking books, and this focuses on credit risk. Further, Eurozone banks, which are impacted by the upcoming ECB/EBA stress test in the first quarter of 2016, are beginning to prepare, as most have focused their efforts to date on preparing for the asset quality reviews

(EBA, 2015). The implementation of the bank-wide stress test approach as part of the Basel III Accord could potentially improve the credit ratings of banks and positively impact on the overall health of the global financial system.

3.5 Bank credit risk and corporate governance structure

The central theme in an issuer's credit rating process is the analysis of its risk exposure and propensity to take on more risk. The importance of corporate governance, in particular the composition of the board of directors as well as ownership structure, is that it contributes to the risk-taking attitude of a bank (Buch and Delong, 2008). The major rating agencies also support this position by maintaining that they incorporate information about corporate governance structure in their rating process. Standard and Poor's for example, maintains that in the credit analysis process of a corporate issuer such as a bank, they typically consider non-financial factors including management and corporate governance attitude. These they argue enable an assessment of the risk tolerance and financial policy of such an issuer. The Basel Committee on Banking Supervision (2010) also reiterate the importance of promoting sound corporate governance practices for banking organisations. One of the highlights of its guidance is that 'risks generated by operations that lack transparency should be adequately managed' (p. 5). More importantly, the Basel guidance suggests ways of improving bank corporate governance including the role of the credit rating agencies in reviewing and assessing the impact of corporate governance practices on a bank's risk profile. Switzer and Wang (2013) argue that the mismanagement of the credit risk of banks in the period leading up to the 2007/08 global financial crisis was as a result of poor governance practice. This supports the widely held belief that the failure of bank corporate governance played a central role in the global financial crisis. There is significant evidence to suggest that the corporate governance mechanism contributes significantly to risk-taking of banks and can thus impact on the creditworthiness assessment by rating agencies. Bhojraj and Sengupta (2003) point out that the PD of a firm depends on the availability of credible information to evaluate default risk and agency costs. These are determined by the corporate governance mechanism of the firm. Laeven and Levine (2009) further suggest that bank risk-taking varies with the comparative power of shareholders within the governance structure. Most of the studies on bank corporate governance examine the relationship between bank risk and performance, particularly after the global financial crisis (Erkens *et al.*, 2010; Minton *et al.,* 2010; Mongiardino and Plath, 2010; Cornett *et al.*, 2011; Fahlenbrach and Stulz, 2011). Others investigate how executive compensation and ownership structures influence corporate governance (Wilson and Williams, 2000; Goddard *et al.,* 2004; Chen *et al.,* 2006; Mehran and Rosenberg, 2008). These studies are relevant to understanding the ways in which credit rating agencies assign a rating to a bank. The findings enable judgement to be made on the probability that a particular bank will behave in such a way that will increase the overall PD or its ability to honour its contractual obligations.

Cornett *et al.* (2010) and Minton *et al.* (2010) investigate the relationship between various corporate governance mechanisms and bank performance during the 2007/08 global financial crisis. Using a sample of about 300 publicly traded US banks, Cornett *et al.* find that their corporate governance proxies (number of independent directors and institutional ownership) have positive relationship with bank performance during the crisis period. For example, an increase in institutional ownership and independence of the board leads to better bank crisis performance. Similarly, Minton *et al.* show that the financial expertise of the board is positively related to risk-taking and bank performance before the crisis, but negatively related to risk-taking in the crisis period.

Erkens *et al.* (2010) investigate the relationship between corporate governance and the performance during the global financial crisis of 2007/08 employing an international sample of 296 financial firms from 30 countries. They find that firms with higher institutional ownership experienced worse stock returns during the crisis. They argue that banks with higher institutional ownership engage in riskier dealing prior to the crisis, which results in larger shareholder losses during the crisis period.

Mongiardino and Plath (2010) argue that risk governance in large banks has only improved slightly despite the increasing pressure from regulators, and even though largest banks have a dedicated risk committee, they meet very infrequently. Following their survey of 20 large banks in the US they suggest three remedies for best banking risk governance: 1) a dedicated board-level risk committee of which 2) a majority should be independent, and 3) that the Chief Risk Officer is part of the bank's executive board. Hau and Thum (2009) however, argue that most bank risk committees are not comprised of enough independent and financially knowledgeable members. In a related study, Beltratti and Stulz (2012) investigate the link between corporate governance and bank performance during the credit crisis using an international sample of 503 banks from July 2007 to December 2008. They base their study on the argument that there is a correlation between governance and unobserved characteristics of banks. Beltratti and Stulz argue that banks that are under pressure to exceed set performance levels took risks aimed at maximizing shareholders' wealth before the crisis, but were costly post-crisis because of outcomes that were not expected when the risks were taken *ab initio*. They find that banks with more shareholder-friendly boards as measured by the Corporate Governance Quotient (CGQ) performed worse during the crisis, implying that good governance does not necessarily have to be in the best interests of the shareholders. The CGQ is metric developed by Institutional Shareholder Services (ISS) that rates publicly traded companies in terms of the quality of their corporate.

Most crises originating from within the banking sector may be attributed to 'bad' banking or 'bad' policy, whereby the management of banks take excessive risks at the expense of their investors. Akhigbe and Martin (2008) and Pathan (2009) examine the relationship between corporate governance and bank risk-taking. Akhigbe and Martin study the impact of the passage of the Sarbanes-Oxley rule on the changes in the capital market measure of risk for US financial services firms. The study employs a sample of 768 US financial services firms for the year 2002 to capture disclosure and governance. They find that the risk measures of financial firms vary inversely with the strength of corporate governance. Pathan (2009) also examines the relevance of bank board structure on bank risk-taking using a sample of 212 large US bank holding companies over the period 1997-2004 (with 1,534 observations). In particular, the author investigates whether strong bank boards and CEO power affect bank risk-taking. The study finds that banks with stronger corporate governance mechanisms have a higher profitability in 2008, suggesting that good governance may negate the influence of any adverse effects of the financial crisis on bank financial performance.

Studies examining the impact of bank corporate governance on credit/default risk and risk-taking employ several proxies for governance quality: board size, board independence, the separation between CEO and Chairman, institutional ownership, insider holdings by top management and directors, and directors with CEO positions in private and public organisations (Ryan and Wiggins, 2004; Laeven and Levine, 2009; Aebi *et al*., 2012). From a theoretical point, the resource dependence theory provides a useful framework for examining the significance of board size. The theory proposes that large board benefits firms because diversified board members could provide greater expertise, access to resources, and high quality advice (Hillman *et al.,* 2007). On the contrary, agency theory suggests that large board are not efficient due to coordination and communication problems, director free rider problems and internal conflicts among directors (Zahra and Pearce, 1989; Johnson *et al.,* 1996; Dalton *et al.,* 2007).

There is evidence to show that board independence is negatively related to risk-taking in banks. Pathan (2009) reports that the coefficient of his proxy for board independence, that is, the percentage of the total number of directors who are independent, is negative and statistically significant in relation to all bank risk measures employed. Similarly, Faleye and Krishnan (2010) find that board independence reduces riskiness measured as the borrower's long-term S&P credit rating; this is not however related to the bank's decision to diversify its lending risk through loan syndication. Ellul and Yerramilli (2013) investigate whether strong and independent risk management is significantly related to bank risk-taking and performance using a sample of 74 large US BHCs over the period 1995 to 2010. They construct a Risk Management Index (RMI), using five variables that measure the strength of a bank's risk management. Their findings indicate that banks with a high RMI value in the period prior to the global financial crisis were less risky and performed better (lower tail risk, lower non-performing loans) than before the global financial crisis. Similarly, Aebi *et al*. (2012) find that banks in which the Chief Risk Officer reports directly to the board of directors performed significantly better in the credit crisis. Several studies on financial firms address the issue of the impact of CEO duality on risk-taking. CEO duality refers to a situation whereby the CEO or an executive director of a bank also doubles as the Chairman of the Board of Directors. Evidence suggests that this situation has several implications for the riskiness of a bank. Grove *et al*. (2011) find that CEO duality is negatively associated with bank performance and loan quality. Similarly, Faleye and Krishnan (2010) argue that the probability of lending to high-risk borrowers increases with CEO-chair duality. On the contrary, the study by Pathan (2009) suggests that CEO duality may reduce bank risk. The study finds that the coefficient of CEO power (measuring a CEO's ability to control board decisions including CEO duality) is negative across all bank risk measures used and is statistically significant in most of his regressions.

Using a sample of 287 banks over the period 1989-1993, Simpson and Gleason (1999) find a lower probability of financial distress when the chairman of the board is also the CEO. Wang *et al.* (2012) report a negative impact of CEO duality on efficiency. In contrast, Aebi *et al*. (2012) do not find that CEO duality affects buy-and-hold returns in their sample of US banks. Berger *et al.* (2012) examine the role of management structures in bank defaults during the global financial crisis of 2007/08. Distinguishing between 249 bank failures and 4021 non-default US commercial banks, they do not find that CEO duality influences bank default probabilities.

This thesis contributes significantly to the existing literature because the effect of corporate governance on bank credit ratings is modelled. This is in light of the important relationship between governance and the risk taking attitude of banks. Sound governance and control practices are important in ensuring that banks are operating in the best interests of depositors and not taking risky projects that potentially undermine the stability of the banking institution or lead to contagion.

3.6 Financial innovation and banks' risk assessment

Several reasons have been adduced for the cause of the 2007/08 global financial crisis. In particular, the laxities in regulatory oversight, intense competition, and indiscriminate use of financially innovative products have all contributed in one way or the other to the crisis (Ciro, 2013; Savona and Kirton, 2013). A growing strand of literature now focuses on the various ways through which banks transfer credit risk in the financial system, particularly via the process of securitization. Securitization has the potential to significantly impact a upon a bank's insolvency risk, leverage and profitability, all of which have varying effects on the credit ratings of a bank. The process allows a bank to optimally choose its exposure to different aspects of the credit risk of an underlying pool of assets. Using US bank holding company data from 2001-2007, Jiangli and

Pritsker (2008) provide evidence that banks increase their risk in response to securitization by increasing their leverage.

According to the Bank of England Financial Stability Report (2009) in the credit bubble period, major UK banks securitized 70 per cent of their commercial loans within 120 days of origination. By temporarily transferring the credit risk of their loans to others, banks potentially reduce the likelihood that loan defaults trigger financial distress. Similarly, due to the rapid development in financial innovation, banks significantly increased the securitization of their assets. However, this could potentially trigger a change in behaviour of the affected bank. Wagner (2007) argues that by engaging in credit risk transfer, banks may simply take on new risky loans due to their ability to easily liquidate these assets in times of crisis. Similarly, Cebenoyan and Strahan (2004) find that banks that actively engaged in loan sale markets hold a larger share of their portfolio in risky assets than banks that are not active in loan sales. Nijskens and Wagner (2011) argue that CRT may increase bank risk in a systemic way, even if individual bank risk does not increase. Evidence shows that most banks engage in the simultaneous buying and selling of credit risk CDS, resulting in banks being too correlated with each other (Elsinger *et al*., 2006; Acharya and Yorulmazer, 2007; Wagner, 2007). The implication of this is an amplified systemic risk crisis within the financial system, since it increases the likelihood of banks incurring joint losses.

One may argue therefore that the development of the derivative market aided the reduction in the total risk of banks. Rule (2001, p.26) argues, for instance, that the '[d]evelopment of [the credit derivatives] markets has clear potential benefits for financial stability because they allow the origination and funding of credit to be separated from the efficient allocation of the resulting credit risk'. Credit derivatives allow credit risk transfer within the banking system and also between banks and non-bank financial institutions (Hirtle, 2009). This risk transfer is frequently cited as a stabilizing factor in the financial system, reducing concentrations of exposures in individual banks and spreading credit risk more widely to those parties best able to bear it (Geithner 2006, Greenspan 2005). The development in financial innovative products could have particular implications for the opinions of ratings agencies or the internal assessments of banks.

3.7 The global financial crisis of 2007/8 and its implications for banks

The global financial crisis of 2007/8 impacted significantly upon the liquidity and solvency of banks across the world. The decline in profitability affected the banks' ability to generate internal funds, and hence their reliance on external financing (Salvador *et al*., 2014). The consequence of this is an increase in the cost of financing and a loss of credit quality. Major international banks in developed economies such as the US, the UK, and European Zone collapsed, while others had to be bailed out by national governments. The crisis not only impacts upon the commercial sector, but also cut across all the major sectors within the financial industry such as insurance and investment houses. The period was marked by the collapse of large investment bank giants such as Lehman Brothers and Bear Stern and well as the world's largest insurer AIG. In the UK, the onset of the crisis saw a run on Northern Rock, with the Royal Bank of Scotland (and by implication NatWest) and Lloyds Banking Group coming under state control. The period just prior to the crisis was marked by banks engaging heavily in the use of financial and structured products such as the Assets-Backed Securities (ABS). The downgrades of these products following the collapse of the subprime market in the US had a significant impact on the performance of the originating bank's parent (Higgins *et al*., 2010). This saw a significant decline in the rating notches of banks (downgrades).

The aftermath of the crisis witnessed a series of unprecedented policy and regulatory changes particularly in the US, the EU, as well as most national governments across the world. In the UK for example, the Financial Services Authority (FSA) published the Turner Review which highlighted the role of the CRAs in the 2007/08 financial crisis. The FSA (2009) report suggests that there was insufficient consideration of market and macroeconomic developments as drivers of bank credit ratings. Other policy changes focus on the recapitalization of banks and the injection of funds into the banking industry with the aim of providing both fiscal and monetary stimulus to renew market confidence in the banks (Valdez and Molyneux, 2013).

The Bank for International Settlement (BIS, 2009) identifies certain key macroeconomic and microeconomic factors that led to the 2007/08 global financial crisis. These factors range from the imbalance in capital flows to banks which leveraged up to enhance returns. The role of the rating agencies in assigning ratings to new securitized financial instruments coupled with the growth of securitized markets were highlighted as major causes. The incentives for rating agencies to assign ratings to these instruments were high because of the high level of income they were generating from their issuer-pay model. Conversely, investor and portfolio managers were able to invest in what they perceived were low-risk investments, generating high returns. The various reforms in the financial industry since the onset the crisis aims to cleanse bank balance sheets, increase capital and liquidity requirements, and increase oversight and regulation of securitization business.

3.8 Summary

The assessment of the credit quality of a bank is an important step in assigning an appropriate credit rating to it. The credit quality of the bank portfolio is driven by the credit risk exposure of the bank. Rating agencies such as Fitch and S&P consider other factors such as market position, the level of capital, and the overall risk management policies and practices in their rating process. This chapter examines the issues around bank credit risk exposure, and the impact of the 2007/08 global financial crisis on the banking industry. Of particular interest for a bank is the changing business model and risk appetite in the banking industry. These are driven by issues around bank capital and liquidity position, funding alternatives, the influence of the SIFIs concept, and in particular the propensity to receive external government support.

Capital adequacy regulation has become an important feature in estimating the appropriate buffer for banks particularly during an economic downturn. An important aspect of credit risk exposure is the amount of regulatory capital which should be set aside to cover the risky assets in a bank's books. The transition from Basel II to III Accord saw an improvement in the estimation of capital charges for risky assets. With the introduction of other types of capital buffers (CCB, leverage ratios, liquidity ratios), alongside the core capital provisions, the Basel III Accord aims to The use of both external rating agencies and the internal models of banks (IRB) ensures that banks of all sizes can adequately make enough provision to cover losses resulting from their asset portfolio.

The newly issued Basel III regulations made key amendments to Basel II Accord in terms of enhancing capital requirements, the maintenance of a minimum leverage ratio, and the introduction of new liquidity requirements for banks. Further, the risk-taking attitude of a bank is influenced by the structure of its corporate governance mechanism. The rating agencies maintain that they incorporate information about a bank's corporate governance in their rating process. Studies show that governance issues such as ownership structure, board independence, and the number of non-executive directors on the board impact on the risk-taking attitude of banks

CHAPTER 4. BANK CREDIT RATING DETERMINANTS

4.1 Introduction

This chapter aims to investigate the significant factors driving the assignment of credit ratings to international banks. An investigation of the determinants of bank credit ratings is important. A rating measures the risk of credit loss resulting from failure by the counterparty to uphold a scheduled payment agreement. Rating classifications are an important variable to the portfolio credit risk model as they are mapped onto probabilities of default (Carey and Hrycay, 2001). The 'quantification' of ratings thus involves estimating the probability of default for counterparties assigned to each rating notch.

Prior to the financial crisis of 2007/08, the global banking regulator, under the Basel II guidelines, explicitly recognises the role of the CRAs in financial markets. Due to this regulatory recognition, there was an increased incentive for banks to seek and obtain a favourable credit rating. With greater acceptance of ratings in the marketplace, regulators have increasingly used ratings to simplify the task of prudential oversight. However, the Financial Stability Board (FSB) 2010 published the *Principles for Reducing Reliance on CRA Ratings* report which aims to end mechanistic reliance on CRA ratings by banks, institutional investors and other market participants. The goal is to reduce the "hard wiring" of CRA ratings in standards, laws and regulations and to provide incentives for banks to develop their own capacity for credit risk assessment and due diligence. The FSB (2010) report further reiterates the implications of such reliance during the global financial crisis such as the herding behaviour and of abrupt sell-offs of securities when they are downgraded ("cliff effects"), which in turn amplify procyclicality and cause systemic disruption.

Despite these efforts by the FSB, reliance on ratings persists in the market, particularly in private contracts, investment mandates, internal limits, and collateral agreements (BCBS, 2010). Reliance on ratings also remains to some extent in existing risk-based prudential frameworks for banks and insurers, where such frameworks are largely based on international standards (e.g. the standardized approach to measuring credit ratings under Basel II Accord). All these thus make it imperative to model the determinants of these bank ratings to test their accuracy and predictive power.

Credit ratings are still very relevant in the market place, particularly in the pricing of the cost of borrowings. Poon and Firth (2005) argue that in the case of inter-bank lending there is a need for credit ratings because the lender needs to calculate the counterparty's capital adequacy ratio (as contained in the Basel II Accord) on the basis of such ratings. In a related way, credit ratings are also of great importance as they influence a firm's cost of debt and its capital structure, an argument supported by Graham and Harvey (2001) who find that CFOs of Fortune 500 companies consider credit ratings the second most important consideration after the maintenance of financial flexibility, when deciding whether to issue more debt.

The rest of this chapter is divided into the following sections: Section 4.2 examines the main factors considered by CRAs when assigning credit ratings to banks and reviews evidence from previous studies. Section 4.3 discussed the impact of the *CAMELS* framework on bank credit ratings. Section 4.4 examines other factors that could potentially impact on the assignment of a credit rating to a bank. Section 4.5 summarises the bank rating determinant hypotheses, while Section 4.6 presents the summary to the chapter.

4.2 The main determinants of bank credit rating

The first part of this section examines the criteria set by the major CRAs in assigning credit ratings to banks. This forms the basis for the empirical investigation of the determinants of bank credit ratings and aims to identify the broad categorization of these determinants. It further draws on previous studies that investigate the determinants of bank credit rating. A rating ranks the credit quality of say, a bank, in an ordinal fashion using coded letters assigned by the respective agencies. These rankings are mere ordinal numbers and not absolute values representing the level of risk. The rating of an entity aims to reduce information asymmetry between the issuer and other market participants, and as such, makes the market more efficient. CRAs stress that their ratings constitute opinions on the creditworthiness of an issuer or an issue, and not a recommendation whether to invest or not. The processes and methods employed by the major rating agencies vary widely. However, in general terms, CRAs rely on a variety of criteria ranging from qualitative factors such as competitive position and market share to quantitative assessment including financial variables (e.g. measuring balance sheet strength) in assessing the inherent risk of the issuer (the bank in this case). Rating a corporate entity will always involve some element of qualitative judgements, due to the large number of factors influencing the situation and riskiness of the entity.

The current business models employed by global banks are constantly changing, particularly in relation to raising capital and enhancing liquidity. Following the global financial crisis of 2007/8, banks have been modifying their business models to keep up with the dynamics of the environment and remain competitive. The need to raise more capital, enhance liquidity and perhaps exit from certain businesses (e.g. securitization) may provide greater stability in the banking industry and more stable bank ratings. The financial crisis has resulted in global and regional regulators shifting towards a more protective approach to ring-fencing capital and liquidity (Bank of England, 2015). Some of the changes in the global banking regulatory reforms since the financial crisis (e.g. CRR/CRD IV capital requirements, Basel III Accord leverage ratio (LR), liquidity coverage ratio (LCR), net stable funding ratio (NSFR), reforms in banking structures and the resolution regimes) have significant implications for the banking industry.

It is important that banks' risk exposures are backed by a high quality capital base. Evidence from the global financial crisis shows that bank credit losses and write-downs reduce the equity capital accounts, which is part of banks' tangible common equity base (BCBS, 2011). Further, in response to the regulatory shortcomings in the period leading up to the financial crisis, the Committee in 2009 completed a number of critical reforms to the Basel II framework (leading to the Basel III Accord). Banks are now, under the Basel III Accord, encouraged to estimate their capital requirement for counterparty credit risk using stressed inputs. This aims to address concerns about capital charges becoming too low during periods of compressed market volatility and helps address procyclicality. The issue of capital (particularly Tier 1 capital) constitutes an important factor in measuring a bank's credit rating. According to McKinsey (2012) banks are beginning to adapt their business models to fit in with the Basel III requirements, with greater collateralization of banking business and more capital-efficient product mix. With the Basel III Accord, banks are expected to raise the quality of capital, whilst other forms of regulatory capital become ineligible for regulatory purposes. Further, the European Banking Authority (2012) maintains that banks that qualify as systemically important financial institutions (SIFIs) will be subject to a capital surcharge. This thesis presents models employing measure of bank capital (the core Tier 1 capital) as potential determinant of bank credit rating.

It should be noted that in light of the global financial crisis, strong capital requirements by themselves are not enough to ensure the banking sector stability. A strong liquidity base reinforced through robust supervisory standards is of equal importance. It is interesting to note that during the 2007/08 global financial crisis, many banks despite their seemingly high capital-base still experienced challenges due to their inability to manage their liquidity in a prudent way. The global financial crisis further reiterated the importance of liquidity to the workings of the financial markets and in particular, the banking sector. The period just before the start of the crisis witnessed a boom in the global financial markets, with availability of funding at low cost (Salvador *et al*., 2014). With the crisis, the banking industry came under severe stress necessitating central banks' action to support both the functioning of money markets and, in some cases, individual institutions. With the enforcement of the new liquidity rule, there is bound to be a shift more towards deposits and a reduction in short-term wholesale funding reliance (EBA, 2015).

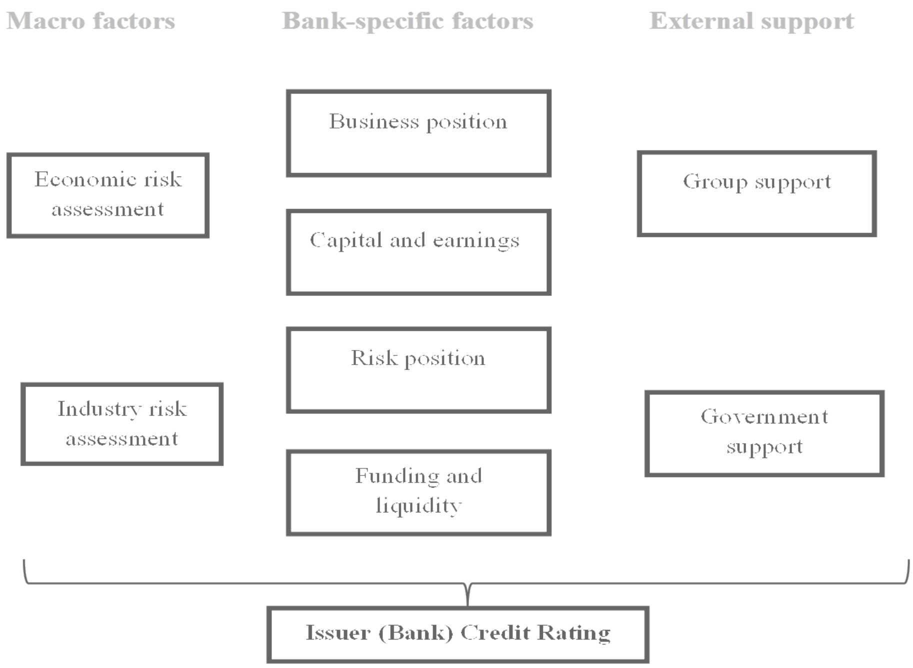
However, these are likely to increase the cost of funding and put pressure on banks' earnings in the short-term. With the changing bank business model with regards to liquidity requirements, this thesis captures the implications of the liquidity and earnings potential of banks on their creditworthiness and hence their overall credit ratings. This thesis employs a variety of variables that could potentially capture the importance of these changes in banks' business model on their creditworthiness. One of the important variables that the thesis employs is the too-big-to-fail (*TBTF*) variable. The size of a bank and its interconnectedness to other part of the economy both within and outside of the country of operations, makes it imperative to examine the *TBTF* effects on credit rating assignment. There is a growing recognition of the importance of SIFIs and this is contained in the Basel III reform where banks identified in this category are levied with a capital surcharge. With the Volcker committee's recommendation on ring-fencing banks and the separation of banking activities, there are bound to be a significant changes in the structure and models of banks globally.

Currently, in the UK, the Vickers commission's recommendations on the structural reform of the UK banking industry are already an integral part of the Banking Reform Act, 2013. The provisions of the Act are due to be in full effect by 1st January 2019. This will require the Prudential Regulation Authority (PRA) to carry out a review of proprietary trading activity within one year of the implementation of the retail ring fence (Bank of England, 2015). This model is being replicated in the EU with the Liikanen report (2012) following on from the recommendations of the Vickers commission (particularly on ring-fencing).

Overall, this thesis tests some of the issues raised and in particular, the bank-specific issues, by employing the *CAMELS* structure. The need for bank to look beyond the capital adequacy requirements, and focus on ways of meeting the other requirements within Basel III Accord (leverage ratio, liquidity ratios) are becoming increasingly important. In addition, this thesis tests the importance of the *TBTF* notion within its alternative bank credit rating determinant models.

Figure 4.1 presents the bank ratings framework drawn from the rating methodologies of the three main CRAs, i.e. Fitch, Standard and Poor's and Moody's. The framework summarises the key factors that drive the way ratings are assigned to banks by the major CRAs. The level of assessment of a bank's creditworthiness may be analysed at two levels, the macro-level analysis of the creditworthiness of a bank (economic risk and industry risk assessments), as well as the micro-level analysis, which captures a bank's business position, capital and earnings, risk position, and funding and liquidity positions. The major CRAs, in response to the 2007/08 financial crisis, reviewed and updated their bank rating methodologies and assumptions to make their processes more transparent. For example, S&P develop the *Stand-Alone Credit Profile (SACP)* and *Issuer Credit Rating (ICR)* for banks. The former considers the potential for additional direct support from the bank's parent group or the sovereign government. This is closely in line with Fitch's *Support Ratings.*

Figure 4.1: Framework for bank credit ratings



Source: Author's conceptualization of the drivers of bank credit rating

Due to the sensitive nature of the banking industry, Fitch (2007) maintains that apart from issuing the conventional long term rating to banks, support ratings are also issued. The support rating aims to provide an opinion on whether a bank would receive support (particularly from government) should this become necessary. The support rating assigned by Fitch can provide more useful information, particularly following the financial crisis as the market may be better informed on the worst case scenario, i.e. when nobody steps in to rescue a bank. Hence, the nature of external support adds to the other two sets of factors in the analysis by providing additional information on the level of support a bank will receive if it becomes necessary. The Eurozone crisis and market speculation on the level of support for sovereign countries within the EU, and in particular Greece, further intensifies the pressure on banks within that zone.

Fitch (2007) maintains that the need to constantly review the market and individual fundamental factors influencing bank ratings is driven by the changing operating environment for banks globally. They further argue that following the onset of the financial crisis some large and highly rated banks face downside pressure. The global financial crisis, and especially its ripple effects throughout the Euro zone, directly impacts on sovereign and bank ratings not just within the EU zone, but globally. Despite the global financial crisis, Fitch maintains that there is a need to employ a consistent ratings framework to reflect a changing world. They argue that there will be no material changes in its rating methodology over the medium term (Fitch, 2007), though the need for an assessment of extraordinary support as captured by Fitch's support rating is reinforced. One may argue that support is more meaningful for banks as banks tend to fail rather than default (with the difference being the provision of support).

Bank-specific analysis (micro-analysis) is largely quantitative in nature. It involves the popular *CAMELS* approach, i.e. the analysis of bank's capital adequacy, assets quality, management, earnings, liquidity, and sensitivity to the market. The analysis involves measuring a bank's business position, capital and earnings, risk position, funding and liquidity. Business position here measures the strength of a bank's business operations, combining a bank's business stability, concentration, management and corporate strategy. The business stability factor is an assessment of the ability of a bank to enjoy continuous operation at the same business level in the face of economic and market fluctuations. A bank's business stability is important for instilling confidence in market participants, especially during financial crises or turbulence in the market. The financial crisis has shown that banks that were exposed to large trading operations, and in particular derivative and structured product markets, are more sensitive to an erosion of confidence. Concentration and diversity of business activities are measured by the contribution of different business lines and geographical locations to a bank's revenues, compared with banks of a similar industry risk (Fitch, 2007). Banks with a broader mix of business activities tend to have lower risk, and those with a narrower mix have higher risk. The management and strategy factor considers the management's ability to execute operational plans in a consistent manner.

Rating agencies maintain that they rate through-the-cycle, that is, firm rating is independent of the state of the business cycle and any short term variation in economic conditions. This position ensures the stability of ratings (Altman and Rijken, 2004). One may argue however that changes in the micro (firm-specific) drivers of bank performance are greatly influenced by the stability or otherwise of the operating macro-environment and fluctuations in the business cycle. Hence there is a certain level of comovement between the likelihood of a change in rating and the overall trend in the level of economic activity of a country. CRAs score the economic risk of the countries in which a bank operates in order to capture the economic risk of that bank. Some of the factors that are taken into consideration here include economic and policy flexibility of a country, as well as the credit risk of the contributors to the economy, i.e. households and enterprises (Fitch, 2007). CRAs employ the proportion of a bank's business in each country to weight the economic risk score.

Over the last couple of decades there have been periods of boom and economic downturn, and evidence shows that market participants are countercyclical in their risk perception (Lown *et al.*, 2000). For example, there is more stringency in the requirements and monitoring of, say, a loan portfolio during an economic downturn, with regulatory authorities tending to be more lax in times of boom than in slowdowns. There have been quite a number reforms and regulatory oversights on the credit rating industry, particularly in the US. In 2006, the US congress passed the Credit Rating Agency Reform Act which required the US Securities and Exchange Commission

(SEC) to set out strict guidelines for determining the CRAs that qualify as Nationally Recognised Statistical Rating Organisations (NRSROs). Being a member of the NRSRO confers a lot of advantages upon a rating agency, particular in their use by global regulators such as the Basel Committee on Banking Supervision. Even though the law prohibited the SEC from regulating an NRSRO's rating methodologies, the *Dodd-Frank Wall Street Reform and Consumer Protection Act* added new requirements for NRSROs. The Act focuses on internal control, conflict of interest with respect to sales and marketing practices, application and disclosure of credit rating methodology, as well as specific and additional disclosure for ratings related to Assets Backed Security (ABS) products.

Following the financial crisis, the UK's Financial Conduct Authority in 2011 proposed the Credit Rating Agencies Regulations III which has now passed to the European Parliament and the Council for negotiation. The major hallmarks in this proposal are the need for more diversity and stricter independence of CRAs to address conflicts of interest. In addition, it seeks to make CRAs more accountable for the ratings they provide, by allowing investors to bring civil liability claims against a CRA before national court where the CRA had infringed either intentionally or with gross neglect. All of these have implications for the way CRAs rate firms, particularly banks. In order to correctly assign ratings to an entity (say, a bank) there is a need for CRAs to determine and analyse bank-specific drivers of strength and performance.

4.3 CAMELS and bank credit rating assignments

This section examines the impact of the measure of bank fundamental performance indicator (i.e. *CAMELS*) on bank credit rating. Determining the credit rating of a bank requires detailed analysis. However, it is difficult to use the same set of criteria as CRAs in modelling bank credit ratings due to the limited guidance provided by such agencies on the weighting assigned to each of the factors. Further, the choice of the variables employed in any empirical study reflects data availability for each bank in a given sample.

This thesis follows the popular classification of *CAMELS* and guidance from the categorization as presented in BANKSCOPE database when identifying the micro (or bank-level) determinants of bank credit ratings. There are a significant number of financial ratios grouped under the *CAMELS* classification. Thus, the hypotheses that are proposed will only capture a broad classification of financial variables, e.g. capital adequacy, asset quality. Further, due to the potentially high level of multicollinearity that exists within the variables of each group, hypotheses will not be stated for specific financial ratios. The treatment of multicollinearity is discussed in Section 5.4.1. The following sections will discuss the broad implications of each of the financial ratio categories.

4.3.1 Capital adequacy

Credit risk in banks cannot be discussed without the consideration of capital adequacy standards. Banks and other financial institutions are subject to a range of controls, especially from regulatory bodies both within and outside their domicile countries, and one such regulation is the level of capital that they must hold to provide a cushion to meet any operating losses incurred. National regulators require banks and other financial institutions to hold a level of capital adequate to protect against credit, market, interest rate, operational and other risks. Capital adequacy is the central focus of the Basel Committee on Banking Supervision, which is the body charged with the responsibility of providing global regulatory guidance for banks. A capital requirement proposed by the Bank for International Settlements, i.e. the BIS regulatory requirement or the Basel capital ratios, has been universally adopted since 1988 (Basel I Accord).

The Basel rules on regulatory capital were motivated by the increasing number of banks engaged in cross-border operations.

The pre-financial crisis capital regimes failed to provide the needed protection to the financial system when the crisis started. Demirguc-Kunt *et al.* (2013) argue that many of the banks that were bailed out in the wake of the financial crisis complied with minimum capital requirements. With the introduction of new capital standards in Basel III Accord, there is the expectation that bank capital will help reduce risk-taking incentives by banks and further provide a buffer to absorb unexpected negative shocks in the market. Basel III Accord aims to strengthen the link between risk taking and capital requirements. The provisions of Basel III Accord include, amongst others, stricter requirements on banks concerning risk management and information disclosure.

There are a number of empirical studies on the impact of bank business models on bank risk and performance during the 2007/08 global financial crisis. Beltratti and Stulz (2011) find that banks with more Tier 1 capital and a higher ratio of loan to total assets performed better in the initial stages of the crisis. Similarly, Berger and Bouwman (2011) show that during banking crises higher capital levels improve bank performance, while a larger deposit base and more liquid assets are associated with higher returns. Cole and White (2012) show that higher levels of capital and stronger *CAMELS* ratings lower the likelihood of bank failure. Similarly, Altunbas *et al.* (2011) find that banks with higher risk are larger and have less capital, greater reliance on short-term market funding, and aggressive credit growth.

Despite the increased attention on capital requirements by banks, coupled with the ability of the capital adequacy ratios to indicate the level of cushion for losses and the exposure of banks to risks, some studies indicate that capital requirements may actually increase risk-taking behaviour (Koehn and Santomero, 1980; Besanko and Kanatas, 1996; Blum, 1999), while others (Kendall, 1991; Beatty and Gron, 2001) provide mixed results regarding the contribution of capital requirements to a bank's risk-taking.

Koehn and Santomero (1980) maintain that in order to establish an explicit relationship between the risk of a bank portfolio, the amount of bank capital held and the chance of bankruptcy, there is a need to establish the characteristics of the distribution of the returns from bank operations. In other words, one would expect that a less risk-averse bank would hold risky securities and therefore would be closely watched by regulators. However, the imposition of a higher required capital-asset ratio on such banks may well have a perverse effect. They argue that for such banks, it would appear that the regulators should find some other instruments to control for the probability of failure, such as asset restrictions, or abandon attempts that essentially prove counterproductive. Regulating bank capital through ratio constraints, therefore, appears to be an inadequate tool to control the riskiness of banks and the probability of failure. Other authors argue that capital requirements reduce monitoring incentives, which could lead to a possible reduction in the quality of banks' portfolios (Besanko and Kanatas, 1996; Boot and Greenbaum, 1993).

This thesis models a variable that proxies for the core (Tier 1) capital adequacy for banks within the bank credit rating determinant framework. The motivation for this is the potential policy implications of the findings for the current regulatory reforms. The current discussion and general intuition is that a stronger capital position should enable banks to cope better with market shocks, particularly during a systemic crisis. With the approval in Europe of the CRD IV, the directive which implements the guidelines that define the new agreement on the minimum capital requirements imposed on banks by the Basel Committee, an investigation of the impact of capital adequacy becomes extremely important. The strengthening of capital requirements under Basel III Accord could be perceived by rating agencies as being positive and as such, banks with higher quality capital in the form of Tier 1 capital could be assigned higher ratings.

4.3.2 Asset quality

Asset quality is perhaps the most important part of bank analysis as it is the main driver of future earnings. Loan portfolios generally represent the largest proportion of a bank's assets, and so analysis will focus on loan quality and the conservatism of loan loss provisioning. Poghosyan and Čihak (2011) show that the asset quality and earnings profiles of banks are important determinants of bank distress next to leverage, suggesting that these should be central to EU-wide financial regulation and supervision. For many commercial banking institutions, lending is at the heart of their business and thus loan portfolios are generally the biggest component of a bank's asset holdings and account for a large share of revenues and costs. Analysis of the quality of this asset class is very important and indicative of the banks' balance-sheet strength.

The sovereign crisis in the EU and, in general terms, the macroeconomic conditions following the global financial crisis, impact negatively on banks' risk and solvency profiles. Farag *et al.* (2013) argue that the main negative outcome relates to the deterioration in the credit risk with an increase in bad debts and non-performing loans exposure. All these have significant consequences for risk in the banking industry. Risks to the solvency of banking institutions very often originate from an impairment of assets, which in turn leads to deterioration in the financial health and profitability of the institution's borrowers. Thus, the quality of a bank's loan portfolio affects the financial health and viability of that bank. Information asymmetry and moral hazard can also result in a reduction in the quality of a loan portfolio. In general, the less transparent the credit information about a particular borrower is, the greater is the bank's risk of default if credit is extended to such a borrower. However, if banks can utilize their uniqueness in gathering vast amounts of information about borrowers, and recycling this information, they can potentially enhance their profitability. In the case of moral hazard, when the borrower takes a loan from a bank, an agency problem may arise in the relationship between the borrower and the bank. The borrower for his part may take on additional risk to the detriment of the bank, hence increasing the likelihood of defaulting on the loan and consequently reducing the quality of the bank's assets.

Borio and Drehman (2009) argue that the r2007/08 global financial crisis and strain on bank funding are closely connected due to the weaknesses on the asset side of banks' balance sheets which tends to trigger funding problems. For banks to achieve financial stability, they must maintain a high quality of assets in their portfolio. The failure to ensure banking stability can cause financial fragility and may lead to a crisis in the event of market illiquidity and/or bank contagion (Swamy, 2015). The EBA (2013) recommendation on asset quality review further illustrates the importance of banks' credit portfolios, including risk classification and provisioning, particularly in maintaining strong financial stability and to support the efforts to provide adequate capital levels to cover the risks associated with these exposures. The report requires banks within the EU to undertake asset quality reviews (AQRs) of their asset classes considered to be high risk. This is consistent with the establishment of the the Single Supervisory Mechanism (SSM) which is a new system of banking supervision for Europe, whose aims are to ensure the safety and soundness of the European banking system, increase financial integration and stability and ensure consistent supervision (ECB, 2015).

There is no doubt that exposure to credit risk continues to be the leading source of challenge to banks and supervisors across the world. With the new Basel III reforms, banking supervisors globally are being encouraged to promote sound practices for managing credit risk. Hence, banks are reinforcing their internal credit risk control process and making provisions to hold adequate capital against these risks (Iannotta and Pennacchi, 2012). This thesis recognises the importance of bank asset quality in the modelling of bank credit ratings. With the renewed call by regulators such as the European Central Bank (ECB) to carry out comprehensive audit stress-tests of bank balance sheets, the assessment of asset quality, asset valuations, and classifications of non-performing loan exposures, collateral valuation and provisions become very relevant to modelling bank credit rating.

4.3.3 Management

The issue of corporate governance is important in the rating of banks because poor corporate governance can easily lead to a bank's financial distress. BIS (2010) maintains that there is a broader implication for banks of not being adequately governed in that it presents a significant cost burden on the public and central bank as lender of last resort, particularly in times of financial crisis. Good corporate governance should provide an incentive for bank management staff and members of the board to pursue the overall interests of the bank and its shareholders. The global financial crisis brought to light a number of corporate governance failures, particularly around board practices, inadequate risk management and internal control, compensation, disclosure and transparency (Laeven and Levine, 2009). Grandmont *et al.* (2009) argue that this failure in corporate governance could have been easily avoided if an adequate governance mechanism had been in place. All of these governance factors have implications for the way rating agencies assign ratings to banks.

The House of Commons Treasury Committee (2009) report highlights the corporate governance failings in the run up to the 2007/08 financial crisis. It maintains that the system of compensation operating in banks contributes in an important way to the crisis by encouraging not just risk-taking, but encouraging excessive risk-taking. One may suggest therefore that the bonus culture in the banking sector creates incentives for taking undue short-term risks rather than taking a longer-term view. In addition, governance failings on the part of non-executive directors to act as an effective check on, and challenge to, executive managers further aggravates the crisis. All these have significant effects on risk management in banks which failed to predict the crisis. Hence, banks were led to falsely believe that their risk had been well managed and diversified by securitisation.

The importance of corporate governance in the overall performance and monitoring efficiency of the banking industry is further underlined by the Basel Committee on Banking Supervision (BCBS). It maintains that corporate governance is important to facilitating a sound financial system. Banks are structurally very complex and opaque in terms of their internal operations and disclosure, thus increasing the level of information asymmetry between shareholders and management. Levine (2004) argues that complexity in banks can take a variety of forms from the quality of loans not properly assessed to financial engineering not being clear. Overall, bank complexity exacerbates the governance problem and presents significant implications for the type of internal risk management processes that are in place.

Zhuang (1999) argue that ownership structure is one of the most important factors in shaping the corporate governance system of banks and that it determines the nature of the agency problem. A lack of transparency has often been cited as contributing heavily to the 2007/08 global financial crisis (Acharya *et al.,* 2010; Dudley 2009), hence one may argue that the financial sector cannot function properly without a sufficient amount of disclosure. The corporate governance issue is further aggravated by the possible effects of insiders or controlling shareholders exercising an inappropriate influence on a bank's activities. In order to maintain a high level of corporate governance, there is a need for banks to have an adequate number and appropriate composition of board members. This thesis makes a significant contribution to the literature by addressing the issue of corporate governance within its various bank credit rating model specifications. It proxies for the influence of three corporate governance measures – the number of independent board directors (non-executive directors –NED), the percentage of directors' ownership, and the influence of institutional ownership. The FCA (2015) maintains that the primary role of all NEDs is independent oversight and challenge of the Executive.

Rating agencies claim to examine the independence of board members and top management staff from major shareholders, and maintain that weak corporate governance can greatly impair a bank's credit quality (Fitch, 2007). Shareholders see the board as the first line of defence on issues pertaining to governance. This has motivated major credit agencies to issue corporate governance ratings which in conjunction with the traditional ratings can help reduce information asymmetry between shareholders and banks (Balling *et al*., 2005). Further, Ashbaugh-Skaife *et al.* (2006) argue that the most important cause of high profile cases of corporate fraud and increases in debt financing cost is weak corporate governance. They maintain that a weak governance structure leads to a downward shift in a firm's future cash flow distribution resulting in a higher likelihood of default and a lower credit rating. Some aspects of corporate governance may also motivate shareholders to compel management to take on riskier projects by using their voting powers. This has the potential to increase the likelihood of default, causing lower ratings.

A number of prior studies in the area of corporate governance concentrate on board independence, institutional ownership structure, and financial transparency and disclosure considerations. The existing literature maintains that there is a positive relationship between board independence and firm performance, implying that better firm performance should result in higher credit ratings. Issues concerning board independence focus on board size and composition, i.e. the proportion of outside and inside directors, board leadership and committee structure, and the engagement and competence of board members (Ashbaugh-Skaife *et al.,* 2006). However, Agrawal and Knoeber (1996) and Bhagat and Black (2000) find no positive relation between board independence and firm performance. Agrawal and Knoeber argue that the significant negative relation between outside membership on the board and firm performance could be due to having too many outsiders on the board. In a related study, Klein (1998) finds no relation between overall board composition and firm performance. However, she finds a positive relation between inside directors with expertise in finance and investment and firm performance.

Bank directors in particular need to bring to the board a unique set of skills and expertise, in particular in their ability to understand and analyse risk positions. Evidence shows that financial expertise is very important, particularly for independent board members. Knowledge of the banking industry, the financial regulatory system, and the law and regulation governing the operation of a banking institution are very important. Bhojraj and Sengupta (2003) however, contend that firms with a greater proportion of outside (independent) directors on the board have a stronger governance culture, and enjoy reduced agency risk and hence higher credit ratings. Generally, one may argue that independent directors (non-executives) have limited conflicts of interest, thus resulting in a positive relationship with bank value. De Andres and Vallelado (2008) argue that an excessive proportion of non-executive directors could damage the advisory role of boards since it might prevent bank executives from joining the board.

Ownership structure relates to the blockholders and institutional shareholders in a company, and plays an important role in determining credit ratings. Jensen (1993) finds that blockholders that hold large equity positions add value to a well-functioning governance system because they help minimize any agency problems by applying their power to put pressure on management. Similarly, Shleifer and Vishny (1986) argue that, due to their block voting rights, active institutional investors or blockholders can exert corrective actions and monitor a management's opportunistic behaviour. Along the same lines, Opler and Sokobin (1997) argue that firms with a large proportion of active institutional shareholders are characterised by above-market performance. The extant literature also provides evidence to support the argument that high levels of institutional ownership and/or blockholders are not necessarily associated with better credit quality (Bhojraj and Sengupta, 2003; Cremers *et al.,* 2004). Similarly, Bhojraj and Sengupta maintain that a high percentage of institutional ownership and/or blockholders are not necessarily associated with better ratings. The top management of banks may exert greater influence for their own benefit which may be detrimental to other capital providers.

Studies also show that financial transparency is critical in reducing asymmetry between the firm and its funding providers. Ashbaugh-Skaife *et al.* (2006) argue that greater financial transparency encourages the monitoring of management behaviour and makes it less likely for management to take advantage of their position. Similarly, Sengupta (1998) argues that firms that are transparent and have good disclosure policies are perceived to be less likely to withhold unfavourable information, and as such may be viewed as less risky, and assigned a higher credit rating. Other studies (Fama and Jensen, 1983; Minow and Bingham, 1995) maintain that directors' shareholdings are a determinant of credit ratings. They argue that increasing the shareholding of directors provides them with the motivation to improve corporate performance due to sharing some of the financial risk of the firm with other shareholders. However, this may also lead to an accumulation of voting rights, giving them the power to keep themselves in office.

For the purposes of modelling, Ashbaugh-Skaife *et al.* (2006) measure institutional ownership as the percentage of outstanding shares held by institution investors, while the number of outside blockholders that owns 5% or more of a firm's outstanding voting stock is employed to represent 'significant shareholders'. Moreover, board independence is defined as the percentage of the board made up of independent outside directors. These measures are common to related studies (e.g. Agrawal and Knoeber, 1996; Bhojraj and Sengupta, 2003). In general, results from existing studies support the hypothesis that there is a significant positive relation between institutional ownership, board independence, director ownership, and firm credit ratings.

The special role played by banks in the economy means that the industry is heavily regulated. Thus regulation may play an important part in monitoring and serves as an added governance mechanism for banks. However, regulatory rules and policies may also aggravate the governance problem, e.g. the regulator might limit the power of markets to discipline banks (Ciancanelli and Reyes-Gonzalez, 2000) or discourage competition by restricting ownership structure (Macey and O'Hara, 2003).

The issue of governance may also be extended to bank efficiency. There is a close relationship between bank efficiency and bank risk in general. Earlier studies by Berger and DeYoung (1997), Kwan and Eisenbeis (1997) and Pastor and Serrano (2005) establish a relationship between bank efficiency and the determinants of bank risk. Berger and DeYoung (1997) find that falls in cost efficiency precede increases in problem loans (the latter further leading to a reduction in cost efficiency. Treacy and Carey (2000) suggest that when analysing a bank credit rating, CRAs should consider numerous factors, including cost and efficiency of information gathering. A review of literature shows that there are several approaches to measuring the efficiency of financial institutions. One of the efficiency ratios popularly employed in literature is the cost-to-income (CI) ratio. This ratio is defined as non-interest expense divided by the sum of net income and non-interest income (Hess and Francis, 2004). It is an important benchmark, particularly among publicly traded banks (Cocheo, 2000). A number of studies find negative relationships between cost efficiency and problem loans (Kwam and Eisenbeis, 1994; Resti, 1995). The evidence suggests that cost-inefficient banks tend to have loan performance problems and this may potentially increase the overall credit risk of bank.

In light of the continued importance of corporate governance, and the implications for regulatory reforms (such as those in Basel III Accord), this thesis seeks to make a significant contribution to the body of knowledge by modelling proxies of corporate governance in bank credit rating model specifications. The BCBS (2013) report emphasizes the critical importance of effective corporate governance for the safe and sound functioning of banks, and this position is part of the motivation for this study. By stressing the importance of corporate governance as part of a bank's overall strategic framework and promoting the value of strong boards and board committees, the BCBS underlines the importance of a sound risk culture in driving risk management within a bank.

4.3.4 Earnings

The earnings of a bank influence the level of rating assigned because the higher the earnings capacity of a bank, the less risky it becomes in terms of debt repayment. A bank’s credit risk strategy recognises the goals of credit quality, earnings and growth (Shen and Lu 2005). The effective management of this category of risk is thus critical to the earnings and balance sheet of banks. Thus, a bank manages this risk to maximize its long-term results by ensuring the integrity of assets and the quality of earnings. The price for taking credit risk must be sufficient to compensate for the risk to earnings and capital. Incorrect pricing can lead to risk/return imbalances, lost business, and adverse selection (Healy and Wahlen, 1999). Rajan (2005) argues that risk in banking is synonymous with earnings volatility. This earnings volatility has the potential to create losses which imposes a need for a bank to hold capital buffer. Every bank, regardless of size, is in business to be profitable and, consequently, must determine the acceptable risk/reward trade-off for its activities, factoring in the cost of capital.

Pettit *et al.* (2004) and Poon *et al.* (2009) maintain that profitability is important in credit rating assignment because the level of profitability is necessary for banks to support growth and for other long-term strategic plans. Previous studies in the area of bank credit ratings employ diverse measures of earnings/profitability in their rating models. However, most tend to employ the return on assets (ROA), the return on equity (ROE), the net interest margin, non-interest expenses to gross income, and interest margin to gross income (Poon *et al.,* 2009; Distinguin *et al*., 2012; Hau *et al*., 2012). In general, empirical studies find a strong positive relationship between profitability and credit ratings, that is, the more profitable a firm, the higher its credit ratings.

4.3.5 Liquidity

The primary business of a bank is to act as an intermediary for both the surplus and deficit parts of the economy. Liquidity ratios are very important to banks because they give an indication of whether or not banks can meet expected and unexpected demand for cash. The level of liquidity thus influences the ability of a bank or the entire banking system to withstand shocks. Assessing the extent to which an asset is liquid or not requires considerable judgement, especially for traded securities, due to the dependence on the liquidity of the secondary markets on which the securities are traded. Banks with sufficiently high liquidity are able to better withstand large shocks in the market or economy and this can strengthen the confidence of market participants and depositors in the banks as well as in the broader banking sector. Thus, liquidity or liability management is a measure of the ability of the bank to finance itself under stress. Access to funding is used to gauge the creditworthiness of the bank, and is especially important for banks without a large deposit base.

Fight (2000) argues that liquidity is an indicator of financial flexibility for a company since it portrays the ability of the company to carry out its activities, even in difficult times, without undermining its credit quality. However, for corporate organisations, having a large amount of 'idle' cash in hand may be a signal that the company is not able to identify valuable investment opportunities; hence liquidity may be negatively related to credit ratings. Similarly, Demirovic and Thomas (2007) argue that a negative relationship between liquidity and credit ratings is possible because the ratios employed in empirical studies may not necessarily proxy for the day-to-day liquidity requirement of banks. For banks, the measure of liquidity is slightly different from that of other non-banking institutions. Poon and Firth (2005) employ six variables to represent liquidity. These are the interbank ratio, loans to total assets, loans to short-term funding, loans to total deposits and borrowings, liquid assets to short-term funding, and liquid assets to total deposits and borrowings. After eliminating those liquidity ratios with high correlations, they employ the ratio of loans to total assets. Loans to total assets represent the percentage of assets of the bank that are tied up in loans. Poon and Firth argue that the higher this ratio is, the less liquid the bank is, and hence the lower the bank's credit rating. Their results confirm that loans to total assets negatively affect credit ratings. Similarly, Poon *et al*. (2009), using that same liquidity variables, find that liquidity is significantly positively related to the credit ratings of banks.

The liquidity risk and credit risks, individually and jointly, have a great influence on the probability of default of a bank. According the Bank for International Settlements, liquidity is the ability of a bank to fund increases in assets and meet obligations as they come due, without incurring unacceptable losses (BIS, 2010). Liquidity risk is the risk that a bank may face difficulty in meeting or financing its short-term commitments. Put differently, liquidity risk is the risk to an institution's financial condition or safety and soundness arising from its inability (whether real or perceived) to meet its contractual obligations (Nikolaou, 2009). In that sense, the probability of not being liquid would suggest that there is liquidity risk. Fundamentally, banks are constantly engaged in the role of maturity transformation of short-term deposits into long-term assets. This makes them vulnerable to liquidity risk. This funding requirement, that is, the funding liquidity risk, can potentially result in a system-wide implication if there is liquidity shortfall. Morris and Shin (2009) argue that a run on a bank could potentially undermine its long-term creditors and suggests that the measure of bank credit risk incorporates the probability of default due to a run (on its short-term commitments). Gopalan *et al*. (2009) argue that there is a greater tendency to observe downgrades if rating agencies underestimate liquidity risk in the process of assigning ratings.

Credit rating has been argued to be a good measure of credit risk (Hilscher and Wilson, 2013). The majority of bank failures in the past have been linked to the poor management of credit risk. Credit risk is the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms (BIS, 2010). Failure to do this will lead to a deterioration of the asset portfolio and subsequently a decline in the overall creditworthiness of a bank (downgrade). For banks, the major sources of credit risk include loan portfolio, interbank transactions, and banking activities, including the derivative markets.

There is a strong relationship between liquidity and credit risks, and evidence indicates that liquidity risk impacts directly on a bank's probability of default (Brunnemeier and Pedersen, 2007; Imbierowicz and Rauch, 2014). Several other studies (Wagner, 2007; Cai and Thakor, 2008; Gatev *et al.,* 2009; Acharya *et al*., 2010; He and Xiong, 2012a) show the influence that liquidity and credit risk have on each other and also how this interaction influences bank stability. Acharya and Mora (2013) examine the role of banks as liquidity providers during financial crises and provide evidence that banks that failed during the crisis suffered from liquidity shortages just before the actual default. This suggests that distressed banks faced severe liquidity issues, especially in comparison to healthy banks. Credit rating agencies may perceive this as being negative and assign a lower rating to a bank or downgrade it a result.

In the existing empirical studies, liquidity tends to be positively related to credit ratings and most of the time is statistically significant. Furthermore, Poon (2003) and Doumpos and Pasiouras (2005) find that liquidity ratios are significantly positively related to credit ratings. Interestingly, Poon and Firth (2005) find that banks with unsolicited ratings are less liquid than banks with solicited ratings. Finally, Adams *et al.* (2003) argue that liquidity is not only a determinant of whether a UK insurance company will get rated or not by a CRA; it also plays an important role in the actual credit rating that the CRA assigns.

4.3.6 Sensitivity to the market

Business risk provides another set of factors employed by CRAs in determining a bank's rating. CRAs assess the business risk of the banking industry by examining the institutional framework in a given country, including the quality and effectiveness of the regulatory authorities, and how the regulators manage financial crises or shocks within financial markets. Further, rating agencies claim to examine the competitive landscape and performance of banks, including the variety of its financial products and services. The level and dynamics of competition within the industry determine the degree of use of complex financial products. The greater the propensity to use complex financial and structured products, the higher the industry risk. Over the past couple of decades, there has been a significant level of deregulation in the financial industry, and many banks now operate internationally (Brei *et al*., 2013). This implies that the strength and effectiveness of a bank's home and foreign regulatory framework are very important. Empirical evidence (e.g. Blume *et al*., 1998; Amato and Furfine, 2004) suggests the use of an industry beta to capture business risk.

Further, Fitch (2007b) maintains that in analysing the market or business risk they cover 'all structural and trading risks across a bank's entire business, including on- and off-balance sheet business' (p. 6). They contend that the analysis of market risk is in line with the requirement stipulated in the Basel II Accord. Amato and Furfine (2004) consider three measures of business risk: firm size, market beta, and the residual standard error from the market model estimation. A number of studies have tested the effect of market beta (a proxy for systematic risk) on credit ratings, and the results show a significant negative relationship. Amato and Furfine, following Blume *et al.*, separate equity risk into its systematic (beta) and idiosyncratic (non-beta) components in order to capture the relative sensitivity of firms to aggregate business conditions (measured by beta). The idiosyncratic variation in equity return captures unique firm specific factors such as the ability of management (Laeven and Levine, 2009). The market model consists of equity data for up to 200 days to the reference date for each rating observation. To adjust for non-synchronous trading effects, i.e. the effects of infrequent trading on time series properties of assets, both studies employ the Dimson (1979) procedure and standardize the estimates of beta and standard error by averaging across all firm estimates for the year in which they are calculated. The studies find that the coefficients of both the market model beta and the market-model standard errors are negative and significant at the 10% level. This is an indication that on average a firm is sensitive to business conditions, and its rating may be conditional on them.

Despite the development of market-based credit ratings (e.g. Moody's KMV), rating agencies generally claim not to allow for market factors (e.g. share prices) to feature in their rating processes. Kaplan and Urwitz (1979) argue for the inclusion of an indicator of market risk, i.e. the market beta of firms. They maintain that market beta integrates a firm's operating and risk characteristics, thus any changes in a fundamental financial ratio indicator is reflected in the market beta and hence may affect a firm's creditworthiness and its overall credit rating. This finding is consistent with Blume *et al.* (1998) who argue that market-based risk measures provide information about a company's creditworthiness. They thus hypothesise a negative relationship between credit ratings and beta. Other studies (e.g. Allen and Saunders, 2003; Gan, 2004; Gray *et al*., 2006) also argue in support of a negative relationship between credit rating and beta. Gray *et al*. maintain that firms with higher expected equity betas tend to have lower ratings, and find evidence of a negative and marginally significant industry beta coefficient. Similarly, Gan argues for the inclusion of beta as a determinant of credit ratings.

In addition to the two measures of business risk (market beta and idiosyncratic stock returns variations), this thesis employs the *Z-score* to measure overall bank risk. Following the literature (Roy, 1952; Laeven and Levine, 2009), the Z-Score is calculated as the ratio of the sum of the return on assets (RoA) and the capital ratio, divided by the standard deviation of the return on assets. The Z-score measures the number of standard deviations a bank's return on assets has to decrease from its expected value before the bank is insolvent because equity is depleted (Roy, 1952). Accordingly, a high Z-score indicates low bank risk. As the regular score is highly skewed, a natural logarithm is applied to the Z-score following Laeven and Levine (2009) and Houston *et al.* (2010).

4.4 Other factors that impact upon bank credit ratings

This section discusses other potential factors that impacts on the assignment of credit rating to international banks.

4.4.1 Bank size

Size has been employed in a number of studies (Poon *et al.,* 2003; Amato and Furfine, 2004; Caporale *et al*., 2009; Distinguin *et al.,* 2012) to capture some of the qualitative characteristics of banks such as geographical presence, competitive position, market share, and product and brand recognition. The major CRAs argue that size may proxy for diversification of activities undertaken by a bank, especially in domestic and international operating environments, and takes into account a bank's franchise and its ability to protect existing business and gain new business. The size of a bank may also be linked to the concept of *too-big-to-fail* (TBTF) which highlights the role of governments in keeping banks afloat due to their magnitude and interconnectivity with other parts of the economy. Allowing banks to fail can cause significant damage to the financial system and the economy, as observed in the global financial crisis. Galil (2003) maintains that TBTF distorts free markets, motivates risky behaviour on the part of the banks and creates unwholesome and unfair competitive advantage for the largest banks. All of these factors can have significant influence on the creditworthiness of a bank. Fitch (2007), in its rating methodology criteria, creates a rating type for banks to capture the level of support banks would receive if they ran into difficulties, i.e. Fitch Support Rating. It also maintains that it analyses the stability of the shareholder structure, as well as the bank's ability to attract support willingly from its owners and home government if needed. Indeed, large banks may arguably become too big to be downgraded by rating agencies (Melaschenko and Reynolds, 2013). International banks have become extremely large and complex, and interconnected with the rest of the financial system. A downgrade of a 'TBTF' bank can trigger a loss in market confidence as well as contagion in the entire financial sector.

Demirovic and Thomas (2007) argue for the need to adopt the market value of assets as a measure of size over historic book value, maintaining that the former is more correlated with long-term credit ratings. They find firm size to be significantly positively related to corporate creditworthiness. Similarly, Amato and Furfine (2004) and Gonzalez *et al.* (2004) argue for the use of market-based values to measure size as this incorporates an element of business risk, though this may also be susceptible to noise and other non-credit events in the market.

Table 4.1 presents Fitch support ratings which maintain the assumption that necessary support is provided on a timely basis. For banking institutions, one measure of bank size is the value of the assets (usually total assets) as stated on the balance sheet. The bigger a bank, the more diversified its asset base and therefore the lower the default risk. Size is usually expressed as the natural logarithms of total assets, to enable 'diminishing returns to scale in respect of diversification' (Galil, 2003: 19).

Table 4.1: Fitch support rating criteria

Fitch support ratings	Definition
1	A bank for which there is an extremely high probability of external support. The potential provider of support is very highly rated in its own right and has a very high propensity to support the bank in question.
2	A bank for which there is a high probability of external support. The potential provider of support is highly rated in its own right and has a high propensity to provide support to the bank in question.
3	A bank for which there is a moderate probability of support because of uncertainties about the ability or propensity of the potential provider of support to do so.
4	A bank for which there is a limited probability of support because of significant uncertainties about the ability or propensity of any possible provider of support to do so.
5	A bank for which there is a possibility of external support, but it cannot be relied upon. This may be due to a lack of propensity to provide support or to very weak financial ability to do so.

Source: Fitch Ratings – Definitions of ratings and other forms of options (2014) *Used with permission of the publisher

For banking institutions, one measure of bank size is the value of the assets (usually total assets) as stated on the balance sheet. The bigger a bank, the more diversified its asset base and therefore the lower the default risk. Size is usually expressed as the natural logarithms of total assets, to enable 'diminishing returns to scale in respect of diversification' (Galil, 2003: 19). Another argument for the transformation by the natural logarithm is that it helps normalise the distribution of assets (Altman, 1968). In a related study, Hau *et al.* (2012) reveal a systematic relationship between the direction (bias) of rating errors and bank size. They maintain that rating agencies assign more favourable ratings to larger banks relative to their expected default risk measured two years later. Further, they argue that there is an incentive for rating agencies to be biased towards large banks, and find that the accuracy of ratings decreases with bank size, i.e. larger banks are characterized by upwardly biased ratings. Hau *et al.,* argue that larger banks are usually more complex and thus more difficult to rate, and this may increase both positive and negative rating errors associated with size as a rating criterion. However, one can argue that size increases with diversification, larger market share and stability, implying a counteracting effect upon the accuracy of bank ratings. In 2010, following the financial crisis of 2007/08, there has been a call to separate banks with trading income from those engaged in loan business only (Dodd-Frank Act, 2010). This may in some way reduce the complexity, opacity and size of banks and make for a more transparent risk analysis process.

Empirically, there is strong evidence of a positive relationship between bank size and the credit rating assigned by rating agencies (see Poon *et al.,* 2009; Bissoondoyal-Bheenick and Treepongkuruna, 2011; Pasiouras *et al*., 2007; Distinguin *et al.,* 2012). All of these studies find a positive and significant relationship between the size of a bank as measured by the natural logarithm of assets and bank credit ratings.

4.4.2 Business cycle and bank credit rating

Several studies, though not directly related to banks, address the issue of timing dynamics, the business cycle and rating stability (Blume *et al.*, 1998; Altman *et al.*, 2002; Amato and Furfine, 2004; Laere and Baesens, 2011). This strand of literature tests rating stringency over time as well as examining whether a firm's rating is independent of the state of the business cycle, conditional on the firm's financial and business characteristics. The studies employ various macroeconomic factor proxies to capture the level of economic activity and risk in the operating environment that may potentially influence the rating assigned.

Amato and Furfine, replicating the work of Blume *et al.*, employ an ordered probit model which includes a trend term. The trend term is introduced to capture time effects which may be due to either changes in stringency of the rating agencies or an overall deterioration in a firm's creditworthiness. Whilst Blume *et al.* employ US data on Moody's and S&P rated corporate debt between 1973 and 1992, Amata and Furfine adopt US data on S&P issuer ratings for the period 1981 to 2001. The two studies model time dummies as intercepts while allowing the slope to remain constant. This allows them to test if rating agencies have become tougher over time, *ceteris paribus.* For Blume *et al.* the dependent variable is a numerical representation of each company's bond rating. Their ordered probit model consists of independent variables which include accounting data, beta coefficients and standard errors of the residuals from the market model. They argue that a decline in the value of the intercept over time indicates more stringency in rating criteria. Their results also find that ratings have on average become worse which may imply that there is an increase in rating stringency over time. Their results indicate that the declining trend is of economic significance following the modelling of rating standards in early periods to forecast firms' ratings in later years.

To achieve this test of stringency, the sample is split into two, with the coefficients estimated for one period and tested on the other half of the period. The authors argue that their results are conditional on firm characteristics. A backward forecast also yields a consistent result of higher ratings for earlier years within their sample size. The results of Blume *et al.* support the argument that part of the decline in the level of credit quality of US corporate bonds over time can be attributed to a higher level of stringency in the credit rating process. Further the findings show that accounting and market-based risk measures are more informative for larger companies than for smaller ones.

The authors maintain that if stringency increases over time, the trend should have a positive coefficient. However the trend variable that captures the movement in the underlying risk factor in their model is negative and statistically significant at 5% level in what they refer to as strong test of procyclicality. This implies that there are more upgrades than downgrades over time. However, their results from the recession period indicate that rating changes show more downgrades than upgrades.

In a related study, Doherty and Phillips (2002) hypothesise that increased stringency of the rating process is linked partly with the need for CRAs to remain competitive. Their methodology is based on the ordered probit model of Blume *et al.* and examines the decline in property-liability insurer ratings. They model this in two ways. By assuming time-invariant slope coefficients on the independent variable and allowing intercept to be time-invariant, they are able to examine the shift in the intercept of their model, thus capturing changes in stringency. Using the same methodology to model the rating process yearly allows them to predict both prior and future ratings. Doherty and Phillips, following Blume *et al.* find that at least part of the average decline in insurer ratings produced by AM Best is attributed to increased stringency. In addition, they find that size is quite significant in motiving a rating, and larger insurers that operate across geographical boundaries are more likely to request a second rating. This is consistent with the notion that more complex firms, particularly those whose customers place a higher value on information, have a greater demand to communicate their financial strength to the market.

Following on from the works of Blume *et al.* and Doherty and Phillips, Pottier and Sommer (1999) examine AM Best and S&P assigned ratings of life insurance companies. Employing the same methodology as these previous studies, they investigate whether both rating agencies increased the stringency of their rating standards and they find results consistent with those of the previous two studies. The authors find that a significant increase in stringency occurs over time, implying that if everything else is held constant, rating agencies consistently assign declining ratings to life insurance firms. Pottier and Sommer attribute this result partly to an increase in stringency and partly to a real decline in overall insurer industry financial performance not captured in the financial variables employed in the model.

This thesis employs cross-country data when modelling the determinants of bank credit ratings, and as such it is important to account for potential cross-country effects. Despite the overarching regulatory role of Basel II Accord, each national government maintains their own regulatory and supervisory oversight which differs greatly across countries and can exert a significant influence on how rating agencies assign ratings to banks. Demirguc-Kunt and Detragiache (2010) and Barth *et al*. (2008) find that regulation and the quality of bureaucracy greatly influences the stability of banking systems. Laere and Baesens (2011) argue that country dimensions go beyond regulatory practice, and propose the inclusion of sovereign ratings as a country level variable in modelling the determinants of bank ratings. Fitch maintains that national or sovereign ratings give an opinion on the assessment of credit quality of the national government and indicate the likelihood that a government will default on its obligations. Cantor and Parker (1997) argue that a sovereign rating allows government to access funds from international capital markets. Hence, country risk is similar to sovereign risk because it takes into account factors that influence the macroeconomic conditions of a country. Hence the sovereign rating of a country may proxy for the economic risk within that country. Sovereign ratings are usually ascribed to a country by rating agencies.

4.5 Bank rating determinant hypotheses

The previous sections provide the theoretical justification for a list of potential drivers of bank credit ratings. This analysis presents the background to the next chapter on the methodological approach and econometric models of this thesis. This section summarises the hypotheses that have been developed based on the empirical evidence reviewed in earlier sections. It incorporates both financial and non-financial factors that could potentially influence bank rating assignments. The banking system is very prone to contagion in which the deterioration or failure of a single key bank can spread rapidly through a variety of mechanisms across the whole banking system. Even though the original shock to a bank may be external or exogenous to the banking institution, paying particular attention to, and taking action on, these identified factors could allow a bank to cushion the effects of the shock and emerge unscathed. The sources of vulnerability for banks can vary from poor asset quality, undue exposure to market and credit risk, and a lack of capital. Table 4.2 presents the bank credit rating determinant hypotheses.

Table 4.2: Bank credit rating determinant hypotheses

Dimension	Hypothesis
Capital adequacy	H_1: There is a positive relationship between bank capital adequacy ratios and credit ratings of banks.
Asset quality	H_2: There is a negative relationship between bank asset quality ratios and credit ratings of banks.
Earnings ratio	H_3: There is a positive relationship between bank profitability and credit ratings of banks.
Liquidity ratio	H_4: There is a positive relationship between bank liquidity and credit ratings of banks.
Market risk	H_5: There is a negative relationship between bank stock betas and credit ratings of banks.
	H_6: There is a negative relationship between bank idiosyncratic stock return variation and credit ratings of banks.
	H_7: There is a positive relationship between bank Z-Scores and credit

	ratings of banks.
Liquidity risk	H_8: There is a negative relationship between bank liquidity risks and credit ratings of banks.
Credit risk	H_9: There is a negative relationship between bank unexpected losses in the current period and credit ratings of banks.
Efficiency	H_{10}: There is a negative relationship between bank cost to income ratios and credit ratings of banks.
Bank size	H_{11}: There is a positive relationship between bank size and credit ratings of banks. H_{12}: There is a positive relationship between Fitch support ratings and credit ratings of banks.
Ownership structure	H_{13}: There is a positive relationship between directors' ownership in banks and credit ratings of banks. H_{14}: There is a positive relationship between institutional ownership in banks and credit ratings of banks.
Corporate governance	H_{15}: There is a positive relationship between director independence in banks boards and credit ratings of banks.
Business cycle	H_{16}: There is a positive relationship between the sovereign rating of a country and the credit ratings of its constituent banks. H_{17}: There is an asymmetry in rating agency actions between recession and expansion periods, i.e. downward rating are more prominent in recessions than in boom periods.

4.6 Summary

This chapter examines the significant factors driving the assignment of bank credit ratings. It reviews both the positions of the major CRAs and empirical evidence of the determinants of bank credit ratings. Credit rating agencies and the ratings they assign have become very important within the context of a financial market and as an invaluable reference tool for investments and regulators. The major credit rating agencies maintain that they consider variety of factors when during the credit rating process of a bank. These range from qualitative to quantitative assessments of the creditworthiness of an entity. The 2007/08 global financial crisis has put further pressure on the CRAs to be more transparent in not just their credit rating criteria, but in addition, their rating methodology. Broadly speaking, the CRAs assess macro- and bank-specific determinants, as well as the level of potential external support available to a bank in assigning a credit rating.

Evidence from empirical research shows that variables employed in credit rating determinants models are consistent with those of the CRAs. However, due to limited access to some of the more qualitative data, most studies are heavily dependent of quantitative measures such as the CAMELS factors. There are strong suggestions in existing studies that quantitative measures such as capital adequacy, assets quality, earnings, liquidity and sensitivity to the market, drive the rating process (Poon and Firth 2005; Distinguin *et al*., 2012). In addition, this thesis makes significant contributions to the literature by incorporating within credit rating models variables that capture corporate governance. The complexity of banks and their opaqueness further aggravates the governance problem.

Another important variable, size, is examined within two context. One is the size of the bank as measured by the asset size, and a second more important measure of size is the influence of a bank size within the economy, and in particular the interconnectedness of banks. The latter is linked to the concept of too-big-to-fail. This thesis employs the Fitch support rating to measure the potential influence of bank size in getting external support when needed, particularly in times of economic slowdown or recession. Based on the review of existing literature and theoretical justifications, the chapter further provides a list of hypotheses to be tested in the subsequent chapter.

CHAPTER 5. A REVIEW OF THE METHODOLOGICAL APPROACHES, DATA AND ECONOMETRIC MODELS

5.1 Introduction

This chapter establishes the methodological approach to be adopted in the first empirical element of this thesis based on the review of the various approaches in the existing literature. As a reminder, the main objective of this first part of the thesis is to test empirically, the factors that drive the determinants of bank credit ratings. There have been few earlier attempts at modelling the determinants of firm credit ratings in the financial services sector (i.e. the banking and insurance industry), though a significant number of studies exist for non-financial company (corporate) and country (sovereign) ratings. This thesis focuses on the banking sector as it plays a crucial role in financial intermediation and the overall health of the economy. A rating measures the risk of credit loss resulting from failure by the counterparty to uphold a scheduled payment agreement. Rating classifications are an important variable to the portfolio credit risk model as they are mapped onto probabilities of default (Carey and Hrycay, 2001). The 'quantification' of ratings thus involves estimating the probability of default for counterparties assigned to each rating notch.

To model the determinants of bank credit rating in an international setting, it is imperative for this study to employ a methodological approach that would capture the ordinal nature of bank credit ratings. Hence, the principles underpinning the choice of models and estimation approaches to be adopted in this first empirical component of the thesis are discussed and established within this chapter. Further, the nature and selection of variables, treatment of dummies (including the TBTF and year dummies), the standardisation of beta and the selection of the econometric models are presented. In addition, this thesis recognises and discusses important econometric issues concerning multicollinearity, endogeneity (with specific reference to omitted variables and reverse causality) and persistence in variables. The chapter presents the data of the study, sampling techniques and descriptive statistics.

The structure of the rest of the chapter is as follows: Section 5.2 reviews the methodological approaches employed in the existing literature for modelling the determinants of credit ratings. The section presents the rationale behind the approach adopted in this thesis. Section 5.3 discusses the choice of econometric model for estimating bank rating determinants. Section 5.4 presents econometric and variable issues. Section 5.5 discusses the issues around the nature of the data employed. Section 5.6 presents data on bank fundamental characteristics. Section 5.7 summarises the chapter.

5.2 Review of empirical approaches in the existing literature

This section examines the approaches to modelling credit ratings determinants adopted in the existing empirical literature as the basis for the approach employed in this thesis. The approach to analysing the determinants of credit ratings and rating predictions has evolved over time from the use of the ordinary least squares (OLS) regression techniques and multiple discriminant analysis (MDA) approaches in earlier studies (Pinches and Mingo, 1973; Cantor and Packer, 1996) to the more established ordered choice regression models of Poon and Firth (2005), Poon *et al.*(2009), Bissoondoyal-Bheenick and Trepongkaruna (2009), Caporale *et al*. (2009) and Distinguin *et al*. (2012). A parallel branch of methodological approach employs artificial intelligence (AI) techniques (Dutta and Shekhar, 1988; Kim, 1993; Bennell *et al.,* 2006; Kumar and Bhattacharya, 2006).

The models and approaches that earlier studies adopt in estimating the determinants of credit ratings are driven by the nature of the ratings as well as the development of more sophisticated econometric techniques. A rating expresses an opinion of a rating agency on the likelihood of default or the relative creditworthiness of an issuer or issue over a specific time horizon. Langohr and Langohr (2008) argue that the unique feature of the credit rating scale or index is its ordinality, which refers to the comparability of all ratings along the scale. Ratings exist in a natural order, usually ranked from those corresponding to higher creditworthiness (say AAA, AA, A, and so on) to those of lower rankings. Credit rating as a dependent variable is qualitative in nature, unlike the more common dependent variable type that is quantitative. The qualitative, ordinal-scaled and discrete-valued nature of credit ratings needs to be taken into account when choosing and estimating an appropriate econometric modelling approach.

Most of the earlier studies on rating assignment focus on the determinants of, and predictive models for, bond ratings (Pogue and Soldofsky, 1969; West, 1970; Kaplan and Urwitz, 1979; Horrigan, 1996). An early methodology employed in the literature to assess the determinants of ratings (for industrial bonds) is the use of multiple discriminant analysis (MDA). Pinches and Mingo (1973) adopt a two-stage approach to assign ratings to particular bond issues. The first stage involves the screening of a set of potential variables that are appropriate as independent variables via factor analysis to account for as much variation in the data as possible. This screening results in a set of six potential independent variables: subordination, years of consecutive dividends, issue size, and three financial ratios. The second stage of their analysis involves the use of MDA to develop the final predictive model and hence classify bonds into rating categories on the basis of the explanatory power of the independent variables. The authors achieve this by producing linear discriminant functions that distinguish between categories. The basic assumptions of MDA are that: i) the groups are discrete and known; ii) each observation in each group is described by a set of measurements on n variables; and iii) the n variables arise from a multivariate normal distribution. Pinches and Mingo argue that using an MDA approach is essential to developing and understanding the model for predicting industrial bond ratings. Their model correctly assigns ratings to approximately 69% of their sample, though the accuracy of their approach drops slightly to 65% when used on the control sample. While their model achieves satisfactory predictive accuracy rates, Kaplan and Urwitz (1979) and Gray *et al.* (2006) argue that MDA does not capture the ordinal nature of credit ratings.

Kaplan and Urwitz (1979) argue that MDA concentrates on differences between categories of variables, though it does not impose an interval scale on categorical data. By treating bond ratings as classifying bonds into separate categories, the approach does exploit the ordinal nature of bond ratings. The MDA treats rating categories as different outcomes, ignoring that categories can be viewed as partitions of perhaps unequal widths of a single risk dimension, the probability of default. It therefore avoids the interval scale assumption.

The nature of credit rating variables has itself been a major influence on the choice of approach in more latter studies, where the relationship between the independent variables and the credit rating is analysed using the ordered choice models. The ordered choice model is a strictly nonlinear transformation of the numbered rating notches and takes into consideration the differences in rating scale intervals. The transformation is captured by thresholds, which are estimated parameters in an ordered choice model (Greene and Hensher, 2009).

Moon and Stotsky (1993) argue that while past studies employ an OLS approach and other discriminant analysis techniques to analyse the determinants of credit ratings, other later studies employ econometric models that are more sophisticated (e.g. probit and logit models), and these are driven by the nature of the credit ratings. Interestingly, Kaplan and Urwitz (1979) make reference to a key assumption made by OLS regarding the distance or interval between rating notches (interval scale assumption), i.e. ratings representing equal intervals on a firm ratings scale. This *interval scale assumption* makes it all the more inappropriate to employ OLS in the modelling of rating determinants. Further, the interpretation of the coefficients of an OLS regression is quite inappropriate for a model in which the dependent variable is ordinal, i.e. the number of units by which the dependent variable changes in response to a single unit change in an explanatory variable. This normal interpretation cannot be employed for a model in which the dependent variable is qualitative, as in the case of credit ratings. Each credit rating corresponds to a specific range within a notch and ratings also have a natural ordering (e.g. AAA is best, AA is next best and so on) which in turn results in higher ratings corresponding to a higher range of creditworthiness values. Two of the earliest studies adopting the ordered probit approach to model and predict the determinants of corporate bond ratings and credit ratings are Ederington (1985) and Gentry *et al.* (1988), and they base the choice of their approach on the qualitative nature of the credit ratings.

The AI technique comes under the branch of modelling approach generally referred to as artificial neural network models. The motivation for an AI approach is that it is can recognise relationships between independent and dependent variables in data that are unknown or complex (Koh and Low, 2004). An artificial neural network (ANN) is a network made up of several simple processors, units or neurons, each one possibly having a local memory (Falavigna, 2012). Earlier studies using ANN (Dutta and Shekhar, 1988; Moody and Utans, 1994; Kim, 1993) all find that neural networks achieve a relatively higher accuracy in predicting bond ratings. Even though the ANN approach presents a promising approach in the area of investigating rating determinants and prediction, it has attracted considerable criticism. Neural networks rely on their computational efficiency and learning capabilities as they do not require any prior specification of a theoretical model. Similarly, due to the difficulty of interpretation, most studies that apply neural networks focus on prediction accuracy. Few efforts to use neural network models to provide a better understanding of the bond-rating process have been reported in the literature (see Galindo and Tamayo, 2000; Huang *et al*., 2004).

5.2.1 The choice of econometric model for modelling bank credit rating determinants

The nature of credit ratings confers on them special treatment when it comes to modelling their determinants. Credit rating as a dependent variable falls under the group of variables referred to as limited dependent variables. Limited dependent variable models are econometric models in which the dependent variable, y, has a range which is basically restricted or limited, and its value is not completely observed (Hill *et al.,* 2008). A credit rating is a qualitative, discrete-valued measure of relative creditworthiness. Each rating corresponds to a specific range within a notch, and ratings also have a natural ordering (e.g. AAA is best, AA next best, and so on), resulting in a higher ratings range equivalent to greater relative creditworthiness. Since credit ratings have this ordering characteristic, modelling ratings falls into the sub-category of limited dependent variable models referred to as ordered regression models (or latent variable models). The two popular models within this latter category are the *ordered probit* and *logit models*. Section 5.2.3 examines the ordered probit model in greater detail.

The methodological approach in this component of the thesis follows the established practice of previous research in the investigation of the determinants of credit ratings. Most of the prior studies (Cheung, 1996; Bouzouita and Young, 1998; Nickell *et al.,* 2000; Adam *et al.,* 2003; Poon, 2003; Poon *et al.,* 2009; Jorion *et al.,* 2009) in this area employ the ordered choice model due to its suitability for analysing a dependent variable that is naturally ordered and discrete in nature.

Cheung (1996) argues that it is important to consider the discrete nature of credit ratings which confers on them the distinctive characteristic of ordinality, as this makes an ordered probit model suitable for the estimation of credit rating determinants. She further posits that each rating corresponds to a specific range on a continuous unobserved creditworthiness index. Indeed, Bouzouita and Young (1998) also maintain that the ordered probit model should be employed when there is an underlying relationship between the different categorical responses.

Further, Amato and Furfine (2004) argue that employing an ordered probit model results in the estimation of the maximum likelihood (ML) of the probability that a firm or its issue will obtain a certain ordered rating, which gives an indication of true creditworthiness by linking the observed credit rating variable to the latent quality one. The term *latent* is used to describe the unobserved credit quality of a firm. When considering rating classes or notches, say, AAA or BB, the former has a higher rating, but no assumption is made about the interval between the two classes. In addition, Gray *et al*. (2006) argue that rating notches are not evenly spaced. This confers another advantage on the use of an ordered probit model over a linear probability model which assumes equal spacing between rating classes.

5.2.2 The ordered regression variable model

In this component of the thesis, the limited dependent variable, i.e. bank credit rating, takes an ordinal form, i.e. all ratings along a credit rating scale are comparable. For example, Fitch assigns ratings as AAA, AA, A, and so on, as a gauge of the creditworthiness of banks. These ratings can be ascribed numerical values which are ranked from say, 1, 2, 3,…, *n.* The ranking is undertaken based on sentiment about the alternative outcomes. The sentiments are unobserved. When variables are unobserved in decision making they are referred to as *latent variables*, and hence sentiments towards the ranked alternatives are denoted by y_i^* (the 'star' signifying that the variable is unobserved).

The ordered logit and probit models present two alternatives to deal with the issue of latent dependent variables. Using either approach requires functions that effectively transform a regression model so that fitted values are bounded with a (0, 1) interval. The difference between the two models lies in the distribution of the error terms. The ordered probit follows a standard normal distribution, while the ordered logit assumes that the random errors follow a logistic distribution. Daykin and Moffatt (2002) argue that the ordered probit model serves as an appropriate framework for statistical analysis whenever the responses are ordinal as distinct from numerical. However, Long and Freese (2005) argue for the need to ensure that models are appropriate for the variable of interest.

In general terms, if there are more than two (ordered) dependent outcomes, it can be assumed that y_i^*, which is the latent dependent variable, lies between $-\infty < y_i^* < +\infty$. Considering a latent variable, y_i^*, that depends linearly on a set of explanatory variables, x_i, the observed response can be modelled in a generalised way as

$$y_i^* = \beta x_i + \varepsilon_i \qquad 5.4$$

where β is a vector of parameters, i consists of n sample observations labelled as 1, 2, 3,..., n, and ε_i are independent and identical distributed random variables. The measurement approach for the ordinal regression model involves dividing y_i, which are the observed credit ratings, into J ordinal categories, given that

$$y_i = M \qquad \text{if } \tau_{M-1} < y_i^* \leq \tau_M \qquad 5.5$$

where M is the number of rating categories from 1, 2,… J, and the τ_1 through τ_{J-1} are the estimated cut points (or thresholds). The observed y_i is obtained from y_i^* based on the following relationship:

$$y_i = \begin{cases} 1 & \text{if } y_i^* \leq \tau_1 \\ 2 & \text{if } \tau_1 < y_i^* \leq \tau_2 \\ 3 & \text{if } \tau_2 < y_i^* \leq \tau_3 \\ \vdots & \\ J & \text{if } \tau_{J-1} < y_i^* \end{cases} \qquad 5.6$$

The unknown cut-off points,τ_1, τ_2, τ_3…….., τ_{J-1}, satisfy

$$\tau_1 < \tau_2 < \tau_3 < \cdots < \tau_{J-1} \qquad 5.7$$

The number of thresholds depends on the alternatives, which in the case of credit ratings are represented by the notches. Say there are M alternatives, and then the number of thresholds is given as $M - 1$ (Hill *et al.,* 2008). The value of the observed variable y_i depends on whether or not a particular threshold has been crossed. The logic underlying the ordered regression variable model is to estimate the probability that the outcome will cross a particular threshold following the probability distribution of the random error, which can be standard normal (ordered probit model) or following a logistic distribution (ordered logit model). Another way of understanding y_i is to think of the variable as being a collapsed version of y_i^* where the latter can take an infinite range of values and the y_i can be collapsed into J categories. Using the data in this thesis as an illustration, one might assume that a rating agency has a sentiment about the rating of a bank A. This sentiment may be denoted by y_i^*, and the actual assigned rating may fall within a rating range say, AAA to D, which are numbered from say 1 to 9. These numbered ratings are the y_is.

The panel data employed in this thesis consists of cross-country variables and this presents another challenge around unobserved cross-country heterogeneity due to the possibility of not being able to control for all of the potential country-specific determinants of bank credit ratings. In general, different banks across the sample size are subject to the influence of different factors. Ignoring effects that may exist but are not captured by the explanatory variables in the model can lead to parameter heterogeneity in model specification (Hsiao, 2003). Hsiao further maintains that the use of panel data allows for the control of individual heterogeneity. If one considers the probit model,

$$y_{it}^{*} = \beta x_{it} + c_i + \varepsilon_{it} \qquad 5.8$$

where c_i captures the individual effect or individual heterogeneity which is unobserved and x_i contains x_{it} for all *t*, then the treatment of c_i becomes important. Because of the presence of c_i, the y_{it} are dependent across *t*, conditional only on the observables, x_i. The main assumption of this unobserved effects probit model within panel data is thus

$$P(y_{it} = 1 | \; x_{it}, c_i) = P(y_{it} = 1 | \; x_{it}, c_i)\mathbf{\Phi}(x_{it}\beta + c_i), \qquad t = 1, \dots, T \qquad 5.9$$

Several studies (Maddala, 1987; Lechner, 1995; Wooldridge, 2002; Baltagi, 2009; Greene and Hensher, 2009) discuss whether to treat c_i as a fixed or a random effect. The key issue here is the assumption for c_i , i.e. whether or not it is correlated with the observed explanatory variables $x_{it}, t = 1,2, \dots, T$. If c_i is treated as a *random effect* it follows that there is zero correlation between the observed explanatory variables and the unobserved effect, i.e. $Cov(x_{it}, c_i) = 0, t = 1,2, \dots T$. In most empirical studies where c_i refer to *individual random effects,* it assumes that the individual effect is uncorrelated with the x_{it} , whereas the treatment of c_i as *fixed effects* may be seen as allowing for arbitrary correlation between the unobserved effects c_i and the other observed explanatory variables x_{it} , i.e. c_i is allowed to be correlated with x_{it} (Wooldridge, 2002). He further argues that in a probit analysis, neglecting heterogeneity causes the probit coefficients to be inconsistent even when the country specific variable is independent of the other explanatory variables.

One way of capturing this individual country-specific effect is to include country dummy variables on the right-hand side of the equation. In this case, the quantities of interest, c_i (country dummies) and the x_{it} can be estimated without restricting their relationship. This *fixed effects probit treatment* hence treats c_i as a parameter to be estimated along with the βs (i.e. coefficients of the explanatory variables), with no assumption about the distribution of c_i given x_i. Greene and Hensher (2009), however, argue that estimating the c_i (as dummy variables) alongside β introduces an incidental parameter problem which leads to inconsistent estimation of c_i with a fixed number of time periods (*T*) and the number of individuals *N* approaching infinity, i.e. $N \rightarrow \infty$. It is worth pointing out that the treatment of c_i when *T* is fixed is quite different from that of linear panel data estimation. In the latter, the estimate of β is consistent and this is achieved by first omitting c_i using the *within transformation.* The country specific variable, c_i, does not change over time. The within transformation is achieved by differencing the error-component model similar to Equation 5.8 (but in this case linear), and averaging the equation over time for each *i* (between transformation). The equations are then subtracted from each other for each *t* (within transformation). The resulting model no longer has the c_i, hence no assumption needs to be made on its correlation with the x_{it}. Time-constant unobserved heterogeneity is no longer a problem.

Hsiao (2003) maintains that the within transformation to eliminate c_i is possible because the maximum likelihood estimation (MLE) of β and c_i are asymptotically independent in linear models. Similarly, Greene (2009) argues that despite the large number of incidental problems encountered in the estimation of a fixed effects limited dependent panel model, the performance of MLE by brute force (by adding a large number of dummies) is possible. He maintains though that the fixed effects MLE is biased even when *T* is large, consistent with Hsiao (2003).

To motivate a *random effects probit model*, an assumption is made that c_i and x_i are independent (x_i having a normal distribution), satisfying the condition,

$$c_i|\ x_i \sim Normal\ (0, \sigma_c^2) \qquad 5.10$$

Thus, estimation of the random effects model requires very strong assumptions about the heterogeneity of the individual effects. Butler and Moffitt (1982) present a way round this strict assumption by suggesting a specification that has the same structure as the random effects linear regression model. Their random effects model specifies that the error can be decomposed into two parts, i.e.

$$\varepsilon_{it} = u_{it} + v_i \qquad 5.11$$

where u_{it} is normally distributed with mean zero and is independent across all periods and individuals and assumes that the individual specific term v_i is uncorrelated with the included variables, x_{it}, in all periods, and is *i.i.d.* and time invariant. The expected values of the two terms, u_{it}, v_i, and their covariance, conditional on the other explanatory variables, can be expressed as,

$$E[u_{it}|\ \boldsymbol{X}] = 0; \mathrm{Cov}\left[u_{it}, u_{js}|\ \boldsymbol{X}\right] = \mathrm{Var}[u_{it}|\ \boldsymbol{X}] = 1, if\ i = j\ and\ t = s; 0\ otherwise$$

$$E[v_i|\ \boldsymbol{X}] = 0; \mathrm{Cov}\left[v_i, v_j|\ \boldsymbol{X}\right] = 0, if\ i \neq j, \mathrm{Var}[v_i|\ \boldsymbol{X}] = \sigma_u^2,$$

$$\mathrm{Cov}[u_{it}, v_i|\ \boldsymbol{X}] = 0\ for\ all\ i, t, j, \qquad 5.12 - 5.14$$

where the ***X*** are the exogenous data in the sample, x_{it} for all *i* and *t*. Then

$$\mathrm{Cov}[\varepsilon_{it}, \varepsilon_{is}] = \sigma_u^2 \qquad 5.15$$

and

$$\text{Corr}[\varepsilon_{it}, \varepsilon_{is}] = \rho = \frac{\sigma_u^2}{1+\sigma_u^2} \qquad 5.16$$

Hence the new *free* parameter can be expressed as

$$\sigma_u^2 = {}^{\rho}/_{(1-\rho)} \qquad 5.17$$

Greene and Hensher (2009) give the implied probit model as

$$y_{it}^* = \beta' x_{it} + u_{it} + v_i, \qquad 5.18$$

$$y_{it} = 1(y_{it}^* > 0) \qquad 5.19$$

Therefore,

$$\text{Prob}(y_{it}^* = 1|\ \boldsymbol{x}_{it}) = \text{Prob}(\beta' x_{it} + u_{it} + v_i > 0$$

$$= \Phi(\frac{\beta' x_{it}}{1+\sigma_u^2}) \qquad 5.20)$$

$$= \Phi(\beta_*' x_{it}) \qquad 5.21$$

The implication of this is that the panel model does produce an appropriate estimator of the partial effects in the random effects probit model (Wooldridge, 2002). Maddala (1987) and Greene and Hensher (2009) argue that the random effects model is better suited for probit than logit models. Moreover, the random effects probit model estimates are consistent though inefficient.

Baltagi (2009) argues that the common solution to the incidental parameter problem is to find a minimum statistic for c_i. Mundlak (1978) and Chamberlain (1982) propose a middle ground between the incidental parameter problem of the fixed effects and the assumption that the country (individual) specific effects v_i are uncorrelated with x_i in the random effects model. Mundlak and Wooldridge (2002), propose that the effects in the fixed effects models are projected on the mean of the time varying independent variables (Greene and Hensher, 2009), i.e.

$$\alpha_i = \boldsymbol{\theta}'\bar{\mathbf{x}}_{\mathbf{i}} + w_i \qquad 5.22$$

where w_i is normally distributed with mean zero and standard deviation σ_w and is uncorrelated with the mean of the explanatory variable, $\bar{x}_i$, or with x_{it}. Inserting Equation 5.22 into the fixed effects model produces

$$y_{it}^* = \beta' x_{it} + \theta' \bar{x}_i + \varepsilon_{it} + w_i \qquad 5.23$$

which in reality gives a random effects model.

Similarly, Chamberlain (1980) finds that in a logit model, the summation of the dependent variables across the fixed period *T*, i.e. $\sum_{t=1}^{T} y_{it}$, is a minimum *sufficient statistic* for c_i, and suggests maximizing the conditional likelihood function:

$$L = \prod_{i=1}^{n} \Pr(Y_{i1} = y_{i1}, \dots, y_{iT} \mid \boldsymbol{X}_i, \sum_{t=1}^{T_i} y_{it}) \qquad 5.24$$

to obtain an expression free of incidental parameters. He argues that the conditional logit estimation for β through this approach is consistent and unbiased. However, the conditional likelihood approach for a fixed effects logit model cannot be adopted for a fixed effects probit model. Rather, the popular specification for the latter is the random effects model (Greene, 2004; Wooldridge, 2002; Arellano and Hahn, 2006).

A test for the choice between the fixed and random effects ordered model based on the likelihood function is not readily available. Unlike the linear model which employs the Hausman (1978) test, the nonlinear fixed effects estimator is inconsistent even when it appears to be the appropriate estimator, due to the incidental parameter problem (Greene, 2003). Baltagi (2009) proposes strategies for a choice between the fixed and random effects ordered models. He bases his strategy on the variable addition test. He proposes that group means can be added to the random effects model to account for correlation between the common effects, and the explanatory variables. If the test shows the presence of correlation then the fixed effects approach is the appropriate model, otherwise a random effects model is appropriate. Greene and Hensher (2009) argue that the power of the test is unknown and propose a simple likelihood ratio variable addition test of the joint significance of the group means in the expanded random effects model. However, the usual choice of approach for treating the issue of heterogeneity in nonlinear panel data is via the random effect probit models (e.g. Baltagi, 2009).

5.2.3 Estimating the ordered probit model

Let us assume that the rating of a bank *i* at time *t* is denoted by y_{it}, and a vector of independent variables at time *t* that drives the ratings of bank *i* is denoted as X_{it}. Given a vector parameters of β and error terms, ε_{it} (normally distributed), then the ordered probit model can be derived in the form

$$y_{it}^{*} = \beta x_{it} + c_i + \varepsilon_{it} = W_{it} + \varepsilon_{it} \qquad 5.25$$

Due to the non-linearity and specification, the model in Equation 5.25 is estimated using a maximum likelihood (ML) approach. Maddala (1987) and Cheung (1996) further argue that the asymptotic properties of ML estimators, i.e. consistency, normal distribution and efficiency make ML a suitable estimation method. Another important consideration in the estimation of the probit model is the functional form of the equation. The probit function follows a standard normal probability distribution such that if Z is a standard normal variable, then its probability density function can be expressed as

$$\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-0.5u^2} du \qquad 5.26$$

The cumulative distribution function (*cdf*) is then

$$\Phi(z) = P[Z \leq z] = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{-0.5u^2} du \qquad 5.27$$

In order to perform a ML analysis, there is a need to derive from the underlying model the density of y_i given x_i, c_i. The ML estimation seeks to obtain the parameter values that maximize the likelihood of observing the outcomes actually obtained. In other words, the *random effect probit model* approach that fits the estimates via maximum likelihood is given as:

$$\Pr(y_{it} > j \mid \boldsymbol{\tau}, X_{it}, c_i) = \boldsymbol{\phi}\,(X_{it}\beta + c_i - \boldsymbol{\tau}_J) \qquad 5.28$$

for $i = 1, \dots, n$ panels, where $t = 1, \dots, T$, v_i are independent and identically distributed ($N(0, \sigma_c^2)$), and $\boldsymbol{\tau}$ is a set of cutpoints or thresholds $\tau_1, \tau_2, \dots, \tau_{J-1}$, where J is the number of possible outcomes, and $\boldsymbol{\phi}\,(\cdot)$is the standard normal cumulative distribution function.

As specified in Equation 5.6, the probit model links the y_{it}^* and y_{it} according to following set of equations:

$$y_{it} = 1 \text{ if } y_{it}^* \in (-\infty, \tau_1) \qquad 5.29$$

$$y_{it} = M \text{ if } y_{it}^* \in (\tau_{M-1}, \tau_M) \qquad 5.30$$

$$y_{it} = J \text{ if } y_{it}^* \in (\tau_{J-1}, \infty) \qquad 5.31$$

where M = 2, 3,…, J and the condition in Equation 5.7 is met, that is $\tau_1 < \tau_2 < \tau_3 < \cdots < \tau_{J-1}$

Based on the above the maximum likelihood estimation, the following gives the probability of observing outcome j for response y_{it} as

$$p_{itj} \equiv \Pr(y_{it} = j \mid \boldsymbol{\tau}, X_{it}, c_i) = \Pr(\tau_{j-1} < X_{it}\beta + c_i + \varepsilon_{it} \leq \tau_j) \quad 5.32$$

$$= \Pr(\tau_{j-1} - X_{it}\beta - c_i < \varepsilon_{it} \leq \tau_j - X_{it}\beta - c_i) \quad 5.33$$

$$= \Phi(\tau_j - X_{it}\beta - c_i) - \Phi(\tau_{j-1} - X_{it}\beta - c_i) \quad 5.34$$

Here there is no constant term because its effect is absorbed into the cut-points (i.e. τ). Given a set of panel-level random effects c_i, one can define the ordered probit conditional distribution for response y_{it}as follows:

$$f(y_{it}, \boldsymbol{\tau}, X_{it}\beta + c_i) = \prod_{\tau=1}^{J} p_{it\tau}^{I_\tau(y_{it})} \quad (5.35)$$

$$= \exp \sum_{\tau=1}^{j} \{I_\tau(y_{it}) \log(p_{it\tau})\} \quad (5.36)$$

where

$$I_\tau(y_{it}) = \begin{cases} 1 & \text{if } y_{it} = \tau \\ 0 & \text{otherwise} \end{cases} \quad 5.37$$

For panel $i, i = 1, \ldots, n$, Wooldridge (2002) gives the conditional distribution of $\boldsymbol{y}_i = (y_{i1}, \ldots, y_{in})'$ as

$$\prod_{t=1}^{n_i} f(y_{it}, \tau, X_{it}\beta + c_i) \quad 5.38$$

and the panel-level likelihood l_i is given by

$$l_i(\beta, \boldsymbol{\tau}, \sigma_c^2) = \int_{-\infty}^{\infty} \frac{e^{-c_i^2/2\sigma_c^2}}{\sqrt{2\pi}\sigma_c} \{\prod_{t-1}^{n_i} f(y_{it}, \boldsymbol{\tau}, X_{it}\beta + c_i)\}\, dc_i \quad 5.39$$

$$\equiv \int_{-\infty}^{\infty} g(y_{it}, \boldsymbol{\tau}, x_{it}, c_i)\, dc_i \quad 5.40$$

The log-likelihood function is then maximized with respect to β and the thresholds τ_1, τ_2, τ_3, …, τ_{J-1} to give maximum likelihood estimates of all of the parameters.

5.2.4 Interpreting the parameter estimates

The ordered probit model is estimated by means of a maximum likelihood approach. The interpretation of the estimates is quite different from that of a linear probability regression model due to the non-linear nature of the model as well as its specification. The β in the probit model cannot thus be interpreted directly as the impact of a small change in x on the dependent variable y. Greene and Hensher (2009) maintain that dependent variable, y, is simply a *label* for the non-qualitative outcomes, and to give meaning to the estimated coefficients ($\hat{\beta}$), one should treat them as probabilities. Thus, the probit model describes the probability of outcomes and does not directly explain the relationship between the dependent and explanatory variables. In order to achieve this, the marginal effect is calculated of a small change in an independent variable on the probability that the observed dependent variable, y_i, falls into one of its ordinal notches as specified by the threshold parameters. The interpretation usually focuses on the sign of the coefficients and the magnitude of the marginal effects. The sign gives an indication of the direction of the effect, i.e. whether positive or negative. In calculating the marginal effect, (i.e. the effect of a change in the independent variable), everything else is held constant. The marginal effect of an ordered probit model may be expressed mathematically as:

$$\delta_j(x_i) = \frac{\Pr(y = j|\ x_i)}{\delta x} = \frac{\delta\Phi(\beta x_i)}{\delta x} = [\phi(\tau_{j-1} - \beta x_i) - \phi(\tau_j - \beta x_i)]\beta \qquad 5.41$$

where $\phi(x) = \frac{d\Phi(x)}{dx}$ is the probability density function (standard normal).

In order to interpret how a small increase in x affects the probability of obtaining, say, $y = 1$ $(Pr(y = 1|\ x) = \Phi(\beta x_i))$, the estimated β is multiplied by the density estimated at βx_i, $\phi(\beta x_i)$.

Apart from the coefficient parameters, the threshold parameters are also estimated. Daykin and Moffatt (2002) argue that in most treatments, the threshold parameters do not hold any meaning and hence are not interpreted. However, Greene and Hensher (2009) argue that the threshold estimates differentiate the adjacent levels of the response variable. These parameters help to separate the notches and thus give an indication in which category the y_i actually falls.

5.2.5 Country Effects

The bank credit rating documents of the major CRAs show that sovereign (country) credit risk is important in assessing the credit standing of banks and corporations. This thesis recognises the need to capture this country effects within its bank credit rating determinant model. Section 5.2.3 discusses the issue of random and fixed effects and how these impact on the modelling of bank credit rating, and in particular the implications of employing too many country dummies. This thesis follows Poon (2003) and Poon and Chan (2010) by employing sovereign credit ratings (SOV) in the bank credit rating determinant models to explain the impact of country effects on bank credit ratings. Sovereign credit ratings are widely used measurements for "country risk" in international capital markets (Bissoondoyal-Bheenick *et al.*, 2005). Country risk underlies the business risk assessment of a bank operating within a particular country. Gültekin-Karakas *et al.* (2014) argue that a sovereign credit rating is indicative of the performance of a national economy, and that changes in this rating, especially downgrades, frequently trigger a negative market response. A sovereign credit rating includes a variety of information about a country, and hence helps provide an efficient opportunity for cross-country comparisons. Caporale *et al.* (2011) model EU countries' bank ratings using financial variables and allow for intercept and slope heterogeneity. They find that country-specific factors (in the form of heterogeneous intercepts) are a crucial determinant of ratings. This result is consistent with Bellotti *et al.* (2011) who find that country-specific effects affect a bank's rating within their ordered choice models and support vector machines.

5.3 Econometric models and variables

This section presents the empirical models and variables that are employed in this component of the thesis. Section 5.3.1 presents the ordered probit rating determination models and the corresponding independent variables. The definitions of the variables are explained, and issues related to the variables are discussed.

5.3.1 The rating determinants model

Table 5.3 presents the hypotheses tested within the first empirical component of this thesis. The study starts with a base model which draws upon the works of Poon (2003), Poon *et al.* (2009), Bissoondoyal-Bheenick and Treepongkaruna (2009), Distinguin *et al.* (2012) and Hau *et al.* (2012) for the purposes of examining the determinants of international bank credit ratings of the general form:

$$CR_{it} = \beta_0 + \beta_1(TIER1)_{it} + \beta_2(LLR/GL)_{it} + \beta_3(ROA)_{it} + \beta_4(INTER)_{it} + \beta_5(BETA)_{it} + \beta_6(IDIO)_{it} + \beta_7 In(Z - Score)_{it} + \beta_8(LR)_{it} + \beta_9(CRK)_{it} + \beta_{10}(CI)_{it} + \beta_{11}(lnTA)_{it} + \beta_{12}(TBTF)_{it} + \beta_{13}(OWN)_{it} + \beta_{14}(INST)_{it} + \beta_{15}(INDD)_{it} + \beta_{16}(SOV)_{it} + \beta_{17}(YEAR)_{it} \qquad 5.52$$

where:

CR_{it} = bank i credit rating at time *t*. It is a discrete variable that ranges between 9 (AAA) and 0 (BB+ and below)[4].

$Tier1_{it}$ = a measure of the level of liquid capital available to cover losses

LLR/GL_{it} = a measure of the quality of assets held by the bank. It is the ratio of the loan loss reserve to gross loan.

---

[4]The breakdown of the different rating grades are presented in Appendix C

ROA_{it} = a measure of profitability and is defined as net income/total assets

$INTER_{it}$ = a measure of the interbank ratio. It is the money lent to other banks (due from other banks)/money borrowed from other banks (due to other banks).

$BETA_{it}$ = market beta. The beta is defined as a measure of the volatility or systematic risk of a security (or portfolio) in comparison to the market as a whole. It gives an indication of the tendency of a bank's equity securities to respond to 'swings' in the market. For the purposes of this research, it is calculated for each bank following the works of Amato and Furfine (2004) and Blume *et al*. (1998). This thesis follows Amata and Furfine by estimating the market model using 200 days of daily equity returns up to the end of the year for each bank in order to ensure consistency.

$(IDIO)_{it}$ = idiosyncratic risk for a specific bank. This is defined as the risk specific to an asset or small group of assets. Evidence shows that no correlation exists between idiosyncratic and market risk, and idiosyncratic rather than market risk accounts for most of the variation in the risk of an individual stock (Amato and Furfine, 2004).

CRK_{it} = a measure of a bank's credit risk. It measures the net loan losses in the current period to the provision made in the bank's book for these loan losses in the previous period. It represents the current riskiness of a bank's loan portfolio and shows how accurate a bank is in anticipating short-term loan losses.

$(CI)_{it}$ = a measure of bank's cost to income ratio.

LR_{it} = a measure of a bank's liquidity risk. It measures the short-term funding risk of a bank. The variable shows the relationship between short-term bank liabilities and short-term assets. Hence, it can be seen as representing a measure of a *bank run* risk, i.e. the risk of a bank not being able to meet all of its short-term obligations. The variable shows the degree to which a bank can cover its liquidity demands with readily convertible assets.

$InTA_{it}$ = a measure of bank size defined as the natural logarithm of total assets for a particular year.

$In(Z - Score)_{it}$ = is a measure of bank stability risk. It measures the sum of the returns on assets and the ratio of total equity to total assets divided by the standard deviation of the returns on assets. It gives an indication of a bank's distance to solvency. Leaven and Levine (2009) suggest taking the natural logarithm of this variable because of its high degree of skewness.

$TBTF_{it}$ = a measure of the too-big-to-fail concept, that is, the impact of government intervention. This follows the Fitch Support Rating which is an assessment of the potential for a bank to receive support in a time of financial difficulty either from the government as lender of last resort or from other external sources. The Fitch Support Rating takes a value of 1 to 5, with 1 having the highest propensity to receive support. Thus the TBTF variable takes a value of 1 if the bank is assigned 1 or 2, and 0 otherwise.

$OWNS_{it}$ = a measure of the impact of directors' ownership. This is calculated by splitting the shareholdings of directors into 'inside' and 'outside' (Ashbaugh-Skaife *et al.*, 2006), and is defined as the percentage of company shares held by inside and outside directors. Inside directors for the purpose of this study refers to executive directors, and outside directors refers to independent non-executive directors.

$INST_{it}$ = a measure of the impact of institutional ownership. Following Roberts and Yuan (2010), institutional ownership is calculated as the total ownership held by institutional investors as a proportion of the total shareholding. Institutional ownership represents an important measure of corporate governance because it facilitates monitoring of executive activities.

$INDD_{it}$ = a measure of the impact of independent directors. This is defined as the ratio of non-executive independent directors on the board of directors to the total number of board members. Bhojraj and Sengupta (2003) find that independent directors have a stronger governance culture, reduced agency risk, and have limited conflicts of interest, thus resulting in a positive impact on overall value of a bank.

SOV_{it} = the change in a sovereign rating between time *t* and *t+1*. The sovereign rating is defined as the sovereign risk of a national government or sovereign entity and it indicates the level of risk of the operating and investing environment of a country. Importantly, it takes into account political risk. SOVAA (country takes dummy variable 1 if assigned AA and above, 0 otherwise); SOVA (country takes dummy variable 1 if assigned A, and 0 otherwise); SOVBBB (country takes dummy variable 1 if assigned BBB and below).

YEARD = this captures the asymmetry in rating agency actions between recession and expansion periods, i.e. downward rating are more prominent in recessions than in boom periods. This is measured by assigning a dummy equal to 0 in pre-crisis periods and 1 otherwise.

The alternative models to the base form models are presented below.

Lagged form:

$$CR_{it} = \beta_0 + \beta_1(TIER1)_{it-1} + \beta_2(LLR/GL)_{it-1} + \beta_3(ROA)_{it-1} + \beta_4(INTER)_{it-1} + \beta_5(BETA)_{it-1} + \beta_6(IDIO)_{it-1} + \beta_7 In(Z-Score)_{it-1} + \beta_8(LR)_{it-1} + \beta_9(CRK)_{it-1} + \beta_{10}(CI)_{it-1} + \beta_{11}(lnTA)_{it-1} + \beta_{12}(TBTF)_{it-1} + \beta_{13}(OWN)_{it-1} + \beta_{14}(INST)_{it-1} + \beta_{15}(INDD)_{it-1} + \beta_{16}(SOV)_{it-1} + \beta_{17}(YEAR)_{it}. \qquad 5.53$$

Predictive form:

$$CR_{it} = \beta_0 + \beta_1(TIER1)_{it+1} + \beta_2(LLR/GL)_{it+1} + \beta_3(ROA)_{it+1} + \beta_4(INTER)_{it+1} + \beta_5(BETA)_{it+1} + \beta_6(IDIO)_{it+1} + \beta_7 In(Z-Score)_{it+1} + \beta_8(LR)_{it+1} + \beta_9(CRK)_{it+1} + \beta_{10}(CI)_{it+1} + \beta_{11}(lnTA)_{it+1} + \beta_{12}(TBTF)_{it+1} + \beta_{13}(OWN)_{it+1} + \beta_{14}(INST)_{it+1} + \beta_{15}(INDD)_{it+1} + \beta_{16}(SOV)_{it+1} + \beta_{17}(YEAR)_{it}. \qquad 5.54$$

5.4 Econometric and variable issues

The *CAMELS* classification presented by BANKSCOPE database classifies the financial/accounting ratios into four main categories. Within these categories, there are several ratios and this presents a high likelihood of multicollinearity between some of the variables. This study makes use of many such variables to ensure that no relevant variables are omitted. The classification by asset quality, capital adequacy, earnings, funding and liquidity means that the level of correlation among the variables within these different categories is potentially high. To resolve this, this thesis employs a stepwise analysis of the level of correlation within each category by first running a correlation matrix, and then measuring variance inflation factors in order to choose the most appropriate variable under the *CAMELS* specification. The econometric and variable measurement issues that warrant additional explanations are thus the treatments of multicollinearity, the calculation of a bank's systematic risk (beta), endogeneity (with specific reference to omitted variables and reverse causality), persistence in variables, and measures of corporate governance.

5.4.1 Multicollinearity

Multicollinearity occurs when two or more independent variables in the model are approximately determined by a linear combination of other independent variables in the model. For example, we would have a problem with multicollinearity if we had both height measured in inches and height measured in feet in the same model. The degree of multicollinearity can vary and can have different effects on the model. When perfect collinearity occurs, that is, when one independent variable is a perfect linear combination of the others, it is impossible to obtain a unique estimate of regression coefficients with all the independent variables in the model. What an econometric package such as Stata does in this case is to drop a variable that is a perfect linear combination of the others, leaving only the variables that are not exactly linear combinations of others in the model to assure unique estimate of regression coefficients. When severe multicollinearity occurs, the standard errors for the coefficients tend to be very large (inflated), and sometimes the estimated logistic regression coefficients can be highly unreliable.

This thesis deals with multicollinearity by following a step-wise approach by employing the variance inflation factor (VIF). The thesis calculates the VIF for the regression of one independent variable on the other independent variables within that category (e.g. those measuring profitability). The presence and magnitude of multicollinearity in the estimation is then considered be examining the size of the respective VIFs. This thesis follows the rule of thumb is that if VIF is greater than 10, then multicollinearity is high (Studenmund, 2006). As a means of validating the choice, the thesis dropped sone or more of the regressors and re-ran the model to see if the multicollinearity improves. Following these two steps, the study was able to select the final independent variables it employed in its model.

5.4.2 Endogeneity

This thesis recognises the impact of the presence of endogeneity within its modelling approach. The endogeneity relates to the correlation between the explanatory variables and the error term in a regression (Roberts and Whited, 2012). This could potentially lead to bias and inconsistent parameter estimates that make reliable inference difficult. One of the issues relating to endogeneity is the omitted variable bias. This relates to variables that should be included in the model as explanatory variables, but for various reasons are not. This thesis accounts for this within its fixed variable models for the determinants of bank credit ratings. Apart from omitted variables, there is the potential for reverse causality whereby the credit ratings drive the independent variables, and not the other way round. This study follows Poon (2003) by replacing current variables by lagged variables for all both the financial and non-financial variables in the alternative bank credit rating models (lag specification. It further adopts Wooldridge (2002) instrumental variable (IV) approach to account for any endogeneity in the models. In the context of omitted variables, an instrumental variable is redundant in the structural model and is uncorrelated with the omitted variable. Stata software package allows for a choice of IV within its application.

5.4.3 Beta and idiosyncratic risk

Amato and Furfine (2004) present two measures of business risk obtained from estimating the market model. Their study follows Blume *et al.* (1998) and separates equity risk into its *systematic* (or beta) and *idiosyncratic* (or non-beta) components, with the latter estimated using the standard error of the residuals of the market model. A higher beta indicates that bank operations may be relatively sensitive to aggregate business conditions in the market. It thus provides a measure of 'the relative cyclicality of the firm's operations' (Amato and Furfine, 2003, p. 8). A higher idiosyncratic risk, the risk unique to a bank, proxies for firm-specific factors, and in particular the ability of management. It is obtained from the standard errors of an estimation of the market model. The market model from which the beta and idiosyncratic variation are computed employs 200 days of daily equity returns in any given year. The estimates of the beta and standard errors are further averaged across all bank estimates for the year in order to standardize them. In addition, the market indices employed as the benchmark index are those on which banks are primarily listed.

5.4.4 Corporate governance factors

The issue of corporate governance is very important to banks, especially following the financial crisis. For this study, the measures of corporate governance are the degree of director's ownership (*OWN*), the proportion of institutional shareholding (*INST*), as well as the number of independent directors on the board (*INDD*). Fama and Jensen (1983) maintain that increasing share ownership by directors enables them to accumulate considerable voting power to ensure their position within the firm. However, evidence also shows that increasing directors' shareholdings provides them with the incentive to improve governance due to sharing some of the financial risk of the company with other shareholders (Minow and Bingham, 1995). This study measures the level of directors' ownership as the percentage of company shares held by inside and outside directors. For institutional ownership, the percentage of outstanding shares held by institutional investors is employed to compute *INST*. Following Robert and Yuan (2010), this thesis employs the proportion of ownership held by institutional block investors (those holding more than 5%) to proxy for significant shareholders. The presence of independent directors on the board of a bank is very important as this gives rise to a monitoring incentive for board members. In this thesis, the *INDD* is measured as the proportion of outside directors to the total number of board members, consistent with existing studies (e.g. Bhagat and Black, 2002; Bhojraj and Sengupta, 2003; Robert and Yuan, 2010).

5.5 The data sample

This section presents the data employed in this study and discusses a number of data-related issues. In addition, it discusses the sampling methods employed and briefly describes the sample of the study. This thesis examines three aspects of bank credit ratings: i) the determinants of bank ratings, ii) an event study on the impact of bank rating changes on bank stock returns, and iii) bank rating transitions over the sample period, i.e. 2000-2012.

5.5.1 Data of this study

This thesis employs secondary data for listed commercial banks operating across the world over the period 2000-2012. The following are the reasons for choosing the time period as well as the data set:

1. The data span a thirteen-year period from 2000-2012 and this cover periods of the 2007/08 financial crisis. This presents added value during the analysis because its enables the effects of the crisis on the banks in the sample to be captured. Thus, this differentiates the current study from the previous related studies in the area of bank credit ratings.
2. The data for the period 2000-2012 presents an update for similar studies employing earlier data periods. It therefore gives the opportunity to inform and update the empirical evidence in the areas of bank credit ratings, especially against the backdrop of the global financial crisis. Further, it allows comparisons to be made with empirical evidence from previous studies.
3. The 13-year period (2000-2012) is employed in order to maximize available data and, at the same time minimize missing observations for the bank credit rating variables[5]. Since the banking industry is relatively well regulated, there is a relative stability in rating actions within the industry; hence the number of bank credit rating actions (upgrades and downgrades) captured is enhanced by employing longer period of coverage.
4. The data set employed in this thesis consists of banks whose country of primary domicile varies, that is from developed to emerging and developing economies. Hence, the period is also sufficient to provide an insight into the issue of bank

[5] It is worth noting that there were a lot of consolidation, i.e. mergers and acquisitions in the banking industry across the world during the 1990s and early to mid-2000. This resulted in new ratings being issued to several banks. More importantly, the depth of rating varies markedly across different economies and geographical locations.

rating stability and to investigate the effects of crisis on banks operating in different economies.

The sample of this study consists of three types of data:

1. Banks' financial and non-financial information over the period 2000-2012. The sources of these data are BANKSCOPE, DATASTREAM and the REUTERS 3000Xtra databases, as well as the annual financial reports of the banks in the sample size. The latter is employed primarily to generate non-financial information of the banks e.g. ownership structure and the number of independent directors during the same sample period.
2. Banks' market information, that is, daily stock price information over the period 2000-2012. The sources of this data are BANKSCOPE and the REUTERS 3000Xtra databases. The raw bank stock prices are not use directly, but rather daily bank stock returns are calculated for each bank over the sample period as well as sub-sample periods. These data are employed in the empirical investigation in the event study. Similarly, the market index used in the calculation of the betas in the market model is the index for the exchange on which the banks are primarily listed.
3. The banks' credit rating over the period 2000-2012. The source of this data is BANKSCOPE, the REUTERS 3000Xtra and FITCH SOLUTION databases for the period 2000-2012, which have been employed by a number of other related studies in the past (e.g. Poon, 2003, Poon and Firth, 2005). BANKSCOPE contains comprehensive information for over 30,000 banks across the globe, including up to 16 years of detailed accounts for each bank. The Fitch Bank Credit Model which is a statistical model that produces financial implied ratings for over 11,000 banks across the globe is incorporated in BANKSCOPE search. This make BANKSCOPE appropriate for accessing ratings and ratings reports

from Fitch Ratings as well as stock data for listed banks. Any gap in the credit rating data is supplemented by the FITCH SOLUTION and the REUTERS 3000Xtra databases. The bank credit rating data employed are the long-term local currency during the period 2000-2012. In addition Fitch Support Ratings are also employed as part of the independent variables to help assess the concept of *too-big-to-fail (TBTF)* within this study.

An important novelty in this thesis is the inclusion of the TBTF variable which presents a significant addition to the bank credit rating determinant model. The global financial crisis of 2007/08 highlights the importance of the concept of TBTF, a situation where national governments perceive that the failure of a financial institution would cause severe disruption to the overall financial system due to its size or interconnectedness (Molyneux *et al.,* 2010). Labonte (2015) argues that this may create a moral hazard issue if TBTF firms believe that government will protect them from losses in times of economic shock or downturn. Thus, such firms may have more incentive to take on greater risks because of their supposed protection from the negative consequences of those risks. Alfonso *et al.* (2014) find that banks that are classified by CRAs as being more likely to receive government support engage in more risk taking. The importance of including a variable to measure a bank's propensity to receive external help has significant policy implications. This thesis relies on ratings issued by Fitch that explicitly measure external support, independent of the intrinsic credit quality of the bank. Support ratings (SRs) rely on Fitch's assessment of a supporter's propensity and ability to support a bank. External support can be of two types: sovereign states and institutional owners. The use of the Fitch support ratings is consistent with the studies by Gropp *et al.* (2011) and Gadanecz *et al.* (2012). Following the global financial crisis, there have been global regulatory reforms, e.g. the Wall Street Reform and Consumer Protection Act (2010), the Financial Stability Board (FSB, 2010), and the Basel III Accord, to address the TBTF problem. In addition, these current regulatory reforms present an interesting area for future research on the extent to which the new regulations impacts on the likelihood of governmental support, bank risk-taking policies and overall bank creditworthiness.

5.5.2 The treatment of outliers

This study employs non-financial data as well as international bank credit rating data that need to be transformed into numerical values to investigate bank credit ratings. Hence, due to the nature of the investigation to be carried out in this study, the need to address outliers presents an important issue. Outliers are observations or measures that are suspicious because they are either much smaller or much larger than the vast majority of the observations, i.e. numerically distant from the rest of the data included in the data set (Cousineau and Chartier, 2010). They may cause distortions in model estimation and may affect the performance of such models leading to biased or spurious estimates.

There exist arguments for the inclusion of outliers in studies around the modelling of credit risk involving the use of ratio-based models (e.g. Hossari *et al*., 2007). The main argument has to do with the nature of such studies. Hossari *et al*. argue that credit rating studies essentially focus on examining the 'abnormalities in the financial ratios of companies' (p. 18) and eliminating such outliers might lead to the removal of certain key features from the dataset, thus distorting the objective of these studies. Similarly, removing such outliers from the sample may grossly undermine the predictability of such models and significantly reduce the number of firms remaining in the dataset. Kaplan and Urwitz (1979) further contend that the removal of outliers for statistical reasons (assumptions of specific modelling techniques) takes away valuable information and reduces the volatility in the data that is central to the estimation of relative credit risk.

For the purposes of this thesis, the presence of outliers within the data, e.g. financial data (ratios), the ratings of banks and share prices, is taken into consideration in the interpretation of the model out. Within this thesis, outliers might be correct values which are distant from the rest of the observations, but only contextual in nature. The financial ratios this thesis employs have a tendency to be skewed, flat or dominated by issues of sample variance. However, the use of a large dataset helps to solve this problem. Ghosh and Vogt (2012) argue that studies employ various techniques to treat the concern of extreme values (or outliers) in the data, including winsorizing, trimming, and transformation into logarithmic, squared or inverse form. Literature around credit rating determination, (e.g. Poon *et al.,* 2000) suggests transformation of data and tends to use winsorising and trimming, depending on the sample size. It is argued however, that the issue of extreme observations may not be completely resolved by simple log or square transformation (Deakin, 1976; Frecka and Hopwood, 1983)

The treatment of outliers for the purposes of this study follows the established process in the existing literature in this field (e.g. Gonis *et al*., 2012) by performing some data transformation and winsorizing (replacing the smallest and largest values, i.e. extreme values of a dataset with a certain percentile from each end) of the independent variables due to their non-normality. This latter strategy sets all outliers to a specified percentile of the data (usually at the 5% level). The data winsorized includes stock prices and the book value of assets, as well as the financial ratios employed.

5.5.3 The sample and sampling method employed in this study

The banks within the sample are drawn from across the globe and this gives a holistic treatment to the issues around bank credit ratings determination and market reaction to rating changes. Following previous studies related to the investigation of credit rating determinants and events studies (Horrigan, 1966; Pogue and Soldofsky, 1969; Pinches and Mingo, 1973, 1975; Wansley and Clauretie, 1985; Hand *et al.,* 1991; Adam *et al*., 2003; Poon, 2003; Richard and Deddouche, 2003; Amato and Furfine, 2004; Poon and Firth, 2005; Jorion *et al.,* 2009; Bremer *et al*., 2011), the criteria for selecting the sample of the study are:

1. The sample includes listed international banks engaging in commercial banking activities from around the world, and operating in different geographical regions during the period 2000-2012.
2. The sample includes only banks in order to maintain a level of homogeneity among the individual firms in the sample (e.g. Poon, 2003; Distinguin *et al.,* 2012). Further, the use of firms in the same industry allows for uniformity in the interpretation of financial ratios (Poon and Firth, 2005) as well as the fact that most of the banks follow to a large extent similar global regulations, e.g. Basel (or some variant of it). This is true particularly in the case of the requirement for a minimum capital buffer as stipulated by Basel regulations. While Basel requirements are not binding, virtually all national governments incorporate an aspect of them into their banking industry requirements.
3. In terms of the concentration and geographical distribution of banks, the sample consists of commercial banks operating in more than one country (i.e. branches and subsidiaries exist outside the country in which the banks primarily operate). This allows a more holistic approach in the investigation of bank credit ratings and enables the thesis to examine the impact of any credit changes on markets across the world. There is the argument that credit rating employs the same criteria and methodology in their approach (following strictly the specifications for US standards) in rating across other geographical locations (Fight, 2000). In addition, credit rating agencies maintain that they employ a comparable rating methodology across the same industry; the analysis of the determinants of credit

ratings for banks on a global scale should therefore be comparable, i.e. across geographical locations for a specific industry. CRAs also argue that their models are calibrated to take into account other country-specific variables.

4. This study employs the Fitch Long Term Local Currency credit ratings for the banks in the sample. The ratings are those assigned to the parent companies in the country where they are primarily domiciled. Evidence shows that the major credit rating agencies, e.g. Fitch, rely on consolidated accounts to carry on the assessment of a company's creditworthiness (Pasiouras *et al.*, 2007). The data shows that most subsidiaries of a bank are assigned the same rating as the parent firm; however, in the case where this is to the contrary, say due to reasons such as a peculiarly hostile operating environment, or for the purpose of debt issuance, the study takes into account only the parent bank credit ratings.

   Fitch, along with the other major credit rating agencies, Moody's and Standard and Poor's, assigns credit ratings to entities and their issues. This study employs only Fitch ratings due to data availability issues (cost). Although CRAs have different methodological approaches and definitions of what constitutes the probability of default, studies comparing the ratings of the major agencies find great similarity for their grading (Cantor and Packer, 1996; Ammer and Packer, 2000). The BCBS (2000) however argues that there might be differences attributed to sample selection bias amongst the three largest CRAs. They maintain that regardless of rating differences, the market appears to reward issuers with lower interest costs when a second or third rating is assigned, especially when the ratings are higher. It is interesting to note that Fitch and the Egan-Jones Rating Companies have accused the big two CRAs (Moody's and S&P) of practising the "notching", a practice whereby they initiate an automatic downward rating of structured securities if the two agencies were not hired to rate them (Egan-Jones Ratings Company, 2002). Elkhoury (2010) finds ratings to be a trade-off between accuracy and stability, with the major CRAs being averse to reversing ratings within a short period of time.

5. The study includes only active banks whose daily bank stock prices as well as financial statements are available on BANKSCOPE and DATASTREAM databases. Only banks rated by Fitch Rating Inc. are employed due to data availability issues. The study employs market information on the banks in the sample, that is, stock prices, betas, market returns, hence non-listed banks and delisted banks are excluded from the final sample. The use of these databases thus allows for access to the information required for the variables to be included in the empirical models employed by this study. It further allows the study to obtain a relatively large sample of banks from across different geographical markets.
6. The event study component of this thesis is designed to capture the impact of specific types of new information (bank credit ratings). Konchitchki and O'Leary (2011) argue that if another event type occurs at roughly the same time as the event of interest, there would be a question as to what was the true cause of a change in market price. Hence, this thesis conducts a thorough research design to investigate other announcements during the window of interest to determine whether there are any confounding events. Apart from news events relating to bank credit ratings, the financial market is impacted upon by the flows of other firms or industry related news announcements that could potentially trigger changes in bank stock prices (Brown and Warner, 1985; Morck and Yeung, 1992; Cannella and Hambrick, 1993). Specifically, Brown and Warner (1985) argue that a longer event window makes it more difficult to eliminate potential confounding events. Hence, the focus of short event windows in this thesis which reduces the potential for confounding events to interfere with the markets' response to the event of interest.

DeFond *et al.* (2010) suggest a stepwise approach to dealing with contamination or confounding events. The authors suggest a first step of gathering event data on related news announcements around the event window. Second, news published about firms are then analysed using major news channels such as the Bloomberg and Reuters databases. The analysis can then take multiple stages, culminating with the removal of all confounding events around the event window. Such an analysis can provide an investigation of the robustness and causality of the evidence.

In this thesis, for every event day *t*, i.e. the day of the bank credit rating news announcement, other unrelated news items (such as dividend or earnings announcements, merger and acquisition activities) are identified. Whenever there is conflicting news around day *t-1* to *t+1*, the credit rating announcement is classified as being contaminated and removed from the sample. The study further considers the impact of unanticipated news and conditions the rating actions (upgrades/downgrades) on any previous announcements regarding credit rating outlooks and placement on a Watchlist.

7. The structure of the data is an unbalanced panel data. This implies that there are missing observations. Banks with missing observations for any of the variables and for any year in the models are still included in the sample. This is to prevent the loss of data which may reduce the overall efficiency of the models. This thesis follows Allsion (2001) by employing the conditional mean imputation. This involves selecting cases with complete information and regressing this on all the other independent variables. The estimated equation is then used to predict the missing value for those cases it is missing.
8. The study employs the EViews and STATA econometrics software to analyse the determinants of banks credit ratings as well as the event study component. The software enables model estimations with samples that have missing

observations. The missing variables particularly relates to the first component of the study on the determinants of bank credit ratings. More importantly, the STATA software presents an advantage due its robustness and the fact that it facilitates the estimation of all statistical and econometric techniques that this study employs.

The cut-off for the initial sample of the set of all banks for which credit ratings are available on BANKSCOPE database is 31/12/2012. Following the criteria above, the initial and final sample are presented in Table 4.1 for banks rated within the period 2000-2012 of this study. Table 4.1 shows that 738 commercial banks and bank holding companies (BHC) are assigned Long Term credit ratings by Fitch on BANKSCOPE at the end of 2012. The exclusion of inactive banks (e.g. due to bankruptcy, liquidation, M&A, or active but no longer with accounts on BANKSCOPE) results in a reduced number of 726. An important criterion for the data set in this study is that banks must be publicly listed. This is to allow for the collection of market data, e.g. share price. This further limits the sample size to 322. These factors yield the study's final sample of 322 banks over the period 2000-2012.

This thesis considers the issue of survival bias (Carpenter and Lynch, 1999), that is, the effects of the exclusion of inactive banks on the interpretation of the results. The inactive banks that fail during the sample period drop out, so the sample may be biased towards the healthier institutions. To assess the potential extent of this source of bias, the study examines the percentage of banks on BANKSCOPE database that are assigned Fitch Long Term credit ratings but are however inactive during the sample period. Of the 738 commercial banks and BHCs that assigned the Fitch Long Term, 726 of these are active. This implies that only 1.62% of the initial sample is inactive. This percentage of inactive banks is relatively small compared to the active banks and hence the results are not expected to be significantly affected by their non-inclusion. The final sample of banks employed in the thesis survived throughout the sample period.

5.5.4 The distribution of banks

The sample includes 322 international banks whose ratings are assigned by Fitch Rating. The geographical locations where the banks are primarily domiciled are presented in Table 5.1[6]. Column (2) provides the number of banks rated by Fitch Rating in the sample size for each of the regions. Columns (3) and (4) provide the relative and cumulative frequencies respectively for the regional distribution of banks.

In addition, the results in Table 5.1 can be represented graphically in Figure 5.1. **Table 5.2** and Figure 5.1 show that the majority of the banks in the sample are primarily domiciled in the Far East and Central Asia.

Table 5.1: Sample collection of rated banks for the period 2000-2012

Criterion	Subtotals	Number of sample banks
Initial sample (Commercial banks assigned the Fitch long term credit rating)		738
Inactive banks	(12)	726
Non-publicly trading banks	(404)	322
Geographical distribution		
Western Europe	56	
Eastern Europe	27	
Middle East and North Africa	44	
Far East and Central Asia	74	
South and Central Asia	34	
Sub-Sahara Africa	13	
Oceania	8	
North America	66	
Number in final sample		**322**

Notes: The distribution of banks in the final sample spans the different geographical regions. A large number of banks rated by Fitch on BANKSCOPE are non-commercial banks or subsidiaries of banks involved in other areas of financial activities.

[6] BANKSCOPE database geographical classification benchmark was adopted in the distribution of banks

Banks from the Far East and Central Asian region account for 74 banks (23% of the entire sample). This is not surprising because of the deregulation in the banking industry within that region. North America is second in terms of the number of banks in the sample, and the banks within this region have longer rating history, and are much more established. A close examination of Table 5.2 reveals that Oceania consists of only eight banks, and makes up only 2% of the sample. The remaining regions, Western Europe, Eastern Europe, Middle East and North Africa, South and Central Asia, and Sub-Sahara Africa account for 17%, 8%, 14%, 11% and 4%, respectively.

Table 5.2: Distribution of Fitch rated banks in the sample

Geographical Location (BANKSCOPE benchmark) (1)	Number of banks (Rated) (2)	Relative frequency (%) (3)	Cumulative frequency (%) (4)
Western Europe	56	17	17
Eastern Europe	27	8	25
Middle East and North Africa	44	14	39
Far East and Central Asia	74	23	62
South and Central Asia	34	11	73
Sub-Sahara Africa	13	4	77
Oceania	8	2	79
North America	66	21	100
Total	**322**	**100**	

5.5.5 Bank credit ratings

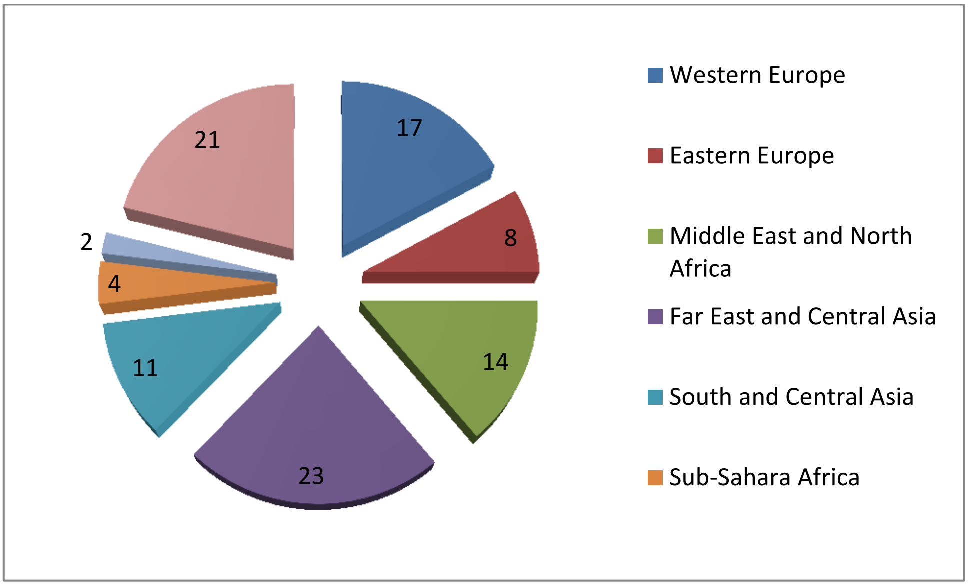
The sample consists of 322 Fitch long term rated international banks over the period 2000-2012. The credit ratings of banks in the sample are spread from AA to CCC over the study period. For the purposes of this thesis, the credit rating of a bank for any given year is the letter assigned to it by Fitch on the year's financial reporting date. **Table 5.3** and Figures 5.2 and 5.3 present information on the distribution of bank credit ratings over the sample period 2000-2012[7].

[7] The detail of the banks and their rating over the sample period is presented in Appendix B.

An examination of Table 5.3 and Figure 5.3 reveal some patterns in the distribution and changes in rating over the period 2000-2012:

1. Table 5.3 shows that none of the banks in the sample are assigned the top rating (AA+ and above) at the cut-off date of 31st December 2012. The investment grade rated banks constitute about 72% of the total sample, while the speculative or noninvestment grade makes up the rest.

Figure 5.1: Geographical distribution of banks in the sample



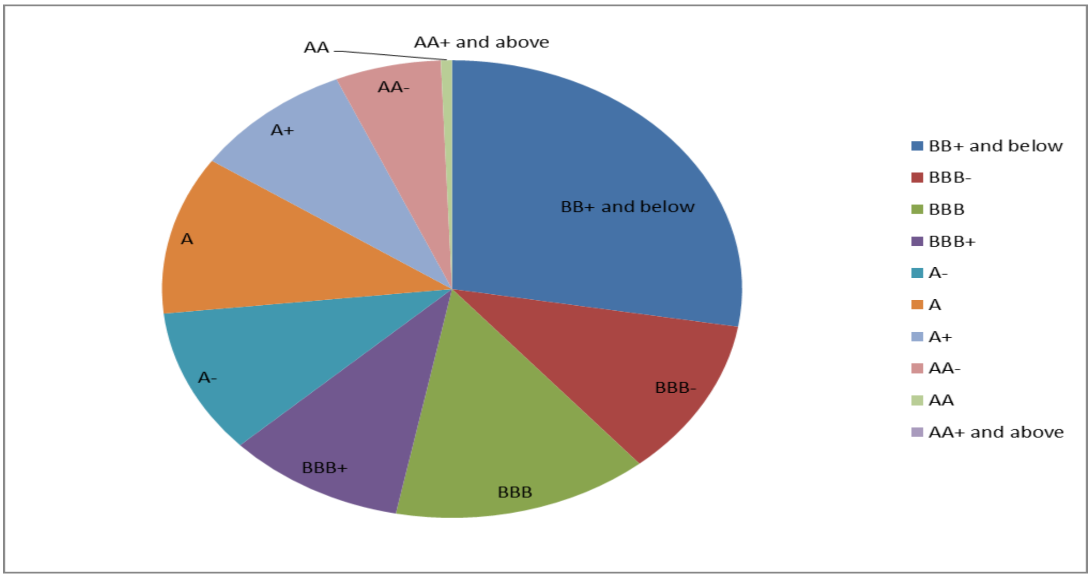
2. The period witnessed a significant increase in the number of rated banks in the international market. Banks rated by Fitch in the sample size increased from 150 in 2000 to 322 by the end of 2012, representing an increase of 114%. This surge in rating assignment may be attributed to the increase in the importance of the rating process, and the opening of new markets, especially the emerging and developing economies of South America, and the Far East. It also highlights the positive propensity for banks to want to take on ratings in order to have access to cheaper funds in international markets. Again, it serves as a form of public risk disclosure for investors willing to invest in the banks.

Table 5.3: Bank credit rating distribution

Ratings	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
AA+ and above	1	1	3	5	5	5	4	4	1	0	0	0	0
AA	10	12	10	9	8	8	11	9	8	6	6	5	2
AA-	21	23	26	25	28	30	31	34	34	27	28	19	19
A+	19	18	18	21	21	18	21	30	36	34	31	28	29
A	15	15	19	21	29	35	39	35	31	33	29	41	36
A-	14	18	25	32	32	32	35	32	39	36	40	33	33
BBB+	18	25	26	32	25	27	26	27	24	29	23	31	32
BBB	11	14	19	22	31	34	27	25	28	31	33	36	46
BBB-	8	10	19	26	25	20	24	30	29	32	41	37	36
BB+ and below	33	43	68	84	90	101	100	96	92	94	91	92	89
Total	150	179	233	277	294	310	318	322	322	322	322	322	322

Notes: Credit rating distribution per year for the 322 credit rated banks in the sample. A bank's credit rating for any given year is the rating assigned to the banks on its year-end date.

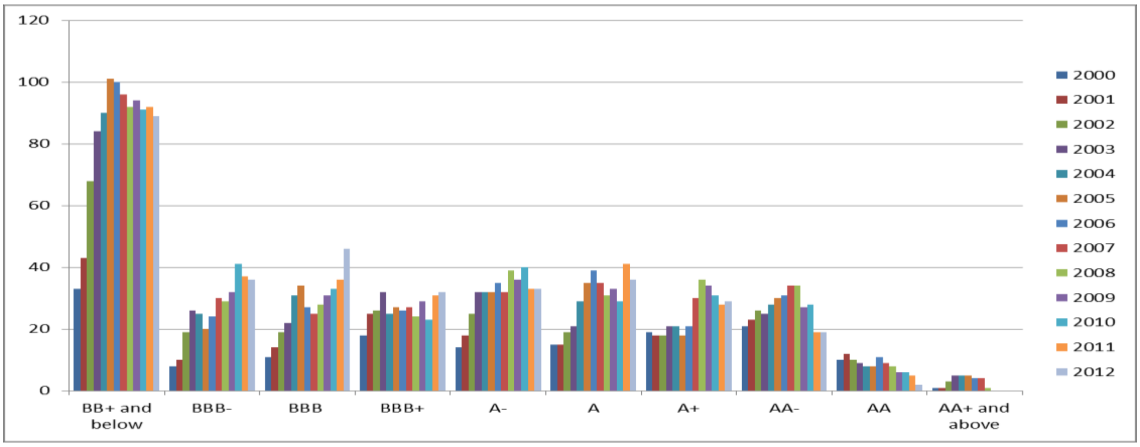
Figure 5.2: Bank credit rating distribution per category



Notes: Credit ratings of 322 rated banks by Fitch per category as at 31st December 2012

1. There is a diverse range of rating categories for banks in the sample. An examination of the sample shows that the banks Fitch assigns rating to varies in creditworthiness from (AA+ and above) highest rating grades to (BB+ and below) lowest rating with the highest riskiness.

Figure 5.3: Growth of bank credit ratings



Notes: Classification of bank credit ratings of 322 rated banks per category over the period 2000-2012

2. During the period under investigation, the highest bank credit rating assigned by Fitch is AA+. On the other, the lowest credit rating assigned is within the speculative grade (BB+ and below). Overall, this shows a diverse range of credit ratings in the sample and thus the banks in the sample vary markedly in their creditworthiness.

5.6 Bank fundamental characteristics

The banking industry is very unique and quite different from other non-financial industry firms[8], and thus the drivers of performance and riskiness vary as well. Commercial banks are unique in terms of the types of assets and liabilities they hold. This section reports the descriptive statistics related to bank fundamental characteristics within the sample of banks in this study. The analyses in this section focus on examining selected financial characteristics of banks, particularly those related to the measure of a bank's riskiness. Evidence from existing studies shows that bank fundamental characteristics are related to bank risk. Leung *et al.* (2015) investigate the impact of US bank holding company (BHC) fundamental variables on bank risk before,

[8] The specific issues relating to bank credit risk which this thesis examines are discussed in great details in Chapter 3

during and after the 2007/09 financial crises. Employing a sample of 227 publicly traded US BHCs with $500 million or more consolidated assets, they find that Tier 1 capital, profitability, and the presence of an effective internal control system relate negatively to bank risk. Hence, banks with larger capital buffers and higher profitability are less risky.

Financial indicators represent important information about banks' credit default risk. The first part of this section examines the bank fundamental characteristics for the sample of banks in this study. Ötker-Robe and Podpiera (2010) argue that bank specific fundamentals, that is, the elements of the *CAMELS* structure, are crucial in measuring the performance of a bank and give an indication of the level of its inherent risk. Evidence from previous studies (e.g. Poon, 2003; Caporale *et al.* 2009; Bissondoyal-Bheenick and Treepongkuruna, 2011) shows significant results for accounting/financial independent variables when modelling the determinants of bank credit ratings.

This section investigates the trends in the fundamental characteristics of the banks in the sample. The choice of ratio follows the approach of Poon (2003) who tested for multicollinearity within each category of financial ratio. The author chose the financial ratios with the least collinearity as representative of each category. This study employs both the fine and coarse rating granularity in its empirical investigation. However, for the purposes of providing statistical/descriptive analyses of the bank financial ratios, a coarse rating granularity is adopted. The coarse-grading has fewer, larger discrete components than the fine-grading. The coarse ratings are presented in four categories, AA-AAA, A, BBB, and below BBB. In addition, the analyses of the banks' fundamental characteristics across the sample period present results of the test differences in mean between pre- and post-crisis periods. These provide evidence of statistical differences between the mean of the financial ratios. The selection of the periods follows Obstfeld and Rogoff (2009) who argue that there was a general contraction in the balance sheet of the European Central Bank (ECB) immediately following the Lehmans Brothers' event. Further, Petitjean (2013) supports the argument of the existence of financial cycles in which financial booms follow busts. Borio (2014) argues that the financial cycle is best captured by the joint behaviour of credit and property prices. He suggests that there the period between 2000 and 2007 witnessed growth in credit and property prices, and defines this as the boom period. Conversely, the period following the global financial crisis (2008 to 2012) was marked by a downward trend in the amount of credit extended globally.

5.6.1 Capital

The first of the *CAMELS* measures, the level of capital held by banks as buffer for loss absorption, and thus, the capital adequacy of a bank, should relate negatively to bank credit risk. This requirement is directly linked to the Basel Accord regulation discussed in Section 3.4. Although, banks are required to maintain a minimum level of capital, losses suffered in their trading books during the 2007/08 financial crisis far exceeded the minimum capital requirements (BCBS, 2009). Table 5.4 shows the description of variables classified under the capital adequacy measure of bank fundamental characteristics. This is based on BANKSCOPE database classification. The database specifies eight variables under the capital adequacy categorization.

Capital ratios have always been used by regulator to assess the stability of banks. An example is in the assessment of the impact of the EU-wide stress test, which is measured in terms of Common Equity Tier 1 Capital ratios. Table 5.5 represents the summary statistics for capital adequacy ratio during the pre- and crisis periods.

Table 5.4: Capital adequacy measures

Capital adequacy measure	Description
Tier 1	Tier 1 bank capital
T_CAP	Total Capital Ratio
EQ_TA	Equity / Total Assets
EQ_NL	Equity / Net Loans
EQ_CSTF	Equity / Cust & Short Term Funding
EQ_LIAB	Equity / Liabilities
CF_TA	Cap Funds / Tot Assets
CF_DSTF	Cap Funds / Dep & ST Funding
CF_LIAB	Cap Funds / Liabilities
SD_CF	Subord Debt / Cap Funds

Notes: This table provides the description and definition of the bank variables under BANKSCOPE classification 'capital'. All values are calculated as yearly averages across all 322 banks.

The table reports the full sample, pre-crisis and crisis subsample means, median and standard deviation (Stdev) of the capital adequacy ratios. In addition, it presents the average values of these ratios for subsamples of banks classified on the basis of the coarse rating grading. As expected, international banks rated in the top-tier of the investment-grade category have higher capital ratios than those in the non-investment category. As an example, the Tier 1 ratio gives an average of 17.21 for banks in the coarse rated category AA–AAA, while on average, international banks rated in the 'Below BBB' rating category have a Tier 1 ratio of 6.94. The result is consistent for all of the capital adequacy ratios. Furthermore, the tests of the means show that there exist significant differences between the pre- and crisis period averages for the capital adequacy ratios. The mean value of the capital adequacy ratios is higher in the crisis period than in the pre-crisis period. This suggests that international raised additional capitals in the period following the 2007/08 global financial crisis. A 2013 report by the Federal Reserve Bank, Boston show that there was dramatic the improvement in capital ratios at large U.S. financial institutions between 2009 and 2012. Further, Demirguc-Kunt *et al.* (2010) find that for undercapitalized and larger banks, better capitalization is associated with greater resilience in dealing with shocks, consistent with the spirit of capital regulation. The increase in the capital adequacy ratio following the financial crisis has brought into question previous views that capital in the financial sector had been both adequate and adequately regulated.

Table 5.5: Average capital adequacy ratios in the pre-and crisis periods and across bank coarse credit ratings grading

Capital adequacy	Mean value	Median	Stdev.	Mean value	Stdev.	Mean value	Stdev.	Test of Mean	Coarse grading			
	Full sample			Pre-crisis period		Post-crisis period		t-test	AA – AAA	A	BBB	Below BBB
Tier 1	12.35	10.91	4.98	12.75	2.66	16.95	6.66	7.21	17.21	16.92	13.32	6.94
T_CAP	15.92	14.36	6.29	17.66	3.94	19.62	4.82	5.22	18.93	17.99	14.93	10.21
EQ_TA	5.98	5.74	0.62	4.21	0.25	8.94	1.64	3.34	10.22	9.31	6.24	3.05
EQ_NL	14.18	13.95	1.40	6.32	0.78	19.51	2.65	3.64	18.71	15.21	14.10	8.21
EQ_CSTF	9.52	9.39	0.84	4.21	0.54	16.23	1.14	4.01	12.99	10.62	9.99	6.65
EQ_LIAB	6.47	6.17	0.71	3.29	0.33	8.91	1.16	3.29	11.59	8.81	7.01	6.48
CF_TA	7.63	7.46	0.59	5.39	0.21	9.54	2.21	2.99	13.65	9.21	6.21	5.55
CF_DSTF	12.39	12.44	0.71	8.31	0.48	15.95	1.65	3.68	22.31	16.64	12.87	12.01
CF_LIAB	8.26	8.07	0.69	4.22	0.37	8.33	2.09	3.85	18.21	12.24	9.61	8.05
SD_CF	18.93	18.35	2.84	10.98	1.15	21.67	4.11	3.62	29.31	22.61	19.21	16.98

Notes: Mean, median and standard deviation of the capital adequacy ratios. Table 5.5 also shows the averages for these ratios for banks categorized using the coarse rating gradation. The test of mean (t test) presents a test of level of significance (at a 95% confidence level) between the averages of financial ratios in the pre- and post- crisis periods

Rosengren (2013) argues that despite the dramatic improvement in bank capital positions, examination of capital erosion during the financial crisis highlights how significant and quick the capital erosion was at some of the largest financial institutions. He restated the need to examine how other tools such as stress tests, tougher liquidity requirements, and resolution plans supplement the higher and more stringent capital standards.

5.6.2 Asset quality

Most of the assets on a bank's balance sheet are made up predominantly of its loan portfolio. It is therefore a major driver of bank earnings and any impairment of this category of item could result in severe consequences for the bank. Asset quality measures the quality of the assets held by banks. Section 4.3.2 discusses the importance of asset quality and the provisions banks make to offset any non-performing or impaired loans. BANKSCOPE provides eight measures of asset quality, all of which focus on loans, i.e. non-performing loans, loan loss provisions, and net charge-offs. Table 5.6 presents descriptions for the asset quality ratios for the banks in the sample.

Table 5.6: Assets quality measures

Assets quality measure	Description
LoanR_GL	Loan Loss Reserves / Gross Loan
LoanP_NIR	Loan Loss Provisions / Net Interest Revenue
LoanR_IL	Loan Loss Reserves / Impaired Loans
ImpairedL_GL	Impaired Loan to Gross Loans
NCO_GL	NCO / Average Gross Loans
NCO_NI	NCO / Net Income Before Loan Loss Provisions
ImpairedL_EQ	Impaired Loans / Equity
UImpairedL_EQ	Unreserved Impaired Loans / Equity

Notes: This table provides the description and definition of the bank variables under BANKSCOPE classification of 'assets quality'. All values are calculated as yearly averages across the 322 banks.

Table 5.7 presents statistics of selected asset quality ratios from BANKSCOPE data. The results show the asset quality ratios for both the pre- and crisis period and the results of the sub sample means tests. In addition, the results present the average value of the asset quality ratio for banks categorized into the four coarse ratings grading. The results show that the asset quality of banks was much better in the pre-crisis period, with a mean value of asset quality ratios lower than the corresponding figures in the full sample. The banks rated in the investment categories, particularly those in the top grades have healthier asset quality. On average, the loan loss reserves to gross loan for banks in the top investment grade is 1.21 compared with the 4.21 for banks in the noninvestment category. This ratio indicates how much of the total portfolio has been provided for but not charged-off. It is a reserve for losses expressed as a percentage of total loans. Given a similar charge-off policy, the higher the ratio, the poorer the quality of the loan portfolio will be.

Similarly, the loan loss provisions to net income revenue for investment grade rated banks are on average 15.96 compared to the 32.84 for noninvestment grades. This ratio shows the relationship between provisions in the profit and loss account and the interest income over the same period. Ideally this ratio should be as low as possible and in a well-run bank if the lending book is higher risk then this should be reflected by higher interest margins. If the ratio deteriorates it means that risk is not being properly remunerated by margins. Generally, the results suggest that the asset quality of loans within the portfolio of a bank is a major driver for the level of assigned ratings. The mean values of all the other asset quality measures show consistent results in Table 5.7, and imply that banks with better asset quality get assigned higher ratings.

Table 5.7: Average asset quality ratios in the pre-and crisis periods and across bank coarse credit ratings grading

Capital adequacy	Mean value	Median	Stdev.	Mean value	Stdev.	Mean value	Stdev.	Test of Mean	Coarse grading			
	Full sample			Pre-crisis period		Post-crisis period		t-test	AA – AAA	A	BBB	Below BBB
LoanR_GL	2.69	2.91	0.74	2.33	7.21	6.32	1.20	4.01	1.21	2.85	2.99	4.21
LoanP_NIR	22.66	30.24	9.76	18.62	5.22	28.21	10.54	3.32	15.36	10.24	12.20	32.84
LoanR_IL	83.23	77.21	8.17	60.24	3.34	106.82	12.14	3.48	66.94	50.21	56.81	110.98
ImpairedL_GL	3.33	1.85	1.18	2.84	3.64	6.62	2.22	2.98	3.14	2.47	3.48	5.21
NCO_GL	2.99	1.21	0.42	1.02	4.01	5.93	1.51	3.36	1.02	1.85	3.97	6.97
NCO_NI	35.55	42.21	15.14	20.84	3.29	42.62	21.36	5.21	18.95	20.21	41.58	62.54
ImpairedL_EQ	25.76	29.64	10.13	16.21	2.99	32.58	11.62	3.62	15.01	21.39	26.34	33.24
UImpairedL_EQ	4.82	6.24	3.58	2.22	3.68	9.82	5.99	3.29	2.94	3.37	5.55	35.61

Notes: Mean, median and standard deviation of the capital adequacy ratios. Table also shows the averages for these ratios for banks categorized using the coarse rating gradation. The test of mean (t test) presents a test of level of significance (at a 95% confidence level) between the averages of financial ratios in the pre- and post- crisis periods.

5.6.3 Operations

BANKSCOPE classification under *operations* contains ratios that measure profitability and the earning power of banks. Table 5.8 shows the 13 earnings ratios based on BANKSCOPE classification. The earnings measures range from the popular return on assets, return on equity and net income margin, to recurring earnings power and dividend pay-out ratios.

Table 5.8: Earnings (operations) measures

Earnings measure	Description
NIM	Net Income Margin
NIR_A	Net Income Revenue / Avg Assets
OOI_A	Other Operating Income / Avg Assets
POIT_A	Non-Interest Expense / Avg Assets
PTOI_A	Pre-Tax Operating Income / Avg Assets
NOTA_A	Non-Operating Items & Taxes / Avg Assets
ROA	Return on Assets (ROA)
ROE	Returns on Equity (ROE)
DPO	Dividend Pay-Out
IND_E	Income Net of Distribution / Avg Equity
NOI_NI	Non-Operating Items / Net Income
C_I	Cost to Income Ratio
REP	Recurring Earning Power

Notes: This table provides the description and definition of the bank variables under BANKSCOPE classification 'operations'. All values are calculated as yearly averages across the 322 banks.

The results in Table 5.9 show that the majority of the profitability ratios presented are, on average, higher for investment grade banks than noninvestment banks. The net income margin ratio, *NIM,* is net interest income expressed as a percentage of earning assets. The higher this figure, the cheaper the funding or the higher the margin that the bank is commanding. Higher margins and profitability are desirable as long as asset quality is being maintained. The results show that investment grade banks have higher net income margins than noninvestment grade banks. The investment grade banks have close to three times the net income margin of the noninvestment grade banks. The returns on assets, ROA, and the return on equity, ROE, are popular ratios employed in modelling the determinants of bank ratings (Poon, 2003, Distinguin *et al.*, 2012).

Table 5.9: Average operations (earnings) ratios in the pre-and crisis periods and across bank coarse credit ratings grading

Capital adequacy	Mean value	Median	Stdev.	Mean value	Stdev.	Mean value	Stdev.	Test of Mean	Coarse grading			
	Full sample			Pre-crisis period		Post-crisis period		t test	AA – AAA	A	BBB	Below BBB
NIM	2.16	1.99	0.34	3.54	0.39	1.97	0.12	3.51	2.21	2.01	1.25	0.84
NIR_A	1.90	1.82	0.25	4.22	0.29	1.76	0.09	3.94	8.63	7.62	5.54	1.55
OOI_A	2.05	1.06	0.80	3.85	0.63	1.34	0.21	3.42	4.21	3.33	2.29	1.29
NOIT_A	2.81	1.10	0.72	5.38	0.77	2.32	0.17	3.33	4.95	3.54	2.22	1.97
PTOI_A	1.05	1.11	0.34	3.33	0.22	0.76	0.26	4.65	2.78	1.85	1.34	0.88
NOTA_A	-0.35	0.64	0.11	1.24	0.11	-0.27	0.06	3.86	1.84	1.55	1.09	-0.55
ROA	0.74	0.99	0.29	2.62	0.18	0.49	0.22	2.98	7.65	5.31	3.54	0.37
ROE	12.29	8.81	5.22	16.38	3.33	7.66	3.14	3.01	19.31	13.95	10.22	4.47
DPO	44.19	20.52	27.06	50.21	4.27	52.78	41.51	3.21	69.14	58.32	44.78	28.24
IND_E	7.87	3.24	3.61	9.95	1.86	4.78	3.03	4.35	6.32	4.51	3.61	3.88
NOI_NI	-23.17	2.85	57.04	11.84	20.24	-47.02	81.95	3.35	5.21	4.98	2.10	-55.21
C_I	61.17	23.52	3.78	17.24	3.47	59.49	3.80	3.84	12.95	8.87	5.09	60.20
REP	1.51	0.60	0.31	2.02	0.22	1.26	0.21	3.35	1.85	1.52	0.99	0.49

Notes: Mean, median and standard deviation of the operations ratios. The table also shows the averages for these ratios for banks categorized using the coarse rating gradation. The test of mean (t test) presents a test of level of significance (at a 95% confidence level) between the averages of financial ratios in the pre- and post- crisis periods.

ROA indicates that top investment grade rated banks achieve a better rate of return from the utilisation of their assets (7.65% against 0.37%), while the *ROE* ratio indicates that top investment grade rated banks enjoy a considerable higher return on equity than noninvestment banks (19.31% versus 4.47%). Distinguin *et al.* (2012) find that banks that are significantly more profitable are associated with higher ratings. In a related study, Poon (2003) argues that the level of profitability is a key factor in the assignment of ratings to banks. Poon find that companies that solicit credit ratings exhibits, have on average, higher *ROA, ROE* and *ROCE* ratio values. Table 5.8 clearly shows that banks performed better in terms of profitability measures in the pre-crisis period when compared to their performance in the crisis period. The mean value of the *NIM* ratio for banks in the pre-crisis period is 3.54 against 1.97 in the crisis period.

5.6.4 Liquidity

The examination of the liquidity ratio in the sample of international banks is based on the six categories of BANKSCOPE categorization of the variable. The ratios include the interbank ratio, the net loan to total assets ratio, and the net loans to deposit and short term funding ratio. Others include the net loans to total deposits and borrowings ratio, the liquid assets to deposit ratio, and the liquid assets to total deposits and borrowing ratio. These ratios are shown in Table 5.10.

Table 5.10: Liquidity measures

Earnings measure	Description
INTER	Interbank Ratio
NL_A	Net Loans /Total Assets
NL_DSTF	Net Loans / Deposit and Short Term Funding
NL_TDB	Net Loans / Total Deposit and Borrowings
LA_DSTF	Liquid Assets /Deposits and Short Term Funding
LA_TDB	Liquid Assets / Total Deposits and Borrowings

Notes: This table provides the description and definition of the bank variables under BANKSCOPE classification ‘liquidity’. All values are calculated as yearly averages across the 322 banks.

Table 5.11 shows the average values of the liquidity ratios based on the classification in Table 5.10. The results present the pre- and crisis-period values, as well as the average values of the ratios based on the coarse rating categorization of bank ratings in the sample. The variable *INTER* represents money lent to other banks divided by money borrowed from other banks. A relatively higher value indicates the bank is net placer rather than a borrower of funds in the market place, and is therefore more liquid. The average *INTER* across the entire sample period is 87.20. When this ratio value is compared with the pre- and crisis-period, the results show that banks were generally more liquid in the pre-crisis era (92.75) compared to the crisis period (66.32). In terms of the coarse rating classification, banks that are rated in the higher rating grades are associated with higher liquidity (112.20 against 63.21 for noninvestment grade banks). Similarly, the variable, *NL_A*, which is a liquidity ratio that indicates what percentage of the assets of the bank is tied up in loans, shows results consistent with the variable, *INTER.* The higher this ratio the less liquid the bank will be. On average, the results show that the pre-crisis value is lower than the crisis period, suggesting that banks are more liquid prior to the crisis relative to the crisis period.

In addition, higher credit ratings are associated with relatively lower *NL_A* (30.25 for the AA-AAA vs 50.29 for the below BBB). The other liquidity ratios show results consistent with the variables, *INTER* and *NL__A*. The variable *LA_DSTF* is very important for banks as it the so called *deposit run off ratio.* It presents the percentage of customer and short term funds that could be met if they were withdrawn suddenly. The higher the *LA_DSTF,* the more liquid the bank is and less vulnerable to a classic run on the bank. Table 5.10 shows that banks were on average more liquid in the pre-crisis era, with an average of *LA_DSTF* ratio of 43.55 against the crisis period value of 34.69. Further, it suggests that banks with higher ratings are associated with higher *LA_DSTF*, that is, higher liquidity.

Table 5.11: Average liquidity ratios in the pre-and crisis periods and across bank coarse credit rating grading

Capital adequacy	Mean value	Median	Stdev.	Mean value	Stdev.	Mean value	Stdev.	Test of Mean	Coarse grading			
	Full sample			Pre-crisis period		Crisis period		t test	AA – AAA	A	BBB	Below BBB
INTER	87.20	52.15	9.31	92.75	9.01	66.32	6.96	2.87	112.20	101.54	89.21	63.21
NL_A	41.30	36.26	2.47	30.91	1.90	43.64	1.56	3.92	30.25	36.65	40.13	50.29
NL_DSTF	66.14	55.84	5.67	43.44	5.56	73.21	1.85	3.25	51.21	58.93	61.39	77.32
NL_TDB	49.76	36.96	2.70	48.53	2.39	56.69	2.08	3.51	40.25	44.98	50.21	63.01
LA_DSTF	40.81	39.28	4.35	43.55	3.00	34.69	4.31	4.23	52.89	49.30	44.02	31.29
LA_TDB	31.11	25.25	3.83	33.83	1.63	19.32	2.57	3.11	36.19	35.99	25.14	18.62

Notes: Mean, median and standard deviation of the liquidity ratios. Table also shows the averages for these ratios for banks categorized using the coarse rating gradation. The test of mean (t test) presents a test of level of significance (at a 95% confidence level) between the averages of financial ratios in the pre- and post- crisis periods.

5.7 Summary

This chapter presents a review of the methodological approaches, data and econometric models that this study employs. First, the data and sampling of the study are presented. The banks within the sample are drawn from across the globe. The banks employed are publicly listed and assigned a Fitch long term local currency rating. The final sample consists of 322 international banks from all geographical regions. The largest grouping of banks in the sample is from the Far East and Central Asia, with about 23% of the sample size. The remaining 77% is made up of banks from the Western Europe (17%), Eastern Europe (8%), Middle East and North Africa (14%), South and Central Asia (11%), Sub-Sahara Africa (4%), Oceania (2%), and North America (21%). Some preliminary descriptive statistics are reported for the growth of the bank credit ratings during the period of study (2000–2012). Over time, an increasing number of banks obtained credit ratings, with a growth in bank ratings in the sample of 114% (from 150 banks in 2000 to 322 in 2012). There is also an observed monotonic decrease in the number of investment-grade bank ratings relative to banks with lower ratings during the period of the study.

A close examination of the bank fundamental characteristics shows that higher banks credit ratings are associated with improved financial ratios. Using BANKSCOPE financial ratio classification (which mirrors the *CAMELS* system), the results show that there is a positive relationship between the capital adequacy ratio, as well as the earnings and liquidity ratios. Similarly, the higher the quality of assets of a bank, the higher is the assigned credit rating. In addition, there is a deterioration of these fundamental bank ratios in the crisis period (2008-2012) relative to the pre-crisis period.

CHAPTER 6. RESULTS OF THE EMPIRICAL INVESTIGATION OF BANK CREDIT RATING DETERMINANTS

6.1 Introduction

Chapter 4 examines the significant factors driving the assignment of credit ratings to international banks. The review of literature shows that bank credit rating assignment is a complex process and that rating agencies attempt to maintain a balance between rating timeliness and rating stability. Further, Chapter 5 reviews methodological approaches in the existing studies and the approach that this thesis adopts. This current chapter aims to build on the previous discussions and presents the results of the first empirical component of this thesis which concerns the modelling of international bank credit rating determinants.

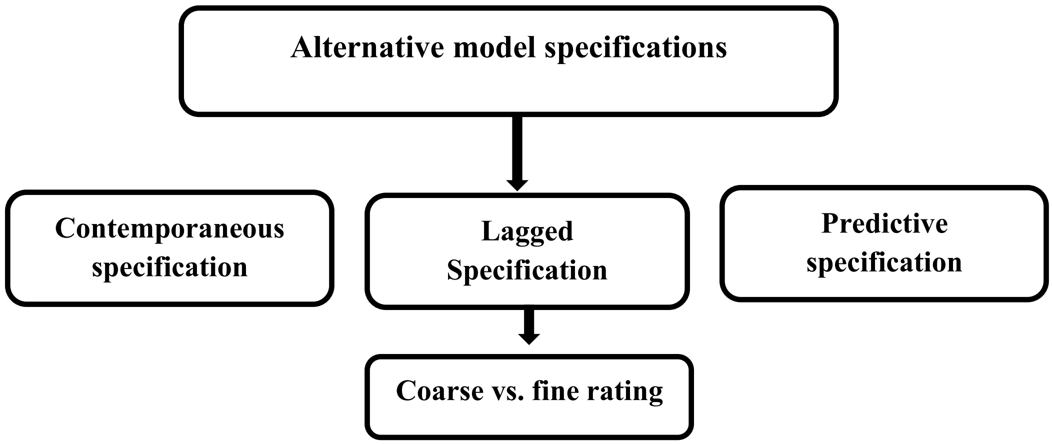
This chapter presents a number of different specifications of the ordered probit model employed in the estimation of the rating determinant equation. Existing evidence suggests the use of ordered response models, that is, the probit or logit model to capture bank credit ratings. The choice is based on the nature of the credit ratings themselves, that is, their discrete-values and natural ordering. The structure of the data, which in this study is a *panel-data framework,* confers additional constraints on the choice of modelling technique in terms of allowing for both fixed and random parameter measurements. The study employs a sample of 322 international commercial banks and bank holding companies from 70 countries. The bank rating determinant models include both financial and non-financial variables that potentially influence the assignment of a specific credit rating notch to a bank. These variables are extracted from Bankscope database, as well as the annual reports of the individual banks over the period 2000-2012. Preliminary analysis of the financial data in Chapter 5 shows significant levels of correlation among the different categories of variables employed, i.e. the *CAMELS* variables. The variance inflation factor analysis gives an indication of the appropriate financial variables to employ as discussed in Chapter 5. In addition, the hypotheses that this component of the study test are presented in Section 5.3.

The rest of this chapter is structured as follows: Section 6.2 discusses three different time specifications of the bank credit rating determinant model, and presents the intuitions behind these specifications. Section 6.3 presents the results of the alternative specifications of the bank credit rating determinant model empirically investigated in this thesis. Section 6.4 discusses the results of the ordered probit tests for the presence of rating strictness over time. Finally, Section 6.5 summarises the main findings of this chapter.

6.2 Bank rating determinant model time specifications

This section examines the modelling of the time dynamics associated with the assignment of credit ratings to international banks by credit rating agencies. This thesis proposes and tests empirically, a number of different time specifications. Some of these tests serve as robustness check and provide valuable insights into the nature of the rating assignment process by credit rating agencies. Broadly speaking, the thesis presents the result of estimations under the lagged, contemporaneous and predictive (lead) time specifications. This approach falls under an area of study referred to time-impact analysis (Odder-White and Ready, 2006). The need to incorporate a time-specification element in the bank credit rating determinant econometric model is linked to suggestions in empirical literature that rating agencies are sometimes slow to respond to new information (Weinstein, 1977; Hand *et al.,* 1992; Hite and Warga, 1997; Johnson, 2003). Odder-White and Ready find that rating changes can be predicted using changes in the level of financial ratios, which is an additional support for the slow response of rating agencies. Hence, rating agencies may in fact be backward-looking relying more on past information (thus, lagging the market). The use of different time-specifications in this thesis, including current year information (contemporaneous specification), future performance indicators (predictive specification) and past data (lagged specification) presents a value-added approach to this investigation. Figure 6.1 shows the details of the alternative specifications this thesis adopts.

Figure 6.1: Alternative model specifications ratings determinant models



The first model alternative is the *contemporaneous* time specification. This specification suggests that credit rating agencies effect a rating action (e.g. upgrade, downgrade) following a review of the overall financial and non-financial position of a bank in the same period. Put differently, this specification makes the assumption that the impact of bank specific characteristics on the assignment of credit rating is of a simultaneous nature with rating agencies reacting to changes in bank's position instantly, that is, within the same period. Many of the existing literature studies in the area of ratings determinant modelling follow the contemporaneous specification (Poon *et al*., 2009; Poon and Firth 2005; Van Roy 2006; Shen *et al.*, 2012; Fracassi *et al*., 2014).

This thesis extends the specifications employed by the earlier studies in the field of bank credit rating determination by examining and presenting the results of other alternative time specifications. For the purpose of this thesis, two additional specifications are presented. The motivation behind these alternatives is that the rating decision by credit rating agencies may be affected by factors that are not of a *contemporaneous* nature. Although, rating agencies, in their rating process have access to private information, their decision to effect a rating action may not be undertaken in a timely manner. Thus, this thesis introduces a time-lag into the analysis. This *responsive* specification employs one-year lagged values of variables included in the model in order to test whether rating agencies are *backward-looking* and slow in their rating assignment process. Hence, the independent variables in this specification are from the year *t-1* relative to a rating action in year *t*. This specification thus makes the assumption that the credit rating assignment to international banks is triggered by past specific events related to the bank.

However, one may argue that bank credit rating assignment is on the basis of future bank performance, thus supporting a *predictive* specification (Boot *et al*., 2006). Banks seek to disseminate forward-looking information to the market through their various meetings with credit rating agencies. Hence, rating action generally should convey new information to the market (Thompson and Vaz, 1990). This is consistent with the position of the major rating agencies that the ratings they assign are forward looking. For example, Standard and Poor's maintains that their credit ratings "express forward-looking opinions about the creditworthiness of issuers and obligations." (Standard and Poor's, 2009). In addition. Fitch argues that their opinions are forward looking and include analysts' views of future performance (Fitch, 2007). Further, they maintain that these views on future performance may include forecasts, which may in turn be informed by non-disclosable management projections, and therefore are based on trends, as well as on historical performance. Thus, one may argue that ratings are inherently forward-looking and embody assumptions and predictions about future events. Fitch Solutions further maintains that the firm employs a variety of credit risk indicators to meet growing market demand for forward-looking risk indicators across the full spectrum of Fitch content. Hence, the *predictive* specification approach presented within this chapter employs all future numerical values (ratios) in the estimation of a model. The specification therefore assumes that the rating assignment in year t is determined by bank estimates for year $t+1$ (Sufi, 2009). Further, the firm and its analysts will have some indications about what is happening in the current financial year (to be published in year t+1 annual report) in addition to the most current accounts (year t). In particular, the ability to forecast comes from this and the ability to discuss with the management of the company, the current and likely near term position and performance of the company.

These time specifications may also be linked to the objectives and performance of rating agencies. Credit rating provides probabilistic opinions about the future creditworthiness of an issue or issuer (Moody's, 2005). For it to be useful and relevant, (re)assignment of credit ratings need to timely and accurate. However, there is a conflict between the accuracy and timeliness of rating assignments. Following the global financial crisis, there has been an increase in the monitoring of rating accuracy (e.g. regular third party reports on rating performance) (CFA, 2014). Thus, in modelling the determinants of credit rating, it is important to incorporate elements of time within the model variables, as this gives more information on the level of ratings performance.

6.3 Rating determinants model results

Section 6.3 presents the results of the rating determinant model, incorporating the alternative time-specifications. The reporting of the results includes the estimation of the ordered probit models, their marginal effects, and the out-of-sample forecast estimates for the model outcomes for each rating category. The financial data employed follows the established data from the *CAMELS* criteria, i.e. measures of capital adequacy, assets quality, management quality, earnings, liquidity and sensitivity to the market. In order to ensure consistency with existing studies, this thesis employs selected financial ratios that proxy these criteria[9] .

Consistent with Poon and Firth (2005), all the model specifications account for any country related unobserved variables by including the sovereign credit rating of the home country. This aims to proxy for a change in macroeconomic variable effects. Further, it helps to avoid the incidental parameter issue highlighted by Greene and Hensher (2009) and Wooldridge (2010) by avoiding the use of many country dummies.

The remainder of this section is as follows: Section 6.3.1 presents the results of the econometric model assuming a contemporaneous specification, with the assumption that international bank credit rating is determined in the same year as financial and non-financial information becomes available. Section 6.3.2 assumes a predictive specification, in which bank's credit ratings are forward-looking and are determined on the basis of expected financial information. Further, Section 6.3.3 presents results for the model assuming lagged specification. These sections employ the fine bank credit rating grading as a measure of the dependent variable. In addition to the use of fine grading, this section presents results of the robustness check employing the coarse grading. The results of the coarse rating specifications are positioned in the appendix.

6.3.1 The contemporaneous specification

This section presents the estimates of the results of the contemporaneous model specification. The specification follows the tradition of a number of existing studies. It assumes that international bank credit rating is determined by bank financial and non-

[9]The final set of *CAMELS* variables, *TIER1, LLR/GL, LTA, INTERBANK, ROA*, are based on the analysis in Chapter Five and are consistent with the existing literature (Poon, 2003; Poon and Firth, 2005)

financial performance in a simultaneous manner. The results presented include the estimation of the ordered probit models, their marginal effects, and the out-of-sample forecast estimates for the model outcomes for each rating category. Table 6.1 presents the estimates of the contemporaneous bank rating determinant model using the fine rating grading (the dependent variable is the bank credit rating). Panel A shows the fitted coefficients of three models, Models I–III. Model I includes only the financial variables hypothesised to affect a bank's rating. Model II includes only the non-financial variables, while Model III gives the full specification (including both the financial and non-financial variables). Panel B shows a selection of model statistics.

In addition, Table 6.2 presents the marginal effects (for the full specification) which are estimations of the effect of a change in an independent variable on the probability of a bank rating falling in a particular rating notch (grade). As a reminder, marginal effects measure the change in a response (in the case of this thesis, a bank credit rating) given a change in an independent variable. The estimation of the marginal effects makes it easier to interpret how changes in the independent variable affect a nonlinear response from a fitted model. Most of the findings based on the contemporaneous specification modelling are qualitatively similar to results from existing literature in the area of bank credit rating determinants.

Table 6.1: Contemporaneous bank rating determinants model results

Panel A Parameter estimates							
Independent variables	Hypothesised Sign	**Model I** Coefficient	Z-stat	**Model II** Coefficient	Z-stat	**Model III** Coefficient	Z-stat
Intercept		-7.2147	-4.11***	1.2547	27.22***	-7.3225	-4.65***
TIER1	+ (H_1)	0.0874	6.11***	-	-	0.0905	6.17***
LLR/GL	− (H_2)	-0.0366	-5.14***	-	-	-0.0411	-5.21***
ROA	+ (H_3)	0.0952	2.22**	-	-	0.0991	2.17**
LTA	− (H_4)	-0.0061	-1.26*	-	-	-0.0079	-1.33*
INTER	+ (H_4)	0.0754	3.10***	-	-	0.0687	3.02***
BETA	− (H_5)	-0.0006	-0.11	-	-	-0.0006	-0.18
IDIO	− (H_6)	-0.0013	-1.28*	-	-	-0.0017	-1.72*
In(Z-Score)	+ (H_7)	0.0541	2.03**	-	-	0.0554	2.31**
LR	− (H_8)	-0.0417	-3.47***	-	-	-0.0488	-3.49***
CRK	− (H_9)	-0.0267	-6.14***	-	-	-0.0284	-7.55***
CI	− (H_{10})	-0.0001	-0.88	-	-	-0.0014	-1.74*
lnTA	+ (H_{11})	0.5147	12.26***			0.6214	12.65***
TBTF	+ (H_{12})	-	-	0.0354	4.21***	0.0383	4.33***
OWN	+ (H_{13})	-	-	-0.0014	-1.77*	-0.0014	-1.73*
INST	+ (H_{14})	-	-	-0.0011	-2.23**	-0.0016	-2.20**
INDD	+ (H_{15})	-	-	0.0009	1.03	0.0010	1.77*
SOVAA	+ (H_{16})	-	-	0.0104	6.87***	0.0119	6.94***
SOVA	+ (H_{16})	-	-	0.0157	5.69***	0.0168	5.87***
SOVBBB	+ (H_{16})	-	-	-0.0064	-2.18**	-0.0063	-2.17**
YEARD	− (H_{17})	-	-	-0.2147	-0.89	-0.2149	-0.85
Panel B: Selected model statistics							
Log-likelihood		-1,124.144		-1,219.201		-1,019.514	
Restr.log-lik.		-1,351.287		-1,621.658		-1,309.198	
No. of group obs.		3,682		3,682		3,682	
χ^2 statistic		684.0147***		628.1574***		712.012***	
Pseudo- $R^2\varsigma$		39.15%		36.21%		42.35%	

Notes: The dependent variable of all ordered probit models is the categorical variable CR (fine ratings). All significance levels are determined using the two-tailed Z-test. ***, **,* denote significance at the 1%, 5% and 10%, respectively. Ç This measure of goodness-of-fit is a simple computational statistic [$\text{pseudo} - R^2 = \frac{\chi 2}{\chi 2+N}$] proposed by Aldrich and Nelson (1984). The upper boundary represents the threshold for each of the rating categories; in this model the categories represent the fine ratings. The SOV (dummies) captures any country related variables as this measure the sovereign ratings of the countries. The data employed are for 322 international banks covering a period 2000-2012.

Table 6.2: Marginal effects of Model III (full specification)

	Rating Category									
Variables	Below BB+	BBB-	BBB	BBB+	A-	A	A+	AA-	AA	Above AA
TIER1	-0.02*	-0.06*	-0.11*	-0.10	0.05	0.08	0.13	0.11	0.12*	0.08*
LLR/GL	0.04*	0.02	0.01	0.00	-0.02	-0.08	-0.16*	-0.19*	-0.23*	-0.09*
ROA	-0.02*	-0.01*	-0.01*	0.02	0.03*	0.05*	0.06*	0.09*	0.01*	0.03*
LTA	0.02	0.00	0.03	0.01	-0.01	-0.04	-0.01	-0.01*	-0.02	0.00
INTERBANK	-0.07	-0.01*	-0.04	0.06	0.06	0.11	0.07*	0.11*	0.06*	0.10*
BETA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IDIO	0.01*	0.01*	0.03*	0.02	0.01	-0.04*	-0.03	-0.04*	-0.01*	-0.04*
In(Z-Score)	-0.09*	-0.05*	-0.01*	-0.06	0.08*	0.07*	0.10	0.12*	0.11*	0.08*
LR	0.07*	0.06*	0.02*	0.01	0.03	-0.09*	-0.13*	-0.08*	-0.11*	-0.07*
CRK	0.06*	0.01*	0.03	0.07	0.08	-0.06	-0.08*	-0.12*	-0.03*	-0.04*
CI	0.04*	0.10	-0.03*	-0.01	-0.06	-0.02*	-0.03*	-0.06*	-0.04*	-0.06*
InTA	-0.09*	-0.02*	-0.06*	-0.02	-0.01	0.04*	0.06*	0.04*	0.02*	0.05*
TBTF	-0.03*	-0.01*	-0.06*	-0.01	0.02*	0.08*	0.07*	0.11*	0.10*	0.21*
OWN	0.01*	0.04*	0.02*	0.02	-0.03	-0.01	-0.02*	-0.01*	-0.02*	-0.05*
INST	-0.02*	-0.01	-0.04*	-0.03	0.02	0.06	0.07*	0.05*	0.03*	0.04*
INDD	0.00	-0.01	0.00	-0.04	0.00	0.00	0.00	0.01*	0.02*	0.02*
SOVAA	-0.03*	-0.01	-0.01	0.00	0.06	0.04	0.04*	0.03*	0.02*	0.07*
SOVA	-0.01*	-0.04*	-0.02*	0.05	0.01	0.00	0.03*	0.01*	0.06*	0.02*
SOVBBB	0.02	0.01*	0.04	0.03	0.00	-0.02*	-0.01*	-0.03*	-0.01*	-0.03*
YEARD	0.01*	0.04	0.02	0.01	-0.02	-0.06*	0.02*	0.01	0.02	0.08*

The results in Table 6.1 show that the measure of regulatory capital adequacy (*TIER1*) is significantly positively related to bank credit ratings at the 1% level, in both Models I and III. This is consistent with Poon and Firth (2005), who provide support for the highly significant positive relationship between a bank's capital and its rating. Poon and Firth argue that, as equity is considered a cushion available to absorb losses; their results suggest that banks with better credit ratings have capital to absorb losses on their loan portfolios. Similarly, Salas and Saurina (2003) find that banks with lower capital tend to operate with higher levels of credit risk, consistent with the moral hazard hypothesis.

Some of the theoretical literature offers conflicting results regarding the effects of capital requirements on bank-risk taking (Freixas and Rochet, 2008), particularly in the area of monitoring incentives, leading to a possible reduction in the quality of a bank's portfolio (Besanko and Kanatas, 1996; Boot and Greenbaum, 1993). However, there is strong evidence that banks with higher capital adequacy ratios tend to have higher credit ratings, thereby providing support for hypothesis $H_{1.}$ The results from Table 6.2 show that the probability of a bank rating falling in the top notch increases by 8% with every percentage increase in the variable *TIER1*, everything else held constant. Conversely, there a 2% decrease in the probability of a bank being rated in the lowest speculative grades (below BB+) with every percentage increase in the variable *TIER1*. Hence, one may argue that within a contemporaneous setting, there is a greater tendency to obtain higher ratings when a bank's capital is adequately maintained

The assets quality ratio (*LLR/GL*) shows the expected negative relationship, and is significant at the 1% level in both Models I and III. The result is consistent with Poon and Firth (2005), Poon *et al.* (2009) and Distinguin *et al*. (2012). At the heart of many commercial banking institutions' activities is lending, and loans thus constitute a significant percentage of bank's assets portfolio. The quality of a bank's loan portfolio affects the viability of that bank. Any impairment of a bank's asset portfolio can increase the risk of insolvency, thus resulting in a negative credit rating. Hence, there is a negative relationship between bank *LLR/GL* and credit ratings. The results from the marginal effects estimation in Table 6.2 indicate that an increase in the assets quality ratio *LLR/GL* decreases the probability of a bank being rated in the higher rating notches, particularly the investments grades, but results in an increasing chance of being assigned ratings that fall in the speculative grades. For example, there is a 9% decrease in a bank's chance of being rated in the 'Above AA' rating grade for every 1% increase in the assets quality ratio *LLR/GL*. Similarly, there is a 4% probability of a bank being rated below the BB+ grade for every 1% increase in this assets quality ratio.

The higher earnings capacity of a bank is usually associated with reduced riskiness. This may explain the positive sign of the earnings coefficient (*ROA*) in Models I and III. The results show a significant positive relationship between earnings and bank credit ratings at the 5% level. Pettit *et al.* (2004) and Poon *et al*. (2009) argue that profitability is important in credit rating assignment because higher profitability is necessary for banks to support growth and other long-term strategic plans. Further, Packer and Tarashev (2011) argue that rating agencies consider banks that consistently retain a greater share of their earnings during tranquil times as more creditworthy. The marginal effects estimations in Table 6.2 indicate that a 1% increase in the *ROA* ratio results in a 3% increase in the probability of being assigned a rating above the AA category. There is a decrease in the likelihood of a bank being assigned grades in the speculative category for every one percent point increase in the *ROA* variable.

In the same vein, the liquidity measures (*LTA* and *INTER*) both show the relationship expected from theory. The coefficient of the *LTA* is negative and significant at the 10% level, whilst the *INTER* measure is positive and significant at the 1% level. The *LTA* measures the proportion of a bank's assets tied up in loans, hence the lower this ratio the more the amount of cash or near cash items available to banks to meet their obligations. Liquidity is very important to a bank, particularly in its maturity transformation role, in addition to its ability to meet obligations to deposit customers at short notice. The result is consistent with the argument of Fight (2000) who maintains that liquidity is an indicator of financial flexibility. Poon and Firth (2005) find that *LTA* is negatively correlated with bank's credit ratings, as the higher the ratio is, the less liquid is the bank. Similarly, Poon *et al*. (2009), using other liquidity measures, find liquidity to be an important determinant of the credit ratings of banks. This result is also consistent with Poon (2003) and Doumpos and Pasiouras (2005) who find that liquidity ratios are significantly positively related to credit ratings. Hypothesis H_4 is thus supported. The marginal effects estimations for the liquidity variables, *LTA* and *INTER* both show the expected directions for the probabilities of a bank being assigned into particular rating notches when there is a unit change in these variables. The implication of these results is that the Fitch rating agency pays particular attention to bank liquidity in a contemporaneous way. With the requirements of the Basel III liquidity ratios, banks continue to pay closer attention to their levels of liquidity. These results strongly suggest the need for banks to be adequately liquid in light of the stress testing framework currently in place in most regions across the world.

The relationship between business risk and the credit rating of a bank is measured by the variables, bank stock beta (*BETA*) and the idiosyncratic risk (*IDIO*). Both of these variables evidence a negative relationship with a bank credit rating. However, only the variable *IDIO* is significantly negatively related to a bank's credit rating at the 10% level in Models I and III. The result is consistent with Amato and Furfine (2004) and Blume *et al*. (1998) who find the idiosyncratic (non-beta) risk variable to be negative and significant at the 10% level. However, in contrast with the two studies, Models I and III show an insignificant result for the *BETA*. Iannotta and Pennacchi (2011) maintain that if raters differentiate between idiosyncratic and systematic default risk, then ratings might reflect risk-neutral probabilities of default if defaults in bad economic times are weighted more heavily than defaults in good economic times. Generally, bank rating assignments are influenced by both business and financial risks, and the interplay of these risks presents an interesting consideration in the rating process. The earlier findings relating to financial risk (as measured by the *CAMELS* framework) suggest that a bank's level of credit quality may be heavily influenced by its business risk. The implication of this contemporaneous approach to estimating the determinants of a bank's credit rating shows that international banks' credit ratings are influenced not only by risk specific to the banks. This may be linked to the level of competition in the market and the need for banks to expand internationally and diversify their portfolio of assets.

The results from Table 6.2 indicate that a percentage increase in the variable *BETA* does not have any marginal effects on the probability of assigning a bank into any particular rating category; however, a percentage change in the variable *IDIO* results in a corresponding decrease in the likelihood of a bank having a higher rating of between 1% and 4%. Conversely, there is an increase in the probability of a bank rating falling in the lower rating classes by between 1% and 3%.

Table 6.1 shows that the variable *Z-score* is positively related to bank credit ratings at the 5% level in both Models I and III. This is consistent with the sign expected from theory and shows that there is a greater likelihood of being assigned a higher rating as the *Z-score* increases. In other words, banks with a lower *Z-score* are riskier. Consistent with this, the marginal effects show the same sign and the effects of a 1% change in this variable is relatively high (between 7% and 12%) when compared with the other financial variables. This thesis follows Laeven and Levine (2009) and Imbierowicz and Rauch (2014) in applying a natural logarithm transformation to the *Z-Score* because of its highly skewed distribution. The results support hypothesis H_7. These results further suggest the importance credit rating agencies pay to risk exposure of banks in assigning those ratings. The use of the *Z-Score* is an innovative addition to the modelling of the determinants of bank credit rating,

The results from Models I and III show a negative relationship between a bank liquidity risk and credit ratings. The liquidity risk variable, *LR*, is significantly negatively related to bank credit ratings at the 1% level. Similarly, the credit risk variable, *CRK* is significantly negatively related to bank credit rating at the 1% level in both Models I and III. Liquidity risk and credit risk are important drivers of bank survival. There is evidence in existing studies that there are individual and joint relationships between these two variables in terms of their impact on bank default probability (Imbierowicz and Rauch, 2014). This highlights the importance of a bank's overall risk measure in the assignment of a credit rating. This finding is broadly consistent with Shin and Moore (2003) and Amato and Furfine (2004) who argue that credit ratings are linked to a bank's overall risk outlook. The results support hypotheses H_8 and H_9. Further support for the probability of a bank rating falling in an investment or a speculative grade following a percentage change in these two risk classes is evident in Table 6.2. A percentage point increase in the variable *CRK* decreases the probability of a bank rating falling within the investment grade by between 3% and 12%; and an increase the likelihood of being assigned a speculative grade by 6%. For the liquidity variable *LR*, a percentage increase results in a decrease in the probability of a bank rating falling within the investment grade category by between 1% and 13%. Conversely, there is a corresponding increase of falling in the speculative grade of 7%.

The coefficient relating to bank efficiency (*CI*), measuring the relationship between the average ratio of costs to net income of bank and a bank rating, is negative and significant, though only in the full specification and at the 10% level. Thus, there is weak support for hypothesis H_{10}. The marginal effects of the efficiency variable, *CI,* show that a percentage point increase leads to between a 3% and 6% probability of not being rated in the top investment grade categories. Only a minority of existing studies (Shen *et al*., 2012; Öğüt *et al*., 2012) employ a variant of bank efficiency in their models. These studies find that efficiency plays an important part in bank rating. The results of the impact of bank efficiency on bank credit ratings indicate that a bank that is able to drive its costs down relative to others may be perceived to be more efficient and therefore awarded a higher rating. Fiordelisi *et al*. (2011) maintain that lower bank efficiency with respect to costs and revenues Granger-causes higher bank risk, which may consequently lead to a bank being assigned a lower rating. Similarly, Berger and De Young (1997) and Kwan and Eisenbeis (1997) argue that the concept of bank efficiency needs to be recognised explicitly when modelling the determinants of bank risk. In addition, Berger and DeYoung suggest that the increase in problem loans is usually a result of cost inefficiency, particularly in thinly capitalized banks. Thus, despite the weak relationship between the variable *CI* and bank credit rating, the marginal effects within a contemporaneous setting shows that CRAs take into account the cost structure of a bank in assigning ratings.

The size measure (*lnTA*) shows a positive relationship with bank credit ratings, and it is significant at the 1% level. Consistent with existing studies such as Poon (2003), Poon and Firth (2005), and Van Roy (2006), and providing support for hypothesis H_{11}, there is a positive relationship between bank size and credit rating. Fitch (2007) maintains that bank size and the diversification of assets are key factors in their rating process. Other things being equal, larger banks are awarded higher ratings than smaller banks. Similarly, UBS believes that 'larger companies tend to have higher credit ratings' and that 'size metrics offer the strongest statistical correlation with credit ratings, reflecting important qualitative factors such as geographic and product market diversification, competitive position, bargaining power, market share and brand stature' (UBS, 2004: 9). Further, Demsetz and Strahan (1997) point out that the large bank holding companies use their size and diversification to operate with lower capital ratios in order to pursue riskier activities. There is a greater potential for banks to incur huge losses as a result of exposure from riskier activities, hence resulting in the lowering of their credit ratings. Evidence from the marginal effects estimation shows that a unit percentage increase in the *lnTA* variable leads to between a 4% and 6% probability of a bank rating falling within the investment grade and a 9% decrease in the chance of being rated within the speculative rating grade.

In addition, Hau *et al.* (2012) argue that there is an incentive for rating agencies to be biased towards large banks despite their complexity, opacity and difficulty to rate. In this thesis, the Fitch index measuring the likelihood that a financial institution will receive extraordinary support to prevent it defaulting on its senior obligations (*TBTF*) has a positive sign and is significant at the 1% level in Models II and III. This further demonstrates the importance of size in the rating process. Larger banks not only tend to have better access to capital markets, they are also more likely to receive government support. This is connected to the too-big-to-fail argument, and the contagion effects that allowing a bank to fail might have on the rest of the banking system. Hypothesis H_{12}, which states that there is a positive relationship between the Fitch support rating for a bank and credit rating, is thus supported by this result. The marginal effects for these two variables (*InTA* and *TBTF*) in Table 6.2 further underline the significance of these results. The size effect increases the chances of receiving higher credit ratings and decreasing the possibility of a bank being assigned lower ratings. The results are consistent with existing studies such as Pasiouras *et al*. (2007) and Distinguin *et al.* (2012), which find positive relationship between bank size and the credit rating assigned by rating agencies.

The variable that captures director's shareholdings in a bank (*OWN*) is negatively related to bank credit ratings at the 10% level in both Models II and III. This result is contrary to the proposed hypothesis H_{13}, and suggests that rating agencies do not favour directors owning higher proportions of a bank's equity since this can lead to them making decisions at the expense of other stakeholders, particularly bondholders, creditors and even other shareholders. The result is also consistent with some existing studies (Ashbaugh-Skaife *et al.,* 2006; Laeven and Levine, 2009). However, other studies (Fama and Jensen, 1983; Minow and Bingham, 1995) argue that increasing the shareholding of directors provides them with an incentive to improve corporate governance. This may however lead to an accumulation of voting rights, giving them the power to keep themselves in office. The marginal effects estimation in Table 6.2 shows that a unit percentage increase in the *OWN* variable leads to between a 1% and 5% probability of a bank not being assigned an investment grade rating, and a 1% probability of being assigned a speculative grade.

The degree of institutional ownership (*INST*) is positively related to bank credit ratings in the full specification, and is significant at the 5% level. The sign is expected and is consistent with existing study evidence (Bhojraj and Sengupta, 2003; Wilson and Williams, 2000; Goddard *et al.*, 2004; Chen *et al.*, 2006; Mehran and Rosenberg, 2008) and thus hypothesis H_{14} is accepted. Existing studies find a strong negative relationship between ownership and the creditworthiness of a firm. The results appear to show that credit rating agencies are more likely to assign lower ratings to banks where ownership is concentrated in the hands of individual owners. This is also consistent with Shleifer and Vishny (1986) who argue that large institutional investors have an incentive to monitor and influence bank behaviour to the detriment of bondholders. Such behaviour may be perceived by rating agencies as being positive.

The variable which measures the proportion of independent directors on a bank's board (*INDD*) is positively related to bank credit rating, though only at the 10% level in the full model specification. The results indicate that a higher number of independent directors is more likely to lead to a higher credit rating, providing only weak support for hypothesis H_{15}, and consistent with existing studies of the impact of independent directors on bank risk taking and overall corporate governance (Ashbaugh-Skaife *et al*., 2006; Buch and Delong, 2008; Hau and Thum, 2009; Switzer and Wang, 2013). The current reforms (e.g. the UK House of Commons Reform of the Banking Sector, 2013) noted the corporate failures in the banking sectors and argue for greater use of independent directors in order to align the interests of the other board members with those of the shareholders. This may potentially be seen as playing a significant role in the rating process because rating agencies can view such a trend as positive impact on bank rating assignments. Therefore, any increase in the number or activity of independent directors warrants a higher rating from credit rating agencies.

Consistent with Poon and Firth (2005), the measure of the impact of changes in the operating environment (*SOV*) all have the expected positive signs from theory, except for *SOVBBB*. It is more likely for a bank to be rated in the lower credit ratings categories if their primary operations are in a country whose sovereign ratings are low. Generally, a higher sovereign rating should lead to banks being rated in the higher investment grade credit rating categories. The coefficient of the year dummy, *YEARD*, is negative and significant at the 10% level. This is an indication of asymmetry in international bank ratings between the pre- and post-crisis period.

In the full specification (Model III), the log likelihood ratio χ^2 of 712.012 is reported which is significant at the 1% level. In addition, the pseudo-R^2 which measures the goodness-of-fit is relatively high at 42.35% in the Model III compared with the results obtained for Models I and II. Poon and Firth (2005) employ the adjusted R^2 and report a value of 53% (although this cannot be interpreted in the same way as the pseudo-R^2). However, this study achieves a relatively close adjusted R^2 figure of 50.87%. Model III is therefore the best at explaining the variables which drive the assignment of a bank credit rating. All of the variables employed in Model III are significant and exhibit the expected signs, and are significant except for the variables *BETA, OWN, YEARD and SOV BBB*. The full contemporaneous rating determinant model shows that the following variables: *TIER1, LLR/GL, ROA, LTA, INTER, IDIO, ln(Z-Score), LR, CRK, CI, lnTA, TBTF, OWN, INDD, SOVAA, SOVA* impact on bank credit rating assignment.

Table 6.3 shows results of the out-of-sample prediction evaluation. This thesis employs data from 2000 to 2008 for estimating the fit period. The results presented, are for the accuracy of the assigned banks rating in the period 2009 –2012. Hence, the *holdout* sample is for the period 2009 and 2012. The table displays the root-mean square error deviation (or error) RMSE. This measures the difference between values (rating classes) predicted by the model and the values actually observed. Put differently, it is the sample standard deviation of the differences between predicted and observed values. In addition, the table displays the mean absolute percentage error, MAPE. This expresses the forecast error as the mean or average of the absolute percentage errors of forecasts. Panels A to D present the actual and predicted values of the dependent variable (i.e. the credit rating notch). The results show a total observed (actual) value for bank rating grades of 322 for the sample. For example, in Panel A, only 47% of the top investment grade ratings (A- to AA+ and above) are correctly predicted for 2009. This is in contrast to the 83% correctly predicted for the speculative grades.

A comparison of the results in Panel A to D shows that the measures of the forecast errors tend to increase as one move forward into the future. The lower these errors are, the more reliable is the forecasting model. The AA+ and above is consistently correctly predicted.

Table 6.3: Contemporaneous rating determinants specification: Prediction Evaluation (Model III)

Estimated Equation (2000-2008):

Panel A Year: 2009

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	97	63	34	34	35.05	1,156
BBB-	1	32	26	6	6	18.75	36
BBB	2	28	32	-4	4	14.29	16
BBB+	3	29	34	-5	5	17.24	25
A-	4	37	26	11	11	29.73	121
A	5	32	12	20	20	62.50	400
A+	6	34	16	18	18	52.94	324
AA-	7	27	8	19	19	70.37	361
AA	8	6	3	3	3	50.00	9
AA+ and above	9	0	0	0	0	0.00	0
Total	**322**	**220**					

Mean Absolute Percentage Error: 35.09% **Root-Mean-Squared-Error Magnitude: 15.65** **Total percentages predicted: 68.32%**

Panel B Year: 2010

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	90	60	30	30	33.33	900
BBB-	1	41	23	26	26	63.41	676
BBB	2	36	22	14	14	38.89	196
BBB+	3	23	22	1	1	4.35	1
A-	4	40	29	11	11	27.50	121
A	5	28	19	9	9	34.14	81
A+	6	31	17	14	14	45.16	196
AA-	7	28	12	16	16	57.14	256
AA	8	5	2	3	3	60.00	9
AA+ and above	9	0	0	0	0	0.00	0
Total	**322**	**206**					

Mean Absolute Percentage Error: 36.39% **Root-Mean-Squared-Error Magnitude: 15.61** **Total percentages predicted: 63.97%**

Panel C Year: 2011

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	92	57	35	35	38.04	1,225
BBB-	1	37	32	5	5	13.51	25
BBB	2	36	28	8	8	22.22	64
BBB+	3	31	16	15	15	48.39	225
A-	4	33	12	21	21	63.64	441
A	5	41	21	20	20	48.78	400
A+	6	28	16	12	12	42.86	144
AA-	7	19	12	7	7	36.84	49
AA	8	5	4	1	1	20.00	1
AA+ and above	9	0	0	0	0	0.00	0
Total	**322**	**198**					

Mean Absolute Percentage Error: 33.43% Root-Mean-Squared-Error Magnitude: 16.04 Total percentages predicted: 61.49%

Panel D Year: 2012

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	89	49	40	40	44.94	1,600
BBB-	1	36	21	15	15	41.67	225
BBB	2	46	23	23	23	50.00	529
BBB+	3	32	12	20	20	62.50	400
A-	4	33	14	19	19	57.58	361
A	5	36	20	16	16	44.44	256
A+	6	29	19	10	10	34.48	100
AA-	7	19	11	8	8	42.10	64
AA	8	6	2	4	4	66.67	16
AA+ and above	9	0	0	0	0	0.00	0
Total	**322**	**175**					

Mean Absolute Percentage Error: 44.44% Root-Mean-Square-Error Magnitude: 18.84 Total percentages predicted: 54.35%

Panel E:

Year	**Mean Absolute Percentage Error**	**Root-Mean-Squared-Error**	**Total percentage predicted**
2009	35.09%	15.65	68.32%
2010	36.39%	15.61	69.97%
2011	33.43%	16.04	61.49%
2012	44.44%	18.84	54.35%

Similarly, the AA category has a relatively lower forecast error across the *n-step-ahead* forecast models. Generally, bank ratings in the speculative categories seem to be better predicted on average, compared with the bank ratings in the investment categories. This is contrary to expectation because it could be argued that the investment-grade banks are more followed by analysts and rating agencies. Hence, there is an expectation for more responsiveness on the part of the rating.

The relatively high predictive accuracy of the lower rating categories could be attributed to lack of monitoring, and thus these ratings tend to be more 'static', compared to banks rated in the higher investment grades (which appears to be more volatile, consistent with their assumed level of monitoring). The average for the MAPE and RMSE for the one-step ahead forecasting models are 35.09% and 15.65 error points, respectively compared with the four-step ahead forecast error estimates of 44.44% and 18.84 error points respectively. There are several possible explanations for this deterioration through time. An immediate implication of the global crisis was the review of rating methodologies by the major credit rating agencies. Evidence in existing literature shows that this has resulted in increased stringency in the way credit rating agencies rate firms (Kondo, 2011, Baghai *et al*., 2013). Further, results from the examination of the strictness in credit rating assignments for international banks are presented in Section 6.4.

6.3.2 The predictive specification

This section presents another set of model results for this component of the thesis based on the predictive specification. The predictive specification employs independent variables from year *t+1*, relative to the credit rating action taking place in year *t*. This specification allows this study to test empirically the claims by the major rating agencies that the ratings they assign are forward looking.

Table 6.4: Predictive bank rating determinants model results

Panel A Parameter estimates							
	Hypothesised	**Model IV**		**Model V**		**Model VI**	
Independent variables	Sign	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Intercept		-5.0154	-7.26***	1.3624	12.32***	-5.2518	-5.24***
TIER1	$+ (H_1)$	0.1026	6.89***	-	-	0.3514	12.54***
LLR/GL	$- (H_2)$	-0.0854	-6.58***	-	-	-0.0941	-6.24***
ROA	$+ (H_3)$	0.1247	4.35***	-	-	0.1298	2.98**
LTA	$- (H_4)$	-0.0154	-3.20**	-	-	-0.0187	-2.20**
INTER	$+ (H_4)$	0.0856	2.00**	-	-	0.0584	2.09**
BETA	$- (H_5)$	-0.0012	-2.78***	-	-	-0.0107	-2.21**
IDIO	$- (H_6)$	-0.0109	-2.30*	-	-	-0.0098	-1.95*
ln(Z-Score)	$+ (H_7)$	0.0847	2.03**	-	-	0.0665	2.22**
LR	$- (H_8)$	-0.0847	-4.68***	-	-	-0.0752	-4.98***
CRK	$- (H_9)$	-0.0924	-6.22***	-	-	-0.0885	-5.98***
CI	$- (H_{10})$	-0.0241	-1.72*	-	-	-0.0254	1.88*
lnTA	$+ (H_{11})$	0.5477	10.25***			0.6221	11.55***
TBTF	$+ (H_{12})$	-	-	0.1054	9.25***	0.1254	8.54***
OWN	$+ (H_{13})$	-	-	0.0101	1.78*	0.0185	2.00*
INST	$+ (H_{14})$	-	-	0.0547	2.20**	0.0625	2.23**
INDD	$+ (H_{15})$	-	-	0.0111	2.23**	0.0160	1.81*
SOVAA	$+ (H_{16})$	-	-	0.0198	6.84***	0.0188	6.54***
SOVA	$+ (H_{16})$	-	-	0.1009	6.22***	0.1254	6.25***
SOVBBB	$+ (H_{16})$	-	-	-0.0857	5.384**	-0.0895	6.66**
YEARD	$- (H_{17})$	-	-	-0.0014	-1.67*	-0.0102	-1.78*

Panel C: Selected model statistics	Model IV	Model V	Model VI
Log-likelihood	-1,152.241	-1.207.665	-1,001.527
Restr.log-lik.	-1,201.847	-1.421.654	-1,175.217
No. of group obs.	3,682	3,682	3,682
χ^2 statistic	721.5477***	695.216***	754.258***
Pseudo- $R^2\varsigma$	46.21%	43.29%	48.68%

Notes: The dependent variable of all ordered probit models is the categorical variable CR (fine ratings). All significance levels are determined using the two-tailed Z-test. ***, **,* denote significance at the 1%, 5% and 10%, respectively. ς This measure of goodness-of-fit is a simple computational statistic [$\text{pseudo} - R^2 = \frac{\chi 2}{\chi 2+N}$] proposed by Aldrich and Nelson (1984). The upper boundary represents the threshold for each of the rating categories; in this model the categories represent the fine ratings. The SOV (dummies) captures any country related variables as this measure the sovereign ratings of the countries.

Table 6.5: Marginal effects of Model VI (full specification)

	Rating Category									
Variables	Below BB+	BBB-	BBB	BBB+	A-	A	A+	AA-	AA	Above AA
TIER1	-0.03*	-0.07*	-0.06*	-0.02	0.05	0.09	0.03*	0.06*	0.10*	0.10*
LLR/GL	0.05*	0.01	0.02	0.01	-0.03	-0.12	-0.17*	-0.09*	-0.18*	-0.12*
ROA	-0.11*	-0.03*	-0.08*	0.03	0.02*	0.06*	0.08*	0.03*	0.06*	0.08*
LTA	0.03*	0.01	0.02	0.02	-0.06	-0.02	-0.04	-0.03*	-0.08*	-0.03*
INTER	-0.03*	-0.02*	-0.03	0.05	0.07	0.05	0.02*	0.01*	0.03*	0.09*
BETA	0.02*	0.01*	0.01	0.03	-0.02	-0.03	-0.01	-0.04	-0.05	-0.06*
IDIO	0.02*	0.02	0.02	0.01	-0.03	-0.03*	-0.03	-0.03*	-0.03*	-0.04*
ln(Z-Score)	-0.08*	-0.04*	-0.01*	-0.02	0.04*	0.10*	0.05	0.02*	0.04*	0.07*
LR	0.08*	0.05*	0.05*	0.02	0.01	-0.07*	-0.11*	-0.10*	-0.07*	-0.13*
CRK	0.02*	0.03*	0.16*	0.03	0.07	-0.11*	-0.08*	-0.06*	-0.10*	-0.06*
CI	0.01*	0.03	-0.03	-0.01	-0.02	-0.01*	-0.01*	-0.03*	-0.02*	-0.04*
lnTA	-0.05*	-0.03*	-0.08*	-0.05	-0.02	0.11*	0.10*	0.02*	0.08*	0.09*
TBTF[a]	-0.01*	-0.02*	-0.02*	-0.01	0.03*	0.05*	0.03*	0.05*	0.10*	0.03*
OWN	-0.02*	-0.06*	-0.04*	0.02	0.01	0.04	0.06*	0.10*	0.07*	0.04*
INST	-0.01*	-0.02	-0.02*	-0.02	0.02	0.04	0.06*	0.04*	0.02*	0.03*
INDD	-0.01	-0.01	0.00	-0.04*	0.02	0.01	0.03	0.04*	0.03*	0.03*
SOVAA	-0.05*	-0.01	-0.02*	0.00	0.04	0.01*	0.02*	0.02*	0.04*	0.06*
SOVA	-0.04*	-0.03*	-0.03*	0.01	0.01	0.02	0.06*	0.02*	0.05*	0.07*
SOVBBB	-0.02*	-0.03*	-0.02*	-0.04	0.00	0.03*	0.02*	0.04*	0.02*	0.06*
YEARD	0.02*	0.03*	0.01*	0.03*	-0.01*	-0.03*	-0.01*	-0.03*	-0.05*	-0.02*

Models IV–VI employs a one-year lead value of the independent variables. For the dependent variable, the fine grading of bank credit ratings is employed. Tables 6.4, 6.5 and 6.6 present the parameter estimates of the predictive rating model specifications, the marginal effects of the full specification, and the prediction evaluation results, respectively. Consistent with the hypotheses in Table 4.2, all of the variables in Model VI have the hypothesised signs, and are statistically significant. Most of the results obtained for the predictive model specification are qualitatively similarly to the contemporaneous model specification. The results show that the determinants of international bank rating include the entire *CAMELS* structure. *CAMELS* combine the financial soundness (credit risk) and market (market risk) indicators, and is commonly employed by the credit rating agencies (Rawcliffe *et al*., 2008) to assess soundness of banks.

The measure of capital adequacy, *TIER 1,* shows the expected positive relationship with bank credit rating. The coefficient of the variable *TIER 1* is significant at the 1% level in both Model IV and VI. This result is similar to the corresponding contemporaneous specification. This result reinforces the strong relationship between capital requirements and the assignment of ratings to international banks. This implies that the higher the bank's capital adequacy ratio, the higher the capital buffers for loss absorption and thus this should correlate negatively with bank credit risk. The results thus support H_1.

The assets quality ratio, *LLR/GL,* the profitability ratio, *ROA,* and the liquidity ratios, *INTER* and *LTA* show expected results in support of their related hypotheses. The results are qualitatively similar to those for the contemporaneous model specifications. The marginal effects of each element of the *CAMELS* variables are similar to those in Table 6.2.

The relationship between business risk and the credit rating of a bank is captured by the variables, bank stock beta (*BETA*) and idiosyncratic risk variation (*IDIO*). Both of these variables evidence a negative relationship with bank credit ratings. The variable *BETA* is negative and significant at the 5% level in the full specification in Model VI. This is consistent with hypothesis H_5. Similarly, the variable, *IDIO,* is significantly negatively related to credit ratings at the 10% level in Model VI. These results are consistent with the earlier models of this thesis and with studies by Amato and Furfine (2004) and Blume *et al*. (1998) who find the idiosyncratic (non-beta) variable to be negative and significant at the 10% level. The results for the marginal effects estimation for *BETA* and *IDIO* support the estimates in Table 6.5, and show that a bank is less likely to be rated in the higher rating categories if it has a high business risk based on the predictive nature of the independent variables. In terms of the magnitude of probability changes, there are higher observed values in the predictive models for these variables than those observed for the contemporaneous models. This suggests that Fitch are more influenced by the predictive nature of these variables.

Table 6.4 shows that the variable *Z-score* is positively significantly related to bank credit ratings at the 5% level in Model VI. This is consistent with the sign expected from theory and shows that there is a greater likelihood of being assigned a higher rating as the *Z-score* increases. Consistent with this, the marginal effects show the expected sign and the effects of a unit increase in this variable leads to between a 4% and 7% probability of a bank being rated in the top investment category. The result supports hypothesis H_7 and is consistent with the earlier models.

Results from Model VI show a negative relationship between bank liquidity risk and credit ratings. The liquidity risk variable, *LR*, is significantly negatively related to bank credit ratings at the 1% level. In the same vein, the credit risk variable, *CRK*, is significantly negatively related to bank credit rating at the 1% level in the full specification Model VI. These results highlight the importance of a bank's overall risk measure in the assignment of a credit rating and give further support for hypotheses H_8 and H_9. Further support for the probability of a bank rating falling in an investment or a speculative grade following a percent change in the *LR* and *CRK* variables is evident in Table 6.8. The marginal effects show that banks are more likely to be rated in the speculative grade categories with every percentage rise in the *LR* and *CRK* variables.

The coefficient relating to bank efficiency (*CI*), which measures the relationship between the average ratio of costs to net income of a bank, and bank credit ratings is negative and significant, both in the Model IV and Model VI and at the 10% level. Thus, there is a weak support for hypothesis H_{10} and the results are consistent with the results for the contemporaneous model specification in Table 6.1. The marginal effects of the variable *CI* show that a unit increase leads to between a 2% and 4% probability of not being rated in the investment categories; similarly there is between 1% and 3% of a bank being assigned a speculative rating.

The size measure (*lnTA*) is significantly positively related to bank credit ratings. Consistent with existing studies such as Poon (2003), Poon and Firth (2005), and Van Roy (2006), and providing support for hypothesis H_{11}, there is a significant positive relationship between bank size and credit rating. Fitch (2007) maintains that bank size and the diversification of assets are key factors in their rating process. Evidence from the marginal effects estimation shows that a unit increase in the *lnTA* variable leads to between a 2% and 11% probability of a bank rating falling into the investment grade. Similarly, the other measure of size, *TBTF*, has a positive effect and is significant at the 1% level in Model VI. This further demonstrates the importance of size in the rating process. Hypothesis H_{12}, which states that there is a positive relationship between the Fitch support rating for a bank and its credit rating, is thus supported by this result.

The corporate governance variables, *OWN, INST* and *INDD*, are all statistically significant. The variable that captures directors' shareholdings in a bank (*OWN*) is significantly positively related to bank credit ratings at the 10% level in the full specification, Model VI. This result provides some weak support for hypothesis H_{13}, and is consistent with the earlier models. The degree of institutional ownership (*INST*) is significantly positively related to bank credit ratings in the full specification, and is significant at the 5% level. Existing studies find a strong negative relationship between ownership and the creditworthiness of a firm. The results appear to show that credit rating agencies are more likely to assign lower ratings to banks where ownership is concentrated in the hands of institutional owners. Similarly, the variable which measures the proportion of independent directors on a bank's board (*INDD*) is positively related to bank credit ratings, though only at the 10% level in the full model specification. The results indicate that a higher proportion of independent directors is more likely to lead to a higher credit rating, providing only weak support for hypothesis H_{15}. Interestingly, all the marginal effects for the variable show higher values when compared to the contemporaneous approach. Thus, further supporting the forward-looking view by Fitch of assigning credit ratings to banks.

Consistent with Poon and Firth (2005), the measure of the impact of change in the operating environment (*SOV*) has the sign expected from theory. It is more likely for a bank to be rated in the higher credit rating categories if their primary operations are in a country whose sovereign rating is high. Generally, a higher sovereign rating should lead to banks being rated in the higher investment grade credit rating categories.

In the full specification (Model VI), the log likelihood ratio χ^2 is 754.258 which is highly significant at the 1% level. In addition, the pseudo-R^2 that measures the goodness-of-fit is relatively high at 48.68% in the Model VI compared with the results obtained for Model III. Model VI is therefore more appropriate in explaining variables driving the assignment of a bank's credit rating. All the variables employed in Model VI are significant and have the expected signs.

Table 6.6 presents the out-of-sample predicted outcome for the different rating grades. For the predictive specification, this thesis employs data from 2001 to 2009 for estimating the fit period. The *holdout* sample is then for range of period 2009 to 2012. The table displays the root-mean square error deviation (or error) RMSE magnitude, the mean absolute percentage error, MAPE, and the total percentage prediction.

The results show a total observed (actual) value for bank rating grades of 322. In Panel A, which displays the results of the one-step-ahead out-of-sample prediction, a total of 78.26% correct predictions are observed. This is higher than the corresponding figure (68.32%) for the contemporaneous rating determinant specifications in Table 6.3. 63% of the investment grade ratings are correctly predicted for 2009, while 74% predicted value is observed for the speculative grade. For the two-step-ahead forecast, 71.43% of the actual observations are correctly predicted. Again, this is higher than the results for the contemporaneous prediction evaluation (68.97%) in Table 6.3. (Panel B). 69 out of the 90 actual speculative grade ratings (i.e. 77%) are correctly predicted. Consistent with earlier prediction evaluations, and with intuition, as one moves forward into the future the reliability of forecast decreases. The percentage of correctly predicted observations is 67.08% and 57.14% for the year 2011 and 2012, respectively. A comparison of the results in Panel A to D shows that the measures of the forecast errors tend to increase as one moves forward in time. The lower these errors, the more reliable is the forecasting model. The AA+ and above category is consistently correctly predicted, similar to earlier prediction evaluation results. Further, the forecast accuracy for the predictive models are better than those of the contemporaneous approach, hence providing additional support for the forward-looking view in in their rating assignments.

Table 6.6: Predictive rating determinants model specification: Prediction Evaluation (Model IX)

Estimated Equation (2001-2009):

Panel A Year: 2009

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	94	72	25	25	25.77	625
BBB-	1	32	36	-4	4	12.50	16
BBB	2	31	31	-3	3	10.71	9
BBB+	3	29	28	1	1	3.45	1
A-	4	36	31	6	6	16.22	36
A	5	33	18	14	14	43.75	196
A+	6	34	19	15	15	44.12	225
AA-	7	27	12	15	15	55.56	225
AA	8	6	5	1	1	16.67	1
AA+ and above	9	0	0	0	0	0.00	0
Total		**322**	**252**				

Mean Absolute Percentage Error: 18.46% **Root-Mean-Squared-Error Magnitude: 11.55** **Total percentage predicted: 78.26%**

Panel B: Year: 2010

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	91	69	21	21	23.33	441
BBB-	1	41	33	8	8	19.51	64
BBB	2	33	28	8	8	22.22	64
BBB+	3	23	18	5	5	21.74	25
A-	4	40	28	12	12	30.00	144
A	5	29	17	11	11	39.29	121
A+	6	31	21	10	10	32.26	100
AA-	7	28	15	13	13	46.43	169
AA	8	6	1	4	4	80.00	16
AA+ and above	9	0	0	0	0	0.00	0
Total		**322**	**230**				

Mean Absolute Percentage Error: 31.48% **Root-Mean-Squared-Error Magnitude: 10.69** **Total percentage predicted: 71.43%**

Panel C: **Year: 2011**

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	92	66	26	26	28.26	676
BBB-	1	37	33	4	4	10.81	16
BBB	2	36	31	5	5	13.89	25
BBB+	3	31	17	14	14	45.16	196
A-	4	33	16	17	17	51.51	289
A	5	41	19	22	22	53.66	484
A+	6	28	19	9	9	32.14	81
AA-	7	19	13	6	6	31.58	36
AA	8	5	2	3	3	60.00	9
AA+ and above	9	0	0	0	0	0.00	0
Total		**322**	**216**				

Mean Absolute Percentage Error: 32.70% **Root-Mean-Squared-Error Magnitude: 13.46** **Total percentage predicted: 67.08%**

Panel D **Year: 2011**

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	89	55	34	34	38.20	1,156
BBB-	1	36	21	15	15	41.67	225
BBB	2	46	29	17	17	36.96	289
BBB+	3	32	16	16	16	50.00	256
A-	4	33	18	15	15	45.45	225
A	5	36	22	14	14	38.89	196
A+	6	29	12	17	17	58.62	289
AA-	7	19	10	9	9	47.37	81
AA	8	2	1	5	5	83.33	25
AA+ and above	9	0	0	0	0	0.00	0
Total		**322**	**184**				

Mean Absolute Percentage Error: 44.05% **Root-Mean-Square-Error Magnitude: 16.56** **Total percentage predicted: 57.14%**

Panel E:

Year	Mean Absolute Percentage Error	Root-Mean-Squared-Error	Total percentage predicted
2009	18.46%	11.55	78.26%
2010	31.48%	10.69	71.43%
2011	32.70%	13.46	67.08%
2012	44.05%	16.56	57.14%

6.3.3 The lagged specification

This section presents the results of the third time-specification, that is, the lagged specification. This lagged specification employs one-year lagged values of independent variables in the model in order to test whether rating agencies are *backward-looking* or lag the market in their assessment of bank creditworthiness. The independent variables are from the year *t-1* relative to a rating action in year *t*. Consistent with the earlier bank credit rating models this specification employs the fine rating grades as dependent variable. Tables 6.7 and 6.8 present the estimated models and the marginal effects for Models VII–IX respectively, assuming a fine grading in the dependent variable. Panel A of Table 6.7 presents the model estimation. Model VII employs only financial variables. Model VIII includes only non-financial variables, while model IX gives the results of a combination of the variables in both Models VII and VIII in a full specification model. In addition, Panel B presents model statistics for the three models.

The results for the lagged estimations are again qualitatively similar to the earlier full model specifications (III and VI) employing the fine bank credit ratings. However, the magnitudes of the marginal effects of the changes in the independent variables are lower than in the contemporaneous and predictive time-specifications. For example, the marginal effects for the variable, *TIER1* show a 5% probability of a bank being rated in the top notch (Above AA). This is lower than the 8% and 10% probabilities observed for the contemporaneous and predictive specifications, respectively. Similarly, the marginal effects of the variable, *LLR/GL,* is higher for the contemporaneous and predictive specification. The results show that with every percentage change in the variable *LLR/GL,* there is a decrease in probability by 12% and 9% in the contemporaneous and predictive specifications respectively, compared to the 6% for the lagged specification. Similar results are obtained for the measures of earnings, liquidity and sensitivity to the market.

Table 6.7: Lagged bank credit rating determinants specification results

Panel A Parameter estimates							
	Hypothesised	**Model VII**		**Model VIII**		**Model IX**	
Independent variables	Sign	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Intercept		-10.6584	-4.11***	2.5414	27.22***	-7.9541	-6.88***
TIER1	$+ (H_1)$	0.2145	8.22***	-	-	0.2204	6.97***
LLR/GL	$- (H_2)$	-0.0458	-6.29***	-	-	-0.0467	-5.62***
ROA	$+ (H_3)$	0.0141	2.13**	-	-	0.0265	2.21**
LTA	$- (H_4)$	-0.0098	-2.02**	-	-	-0.0103	-2.23*
INTER	$+ (H_4)$	0.0554	3.66***	-	-	0.0541	3.99***
BETA	$- (H_5)$	-0.0081	-0.88*	-	-	-0.0012	-0.84**
IDIO	$- (H_6)$	-0.0054	-1.09*	-	-	-0.0083	-1.21*
ln(Z-Score)	$+ (H_7)$	0.0629	2.22**	-	-	0.0865	2.30**
LR	$- (H_8)$	-0.0484	-2.29**	-	-	-0.0529	-2.38**
CRK	$- (H_9)$	-0.0354	-7.01***	-	-	-0.0395	-8.01***
CI	$- (H_{10})$	-0.0025	-1.78*	-	-	-0.0111	-1.82*
lnTA	$+ (H_{11})$	0.5947	13.33***			0.6001	13.88***
TBTF	$+ (H_{12})$	-	-	0.0625	4.61***	0.0776	4.84***
OWN	$+ (H_{13})$	-	-	-0.0105	-1.79*	-0.0119	-1.88*
INST	$+ (H_{14})$	-	-	0.0084	1.36*	0.0099	2.28**
INDD	$+ (H_{15})$	-	-	0.0016	1.19*	0.0063	1.81*
SOVAA	$+ (H_{16})$	-	-	0.0254	7.22***	0.0325	7.65***
SOVA	$+ (H_{16})$	-	-	0.0262	6.59***	0.0339	6.21***
SOVBBB	$+ (H_{16})$	-	-	0.0106	2.98***	0.0128	3.65**
YEARD	$- (H_{17})$	-	-	-0.1224	-1.29	-0.1625	-1.75*

Panel C: Selected model statistics	Model VII	Model VIII	Model IX
Log-likelihood	-1,325.165	-1,401.225	-1,306.110
Restr.log-lik.	-1,621.544	-1,845.214	-1,688.214
No. of obs.	3,682	3,682	3,682
χ^2 statistic	781.1244***	726.0154***	812.5844***
Pseudo- $R^2\varsigma$	33.25%	34.06%	38.56%

Notes: The dependent variable of all ordered probit models is the categorical variable CR (fine ratings). All significance levels are determined using the two-tailed Z-test. ***, **,* denote significance at the 1%, 5% and 10%, respectively. Ϛ This measure of goodness-of-fit is a simple computational statistic [$\text{pseudo} - R^2 = \frac{\chi 2}{\chi 2 + N}$] proposed by Aldrich and Nelson (1984). The upper boundary represents the threshold for each of the rating categories; in this model the categories represent the fine ratings. The SOV (dummies) captures any country related variables as this measure the sovereign ratings of the countries.

Table 6.8: Marginal effects of Model IX (full specification)

	Rating Category									
Variables	Below BB+	BBB-	BBB	BBB+	A-	A	A+	AA-	AA	Above AA
TIER1	-0.03*	-0.05*	-0.05*	-0.06	0.01	0.05	0.04*	0.02*	0.04*	0.05*
LLR/GL	0.02*	0.03	0.02	0.01	-0.02	-0.09	-0.02*	-0.04*	-0.03*	-0.06*
ROA	-0.01*	-0.02*	-0.02*	0.02	0.04*	0.04*	0.04*	0.10*	0.02*	0.02*
LTA	0.04	0.01	0.04	0.02	-0.02	-0.02	-0.06	-0.02*	-0.03	0.01
INTER	-0.03	-0.02*	-0.03	0.03	0.07	0.02	0.05*	0.06*	0.06*	0.03*
BETA	0.04*	0.05*	0.02	0.00	-0.02*	-0.00	-0.01	-0.02*	-0.05*	-0.02*
IDIO	-0.02*	-0.02*	-0.02*	0.01	0.03	0.05*	0.02	0.06*	0.03*	0.03*
In(Z-Score)	-0.05*	-0.06*	-0.03*	-0.05	0.01*	0.02*	0.01	0.03*	0.02*	0.04**
BB	-0.03*	-0.05*	-0.03*	-0.03	0.01	0.06*	0.11*	0.04*	0.02*	0.05*
CRK	-0.05*	-0.02*	-0.05	0.04	0.05	0.04	0.20*	0.03*	0.02*	0.03*
CI	0.02*	0.03	-0.02*	-0.02	-0.04	-0.08*	-0.04*	-0.09*	-0.05*	-0.06*
lnTA	-0.02*	-0.03*	-0.10*	-0.02	-0.02	0.05*	0.06*	0.04*	0.04*	0.02*
TBTF	-0.04*	-0.02*	-0.07*	-0.02	0.01*	0.06*	0.04*	0.04*	0.07*	0.03*
OWN	-0.01*	-0.03*	-0.03*	0.03	0.01	0.02	0.03*	0.01*	0.03*	0.03*
INST	-0.03*	-0.02	-0.02*	-0.04	0.01	0.05	0.06*	0.08*	0.05*	0.02*
INDD	0.00	-0.02	0.00	-0.01	0.00	0.00	0.00	0.03*	0.03*	0.03*
SOVAA	-0.03*	-0.03	-0.01	0.00	0.07	0.02	0.04*	0.04*	0.03*	0.08**
SOVA	-0.05*	-0.01*	-0.04*	0.03	0.02	0.01	0.08*	0.03*	0.04*	0.06*
SOVBBB	0.03	0.02*	0.01	0.02	0.01	-0.01*	-0.04*	-0.02*	-0.02*	-0.09*
YEARD	0.03	0.06	0.03	0.02	-0.05	-0.07*	0.03*	0.02	0.04	0.04

The non-financial variables show expected signs, however their explanatory powers are less than those observed in both the contemporaneous and predictive specifications. As in earlier models, the log-likelihood and χ^2 statistics for Models VII – IX are significant and fit the data well. However, in terms of the goodness-of-fit, the pseudo-R^2 is slightly lower than in Models III and VI. Table 6.9 shows the prediction evaluation results for the out-of-sample estimation based on the Model IX specification.

The table presents the four-step-ahead forecast, including the predicted observations and forecast errors. Panel A of Table 6.9 shows the one-step-ahead forecast results. A total of 239 bank ratings out of the 322 are correctly predicted (74%). This is higher than the corresponding value in Table 6.3 which shows a total predicted value of 68%. The speculative rating grade has an absolute percentage error of 23% which is lower than the 35.05% in Panel A of Table 6.3. The top investment grades (AA+ and above to A-) have a combined predictive power of 67.64%, while the one-step-ahead prediction for banks rated in the lower investment categories (BBB) is 81%. The MAPE and the RMSE are 27.64% and 10.23 error points, respectively. These are lower than the corresponding values in Panel A of Table 6.9. Interesting, the out-of-sample one-step-ahead predictive evaluation for the lagged rating determinant specification performs better in forecasting bank ratings than in the contemporaneous specification.

At the other end of the forecast, the four-step-ahead forecast in Panel D shows that 175 out of the 322 bank credit ratings are correctly predicted. This corresponds to 57% correctly predicted observations against the 54% in Panel D of Table 6.3. Consistent with earlier forecast results, the AA+ and above category is correctly forecasted. Overall, the results in Table 6.9 support the argument that the lagged specification provides better out-of-sample prediction for the fine rating notches than the contemporaneous specification. However, the forecast power for the predictive evaluation shows the best forecast results.

Table 6.9: Lagged rating determinants model specification: Prediction Evaluation (Model IX)

Estimated Equation (2000-2008):

Panel A Year: 2009

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	97	75	22	22	22.68	484
BBB-	1	32	26	6	6	18.75	36
BBB	2	28	25	3	3	14.29	9
BBB+	3	29	21	8	8	27.59	64
A-	4	37	32	5	5	13.51	25
A	5	32	19	13	13	40.62	169
A+	6	34	22	12	12	35.29	144
AA-	7	27	17	10	10	37.04	100
AA	8	6	2	4	4	66.67	16
AA+ and above	9	0	0	0	0	0.00	0
Total		**322**	**239**				

Mean Absolute Percentage Error: 27.64% **Root-Mean-Squared-Error Magnitude: 10.23** **Total percentage predicted: 74.22%**

Panel B Year: 2010

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	90	56	34	34	37.78	1,156
BBB-	1	41	29	12	12	29.27	144
BBB	2	36	21	15	15	41.67	225
BBB+	3	23	16	7	7	30.43	49
A-	4	40	26	14	14	27.50	196
A	5	28	18	10	10	35.71	100
A+	6	31	26	5	5	16.13	25
AA-	7	28	14	14	14	57.14	196
AA	8	5	3	2	2	40.00	4
AA+ and above	9	0	0	0	0	0.00	0
Total		**322**	**209**				

Mean Absolute Percentage Error: 31.56% **Root-Mean-Squared-Error Magnitude: 14.47** **Total percentage gain: 64.91%**

Panel C Year: 2011

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	92	62	30	30	32.61	900
BBB-	1	37	23	14	14	37.84	196
BBB	2	36	22	14	14	38.89	196
BBB+	3	31	19	12	12	38.71	144
A-	4	33	20	13	13	39.39	169
A	5	41	27	14	14	34.15	196
A+	6	28	17	11	11	39.28	121
AA-	7	19	12	7	7	36.84	49
AA	8	5	3	2	2	40.00	4
AA+ and above	9	0	0	0	0	0.00	0
Total		**322**	**205**				

Mean Absolute Percentage Error: 33.77% **Root-Mean-Squared-Error Magnitude: 14.05** **Total percentage gain: 63.66%**

Panel D Year: 2012

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	89	52	47	47	52.81	2,209
BBB-	1	36	26	10	10	27.78	100
BBB	2	46	29	17	17	36.96	289
BBB+	3	32	13	19	19	59.38	361
A-	4	33	18	15	15	45.45	225
A	5	36	19	17	17	47.22	289
A+	6	29	12	15	15	51.72	225
AA-	7	19	11	8	8	42.10	64
AA	8	6	4	2	2	33.33	4
AA+ and above	9	0	0	0	0	0.00	0
Total		**322**	**184**				

Mean Absolute Percentage Error: 39.68% **Root-Mean-Square-Error Magnitude: 19.41** **Total percentage gain: 57.14%**

Panel E:

Year	Mean Absolute Percentage Error	Root-Mean-Squared-Error	Total percentage gain
2009	27.64%	10.23	74.22%
2010	31.56%	14.47	64.91%
2011	33.77%	14.05	63.66%
2012	39.68%	19.41	57.14%

In addition to the use of the fine rating grading as dependent variable, this thesis employs the coarse ratings within a robustness check framework. The results of the various estimations are presented in Tables D.1 to D.9 in Appendix D. The results for the coarse rating grading for the various time specifications are qualitatively similar to their fine rating gradation counterparts. Pagano and Volpin (2010) argue that if ratings are set on a discrete scale, complacent rating agencies can suggest to issuers how to structure their securities or their tranches so that they can just attain a given rating. Further, Johnson (2003) argues that credit rating studies should utilise coarse rating grades, that is, grades that ignore the + and – distinctions (notches) since analysing ratings according to finer distinctions may lead to small samples sizes and low statistical power. In the same vein, there is an increase in the number of observations contained within each coarse grade, thus increasing the efficiency of the model.

In the contemporaneous coarse rating specification, the *CAMELS* variables show the expected signs with much higher magnitudes of change effects. For example, the liquidity variables (*LTA* and *INTER*) are both statistically significant at the 1% level in Table D.1. The *LTA* is negative and statistically significant at the 1% level in both Models X and XII. This is a stronger result than the weak relationship reported in Models I and III where the *LTA* is significant only at the 10% level. The stronger relationship may again be related to the use of coarser credit rating grading in the modelling of bank credit rating determinants.

Similarly, the results relating to the bank risk measure *Z-Score* are consistent with theory. The *ln*(*Z-Score*) is a significant positive driver of bank credit rating. The results from Models X and XII show that the coefficients of the *Z-Score* variables are significant at the 1% and 5% levels respectively. In terms of the impact of an expected change, this measure has more significant impact in Model XII compared with Model

III. The clustering of rating notches (coarse grading) thus enables greater impacts to be observed for this variable across a wider range of banks within a given classification. The global financial crisis has reinforced the need for credit rating agencies to take a holistic approach to assessing the creditworthiness of a bank. Packer and Tarashev (2011) maintain that the creditworthiness of a bank depends on the overall bank exposures the financial system, as well as its interconnectedness in the system.

Within the predictive coarse rating specification, there is evidence of a higher level of significance and impact of variables on the assignment of bank credit ratings. The results further reinforce the importance of these independent variables in the credit rating process. For example, the measure of capital adequacy, *TIER 1*, shows the expected positive relationship with bank credit rating. The coefficient of the variable *TIER 1* is significant at the 1% level in both Model XIII and XV. This result is similar to the corresponding contemporaneous specification. It reinforces the strong relationship between capital requirements and the assignment of ratings to international banks. This implies that the higher the bank's capital adequacy ratio, the higher the capital buffers for loss absorption and thus this should correlate negatively with bank credit risk. The results thus support H_1.

Further, results from Model XV show a negative relationship between bank liquidity risk and credit ratings. The liquidity risk variable, *LR*, is significantly negatively related to bank credit ratings at the 1% level. In the same vein, the credit risk variable, *CRK*, is significantly negatively related to bank credit rating at the 1% level in the full specification Model XV. These results highlight the importance of a bank's overall risk measure in the assignment of a credit rating and give further support for hypotheses H_8 and H_9. Further support for the probability of a bank rating falling in an investment or a speculative grade following a unit change in the *LR* and *CRK* variables is evident in

Table D.2. The marginal effects show that banks are more likely to be rated in the speculative grade categories with every percentage rise in the *LR* and *CRK* variables, with the values for the change being higher for the coarse than the fine rating specification.

In terms of the lagged coarse specification, most of the results are qualitatively the same. The majority of the variables in the full specification, Model XVIII have the signs expected from theory. For example, the coefficients for the bank size proxies, *lnTA* and *TBTF*, are positive. *lnTA* is strongly positively related to bank credit ratings. The Table D.7 shows that the variable *InTA* is significant at the 1% level in Models XVI and XVIII. The marginal effects for *InTA* support the results in Table D.8. In the same vein, *TBTF* is significantly positively related to bank credit ratings, and this shows the importance of having a high probability of external support if the bank were to need it. The results show that large banks and those with a greater chance of receiving external support are more likely to be assigned higher ratings. This result is consistent with extant studies such as Poon and Firth (2005) and Fitch (2007).

6.4 The results of the ordered probit testing for effects of ratings stringency over time

This section presents the results of ordered probit model specifications with the inclusion of the main financial variables employed in the previous rating determinant models. These models attempt to explain the effects of time on rating assignment. In addition, these current models employ year dummy variables, with the year 2000 assigned as the benchmark year (thus omitted from the model). This approach builds upon the results presented in the previous sections by further testing the impact of both changes in financial variables and time on the (downward) trend in bank ratings across banks. Further, the results provide further explanation for the observed significant downward rating moment discussed in Chapter 8 (Section 8.5.3). Table 6.10 presents the results of the estimates employing a contemporaneous model specification (Model I), with year dummies, while Model II presents the estimates employing a predictive model specification. The use of the year dummy variables enables the capture of the trend in rating migration due to changing standards of the rating agencies and/or downward rating drifts. Hence, the focus of the results is on the coefficients of the year dummy variables. Panel A shows the parameter estimates, Panel B presents the estimates of the thresholds for each rating category, and Panel C displays selected model diagnostic statistics.

The results of the two models are very similar. The estimates of the coefficients of the financial variables in both models have the hypothesised signs. All of the coefficients are statistically significant, except for the measure of business risk (*BETA*). The other business risk variable (*IDIO*) has a weak negative relationship with the bank credit rating. The overall explanatory power of Models I and II is relative high compared to the models without the year dummies, as seen in the previous chapter. The estimates of the coefficients of the year dummy variables give an indication of the level of rating standards. An increase in rating standards has the potential of strengthening a downward rating drift within the sample of banks. The year dummy variable for 2000 is omitted, and thus the interpretation of the other dummy coefficients is made relative to this year. All of the estimated coefficients of the dummy variables are negative and significant, with the exception of the dummy for 2001. There is a weak relationship between the estimated dummy coefficients between 2002 and 2004 and credit standards (ratings) for banks, while the coefficients for the dummy variables between 2007 and 2012 are significant at the 1% level. There is an observed increase in the magnitude (negative) of the dummy coefficients, and this may suggest that the Fitch rating standards have gradually increased through the entire period covered by the sample.

Table 6.10: Results of the ordered probit regression model with independent variables being financial variables with the inclusion of year dummies (2000-2012)

Panel A Parameter estimates	**Model I**		**Model II**	
Independent variables	Coefficient	Z-statistics	Coefficient	Z-statistics
Intercept	-8.5141	-5.22***	-8.2511	-5.98***
TIER1	0.1084	3.51***	0.0995	4.22***
LLR/GL	-0.0847	-2.98***	-0.1008	-4.99***
ROA	0.1159	3.02***	0.0854	3.51***
LTA	-0.0514	-3.33***	-0.0253	-3.38***
INTER	0.1165	3.22***	0.0547	3.12***
BETA	-0.0283	-0.54	-0.0022	-0.13
IDIO	-0.0251	-1.58*	-0.0117	-1.62*
ln(Z-Score)	0.0115	2.88***	0.0054	2.89***
LR	-0.0684	-3.69***	-0.0444	-3.05***
CRK	-0.0654	-5.84***	-0.0184	-4.54***
CI	0.0120	2.62***	-0.0088	-3.29***
InTA	0.6584	9.32***	0.5024	10.11***
Year dummy variables				
D2001	-0.2888	-0.88	-0.2684	-0.76
D2002	-0.2954	-1.51*	-0.2711	-1.32*
D2003	-0.3055	-1.66*	-0.2850	-1.55*
D2004	-0.3111	-1.81*	-0.2917	-1.67*
D2005	-0.3284	-2.03**	-0.3051	-1.99**
D2006	-0.3320	-2.23**	-0.3115	-2.01**
D2007	-0.3333	-4.72***	-0.3258	-2.11**
D2008	-0.6521	-5.23***	-0.6832	-3.99***
D2009	-0.7514	-6.21***	-0.7821	-5.39***
D2010	-1.1598	-7.77***	-0.9812	-7.02***
D2011	-1.1665	-8.81***	-1.0072	-6.95***
D2012	-1.2020	-7.32***	-1.1136	-6.28***
Panel B: Cut-off points upper boundary for rating category				
BB+ and below	0.000	-	0.000	-
BBB-	0.425	7.32***	0.365	7.61***
BBB	1.264	9.99***	1.051	8.21***
BBB+	1.495	11.25***	1.332	12.65***
A-	2.658	15.39***	2.125	17.82***
A	2.854	21.23***	2.524	21.33***
A+	3.235	27.65***	3.369	29.95***
AA-	3.785	26.36***	3.854	30.69***
AA	3.999	28.65***	4.625	35.22***
AA+, AAA	+∞	-	+∞	-
Panel C: Selected model statistics				
Log-likelihood	-1,326.854		-1,415.173	
Restr.log-lik.	-1,651.378		-1,784.261	
No. of group obs.	3,682		3,402	
χ^2 statistic	598.267***		587.214***	
Pseudo- R^2ς	42.88%		44.26%	

Notes: The dependent variable of all ordered probit models is the categorical variable CR (fine ratings). All significance levels are determined using the two-tailed Z-test. ***, **,* denote significance at the 1%, 5% and 10% levels, respectively. Ϛ: this measure of goodness-of-fit is a simple computational statistic [$\text{pseudo} - R^2 = \frac{\chi 2}{\chi 2+N}$] proposed by Aldrich and Nelson (1984). The upper boundary represents the threshold for each of the rating categories, and in this model the categories represent the fine ratings.

The coefficient of the dummy variables becomes increasingly negative over the years, moving from -0.2888 in 2001 to -0.333 (2007) and -1.2020 (2012). This partial monotonic decrease therefore suggests either that Fitch's rating review of bank creditworthiness has become stricter or that the credit positions of banks in the sample have become worse over the years.

Further, it is interesting to observe from Table 6.10 that there is a considerable negative increase in the magnitude of the coefficients between 2007 and 2008 (Model I: 0.319; Model II: 0.357). This may signify a paradigm change in the way rating agencies measure, review and estimate the creditworthiness of banks. In other words, this is consistent with changes carried out by rating agencies regarding their rating methodologies. Overall, this may have an influence on the downward rating drift found in the Section 8.5.3.

The sample of bank data employed in this thesis consists of a large number of new ratings. There is a strong tendency for these new bank ratings to have been awarded an inflated initial rating. Hence, there is a high likelihood for such ratings to be subsequently reviewed downward, and this may have an influence on the falling year dummy variable.

This is consistent with Du and Suo (2005) who argue that such reclassification of ratings due to inflated new ratings is sufficient to explain the pattern of declining year dummy coefficients. However, Kondo (2011) suggests that there should not be an annual decline in the coefficients of year dummies if the number of such new ratings remains constant as the effects will be the same each year.

This thesis investigates further the observation of an apparent convergence of ratings towards the investment-grade threshold as observed in the discussion of the results from the transition matrix. Models employing separate sets of year dummies for investment-grade year dummies (Model III) containing financial variables and another model containing non-investment-grade dummies (Model IV) are constructed. This is to allow for a formal test of whether there has been a general downgrading or simply a convergence of bank ratings towards the investment grade threshold. Table 6.11 presents ordered probit result employs year dummy variables.

The results presented in Table 6.11 show the coefficients of the financial variables in both models III and IV, as well as those for the year dummies. The financial variables measuring the *CAMEL* factors and size are significant at the 1% level. The size factor shows a positive relationship with bank credit ratings. Both the liquidity and credit risk measures are significantly negative at the 1% level. The coefficients of the measure of business risk (*BETA* and *IDIO*) are both significantly negative at the 10% level. The coefficients of the investment grade year dummies are positive, but show a gradual decrease in magnitude over time, particularly in the period following the financial crisis. This suggests that the review of Fitch rating methodology increasingly made it more difficult for banks to be assigned higher investment grade credit ratings, particularly in the post-2007 period. This leads to a downward momentum in bank credit ratings.

The results of the coefficients of the non-investment grade year dummies in Model IV are negative and statistically insignificant. Focusing on the magnitude of the coefficients, the results do not present any discernible pattern. There is a relative decrease in the coefficients of the dummy variables in the period between 2008 and 2012, indicating that rating agencies may have tightened their standards for this category of ratings. Overall, the results suggest that it might be relatively easier for banks in the non-investment category to have their ratings upgraded in the pre-financial crisis period, with a stronger likelihood of being downgraded rather than upgraded in the period after 2008

Table 6.11: Ordered probit regression results for bank credit ratings with financial factors as independent variables with the inclusion of category year dummies (2000-2012)

Panel A Parameter estimates				
	Model III		**Model IV**	
Independent variables	Coefficient	Z-statistics	Coefficient	Z-statistics
Intercept	-7.2541	-5.68***	-8.8410	-6.02***
TIER1	0.2152	3.33***	0.1054	3.54***
LLR/GL	-0.1547	-3.01***	-0.1364	-4.29***
ROA	0.2084	2.99***	0.1846	3.01***
LTA	-0.0847	-3.61***	-0.0758	-3.21***
INTER	0.1254	3.98***	0.1021	3.47***
BETA	-0.0656	-1.69*	-0.0219	-1.72*
IDIO	-0.0365	-1.60*	-0.0521	-1.66*
ln(Z-Score)	0.0654	2.51***	0.0984	2.54***
LR	-0.0783	-3.55***	-0.0593	-3.26***
CRK	-0.0841	-4.96***	-0.0325	-4.26***
CI	0.0235	3.59***	-0.0157	-3.12***
InTA	0.7902	8.29***	0.6052	9.19***
Year dummy variables				
D2001INV / D2001NINV	3.1051	8.62***	-7.5122	0.00
D2002INV / D2002NINV	2.9998	9.21***	-9.1261	0.00
D2003INV / D2003NINV	2.6547	9.86***	-8.6579	0.00
D2004INV / D2004NINV	2.4331	8.81***	-8.7481	0.00
D2005INV / D2005NINV	2.2214	8.23***	-8.9254	0.24
D2006INV / D2006NINV	1.9292	7.96***	-9.1511	0.09
D2007INV / D2007NINV	1.8664	7.51***	-8.2257	0.00
D2008INV / D2008NINV	1.8325	6.21***	-7.2541	0.00
D2009INV / D2009NINV	1.7685	5.82***	-7.7643	0.00
D2010INV / D2010NINV	1.5601	4.27***	-8.5812	0.00
D2011INV / D2011NINV	1.2822	4.01***	-9.5269	0.00
D2012INV / D2012NINV	0.8658	3.78***	-9.9584	0.00
Panel B: Cut-off points upper boundary for rating category				
BB+ and below	0.000	-	0.000	-
BBB-	0.551	7.88***	0.684	9.62***
BBB	1.325	16.21***	1.547	17.65***
BBB+	1.547	19.24***	1.954	20.54***
A-	1.984	21.22***	2.265	23.95***
A	2.251	25.14***	2.684	28.65***
A+	2.895	27.98***	3.865	32.24***
AA-	3.214	29.24***	3.924	35.55***
AA	3.547	32.33***	4.695	38.62***
AA+, AAA	+∞	-	+∞	-
Panel C: Selected model statistics				
Log-likelihood	-1,421.547		-1,620.858	
Restr.log-lik.	-1,762.050		-1,952.214	
No. of group obs.	3,682		3,682	
χ^2 statistic	660.141***		695.853***	
Pseudo- R^2ς	45.32%		43.21%	

Notes: The dependent variable of all ordered probit models is the categorical variable CR (fine ratings). All significance levels are determined using the two-tailed Z-test. ***, **,* denote significance at the 1%, 5% and 10% levels, respectively. Ϛ: this measure of goodness-of-fit is a simple computational statistic [$\text{pseudo} - R^2 = \frac{\chi 2}{\chi 2+\text{N}}$] proposed by Aldrich and Nelson (1984). The upper boundary represents the threshold for each of the rating categories, and in this model the categories represent the fine ratings.

6.5 Summary

This section gives a summary of the main findings of this chapter with a view to discussing the main determinants of credit ratings. It further discusses the nature and implications of the rating process by comparing across the specifications of the estimated models used. This chapter, which investigates the key variables influencing bank credit ratings, introduces a number of innovations. First, the credit rating determinants models test both the individual, as well as joint, significance of a number of financial and non-financial variables that have been hypothesised to affect a bank's creditworthiness. The chapter further introduces unique variables such as the Fitch measure of the propensity to receive external help when needed (*TBTF)*, specific measures of credit and liquidity risks (*LR* and *CRK)*, and a proxy for country specific variables, that is, the sovereign rating. The issue of corporate governance as a key driver in the rating process is highlighted in various sections within the chapter. Thus this study adds to the existing body of literature by critically examining the contribution of a more holistic set of variables impacting upon the credit rating process.

The results suggest that bank capitalization (*TIER1*) is important in the bank credit rating process. The coefficient of this variable is positive in all of the full specification models and is statistically significant at the 1% level. In addition, the marginal effects show that a percentage increase in this capital adequacy ratio results in a higher probability of being rated in the investment category. These results are consistent with many of the existing studies (Estrella *et al*., 2000; Poon, 2003; Poon and Firth, 2005; Bissoondoyal-Bheenick and Treepongkaruna, 2009; Beltratti and Stulz, 2012; Cole and White, 2012; Distinguin *et al*., 2012) and confirm the importance for a bank of having adequate capital, particularly in times of financial crisis. The rating process involves an assessment of the potential of a bank to continually generate higher returns, whilst providing an adequate cushion to absorb expected and unexpected losses. Generally, banks with higher Tier I capital and a higher ratio of loans to total assets perform better in the initial stages of a financial crisis (Beltratti and Stulz, 2012). Further, Berger and Bouwman (2011) show that during banking crises, higher capital levels improve bank performance. Similarly, Cole and White (2012) argue that higher levels of capital and stronger *CAMELS* ratings lower the likelihood of bank failure.

With reference to asset quality (*LLR/GL*), the results are consistent with the expected negative sign and show a strong relationship with bank credit ratings. The results show that this variable is negative and statistically significant at the 1% level in all the models that combine both the financial and non-financial variables. In all of the six full models, banks with low asset quality are more likely to receive lower ratings. Asset quality is at the heart of the drivers of credit risk in banks as it represents the credit risk associated with the entire portfolio of assets held by a banking institution and is usually associated with the root cause of most bank failures. Nonperforming loans usually have loan-loss reserves set aside against them which may be ultimately written off due to non-recovery. Golin and Delhaise (2013) argue that such provisioning against loan-loss reserves cuts into profits, and thus impairs the bank's ability to create new capital. In the same vein, writing off a non-performing loan directly reduces existing capital. The marginal effects results for each of the full models show that banks with higher *LLR/GL* ratios have a higher probability of being assigned lower ratings. These results suggest that the rating agencies might place a higher importance on the level of the quality of bank assets vis-à-vis the value of nonperforming loans as well as the amounts set aside as loan-loss reserves. The continued monitoring of asset quality enables rating agencies to assess bank creditworthiness more accurately.

Profitability (*ROA*) is statistically significant in all the full models and exhibits a positive sign as expected. Profitability features as an important determinant of credit ratings, with higher profitability driving up bank ratings. The estimated coefficients for ROA are significant at the 1% level in only the coarse predictive model (XV), while at the 5% in the rest of the full models. The findings for the impact of *ROA* are consistent with the marginal effects in all models, which indicate that a rise in profitability leads to an increase in the likelihood of banks being assigned higher ratings. The results support the expected hypothesis of a positive relationship between profitability and bank credit rating; and are consistent with earlier studies (Adams *et al*., 2003; Poon et al., 2009; Hau *et al*., 2012) which establish a strong positive relationship between profitability and credit ratings. The findings indicate that banks with higher profits have a lower probability of default, as these results in higher earning capacity and less riskiness in terms of debt repayments or meeting customers' deposit demands.

The liquidity variables (*LTA* and *INTER*) are statistically significant in all of the models and both exhibit the hypothesised negative and positive signs, respectively. Liquidity features as a very important determinant of bank credit ratings, with higher liquidity impacting positively on such ratings. The *LTA* measure of liquidity evidences negative coefficients in all of the models and is significant at the 1% level in the coarse specification models. Similarly, the variable *INTER* shows a strong positive relationship with bank credit ratings and is statistically significant in all of the models at the 1% level, except for Model VI where it is significant only at the 5% level. The majority of the existing studies establish a similar strong relationship between liquidity and bank credit ratings (Fight 2000; Poon, 2003; Doumpos and Pasiouras, 2005; Poon *et al*., 2009). In a related study, Poon and Firth (2005) finds that banks with unsolicited ratings are less liquid than banks with solicited ratings. The results indicate that the higher the liquidity of bank, the greater the probability of it being assigned higher ratings.

The results relating to the business risk variables (*BETA* and *IDIO)* are less straight forward. The coefficients of the variables of *BETA* and *IDIO* are negative as expected, though there is mixed evidence in terms of their level of significance. The beta (*BETA*) variable is significant in all six (full) models, except Model III. The results of the latter models indicate that the bank credit rating process is independent of market dynamics (Fitch, 2007, Standard and Poor's, 2005). This is consistent with the results of Purda (2008) who reports an insignificant negative beta coefficient and suggests that market risk does not affect credit ratings at all. The majority of the results are however consistent with Blume e*t al*. (1998) and Shin and Moore (2003) who find a strong negative relationship between the market model beta and credit ratings, and argue that as equity risk increases firms are less able to service their debt obligations. The bank specific risk (*IDIO*) is significantly negatively related to bank credit ratings in all six models. This suggests that the higher is *IDIO* the less likely a bank will be assigned a higher rating. In addition, the *Z-Score* is statistically significant in both the contemporaneous, lagged and predictive models, and bears the hypothesized positive sign. This suggests that higher *Z-Score* banks are more likely to be awarded a higher credit rating. This variable is significant at the 1% level in the predictive models for both the fine and coarse grading.

Liquidity risk (*LR*) and credit risk (*CRK*) are statistically significant in all of the models, and both exhibit the hypothesized negative signs. The results indicate that the higher is *LR* the lower the chances of a bank being assigned a higher rating. *LR* shows the degree to which a bank is capable of dealing with sudden and unexpected liquidity demand. However, Imbierowicz and Rauch (2014) argue that in some cases, a higher level of liquidity risk might be desired by bank management to generate higher profit. Similarly, *CRK* is statistically significant, with a negative sign in all six (full) models and shows the impact of capturing this risk variable in the assessment of a bank credit rating. Taken together, these two risks (*LR* and *CRK*) have a significant influence on bank default probability. Banks experiencing high liquidity risk might not be able to cover short-term withdrawals by customers, and hence may experience a bank run. Employing the *LR* measure in the modelling of bank credit rating determination allows for incorporation of the immediate funding risk a bank might face in the case of sudden liquidity withdrawal or asset deterioration. Similarly, the use within this thesis of the *CRK* variable helps to capture a bank's ability to cover near-term future loan losses. These two measures have not been employed in previous studies relating to bank credit rating determination. This indicates a valuable addition within this current study.

Further, the measures of bank size (*InTA* and *TBTF*) have the hypothesised positive signs and are statistically significant at the 1% level in all six (full) models. The results are consistent with the existing studies (e.g. Amato and Furfine, 2004; Poon *et al*., 2009; Caporale *et al*., 2009; Distinguin *et al*., 2009) and confirm the importance of size in the assignment of credit ratings as it is perceived as a proxy for a bank's geographical presence, competitive position, market share and product and brand recognition (Pasiouras *et al*., 2007). This thesis introduces the Fitch support rating which captures the role of government and external support in keeping a bank afloat when needed. This may suggest that rating agencies perceive big banks as arguably too-big-to-fail, hence assigning them higher ratings.

Bank corporate governance is represented by three different variables in this thesis. Directors' ownership (*OWN*) is positively related to a bank's creditworthiness in all six (full) models. However, this relationship is a weak one, being significant at only the

10% level, except in Model XVIII where it is significant at the 5% level. The results suggest that rating agencies perceive an increase in directors' ownership of a bank positively and may assign correspondingly higher ratings in such cases. This is consistent with earlier studies (e.g. Ashbaugh-Skaife *et al*., 2006). The second corporate governance dimension (*INST*) has the hypothesised positive sign in all the models. The strength of the relationship between the variable, *INST,* and bank credit rating varies among the specifications. The results indicate that increasing ownership by institutional investors does benefit banks in terms of achieving a better rating. The contemporaneous specifications show a weak relationship at the 10% level. The proportion of independent directors (*INDD*) on a bank's board exerts a positive influence on credit ratings. The results show that credit rating agencies perceive the independent oversight of the outside directors as being beneficial in the rating process. Hence, banks that ensure tighter outside monitoring are more likely to achieve a better rating. This result is consistent with hypothesis H_{15} and is consistent with existing studies (Ashbaugh-Skaife *et al*., 2006).

Further, the results of the sovereign rating variables (*SOV)* which capture the effects of country specific changes on bank credit rating assignment is positive and significant in all the six models. The results show that credit rating agencies pay particular attention to the sovereign ratings of the home country in which a bank is operating when assessing their creditworthiness. There is a strong positive relationship between the *SOV* and a bank credit rating, and this is significant at the 1% level.

In general terms, the results in this chapter suggest that assigning a credit rating to a bank is a forward-looking process. The predictive models estimated are found to enjoy higher classification accuracy than the contemporaneous models. This finding is consistent with the argument of credit rating agencies that they are forward-looking in their rating process. It further underscores the importance of future projections and involvement of a bank's management team in providing information to the CRAs about the business and its prospects. The results show that a CRA's ability to forecast a bank's performance is enhanced based on their access to private information.

The results show that non-financial information adds value to the overall classification accuracy as well as the model fit, as evidenced by the higher goodness-of-fit (*pseudo* – R^2) in the full specifications. This finding is consistent with the results by Ashbaugh-Skaife *et al*. (2006) who show a significant improvement following the inclusion of both sets of attributes (financial and non-financial information) in the full models. The results from the tables further indicate that financial information is the major driver of bank credit ratings and that rating agencies assign significant weight to it. The use of non-financial information in this thesis, particularly with regard to corporate governance variables, as well as the dummy variables to capture the impact of the size effects (*TBTF*) and sovereign ratings (*SOV*), potentially adds to the understanding of the bank rating determinant process.

Finally, the findings with respect to the test of stringency suggest that the review of Fitch rating methodologies may have had resulted in a progressively tighter rating process, a consequence of which is the tendency for more observed downgrades particularly within the investment category. Further, the results provide an indication that banks within the non-investment category may have had their ratings positively reviewed in the period before the crisis than afterwards. Similarly, the increased magnitude in the coefficients of the year-dummies suggests that Fitch increasingly made it more difficult for banks to be assigned investment grade credit ratings.

CHAPTER 7. AN EMPRICAL INVESTIGATION OF THE EFFECTS OF BANK CREDIT RATING NEWS ANNOUNCEMENTS ON BANK EQUITY RETURNS

7.1 Introduction

Credit rating agencies have become an integral part of the financial system and are considered an important source of information for the market. There are suggestions that rating agencies do not react fast enough to new developments relating to a particular issue or issuer. Nickell *et al.* (2000), Altman and Rijken (2004) and Loeffler (2005) maintain that rating agencies perform the dual role of managing rating timeliness and providing rating stability. The leading credit rating agencies claim to employ a *through-the cycle* approach neglecting short-term variations in credit quality when assigning ratings. An example is the case of Moody's Investors Services that takes a rating action only 'when it is unlikely to be reversed within a relatively short period of time (Cantor, 2001: 175). There is an expectation on the part of the market for stability in the assignment of ratings to banks. However, timely reaction to significant changes in factors affecting the creditworthiness of banks is important in making the market more efficient.

A rating change conveys to the market that there is a change in opinion of a credit rating agency, regarding the relative creditworthiness of an entity or its issue (Konijn and Rijken, 2010). One may argue that in order to maintain the balance between rating stability and rating timeliness, credit rating agencies may signal to the market the possibility of effecting a rating change. This may be in the form of issuing a rating review or a rating outlook. Whilst a rating outlook gives an indication of the likely direction of an issuer's credit quality, a rating review (or placement on a Watchlist) gives a much stronger indication about the possible future of a rating change (Langohr and Langohr, 2008).

Over the last few years, particularly in the period following the global financial crisis, there has been a need to revisit the claim by the rating agencies that they provide timely and valuable information to the market. The relationship between credit ratings and the market prices of financial assets has been the focus of a number of empirical studies (e.g. Konijn and Rijken, 2010; Bedendo *et al*., 2013; Grothe, 2013) which examine the effect of new ratings, reviews, outlooks and rating changes (upgrades and downgrades) on bond, share and derivatives prices. If credit ratings provide information about the credit quality of companies to capital markets, a change in a company's rating will stem from a reassessment of the company's risk by market participants, thus leading to changes in the prices of securities, such as the bonds issued by the company. A reliable evaluation of the impact of credit rating agency announcements on stock prices depends largely upon the accuracy and precision with which the announcement dates can be identified as well as the way in which abnormal returns around such announcements are measured. In addition, Gannon *et al.* (2006) argue that if one assumes that the stock market is in a semi-strong form efficient state (where share prices rapidly incorporate all publicly available price-sensitive information), then the impact of a news event on a company's share price is captured by measuring the event day return (*abnormal return*) immediately after such an announcement.

This chapter aims to investigate the information relevance of bank credit ratings, and in particular the way bank stock returns behave around ratings announcements for international banks. More specifically, it tests the hypothesis that, on average, bank credit rating announcements have no impact on the behaviour of bank stock returns.

The rest of this chapter is structured as follows. Section 7.2 presents the theoretical background by focusing on the theoretical and empirical studies in the area of news announcement effects, specifically the effects of credit rating changes. Section 7.3 investigates existing methodological event studies approaches, and explains the approach employed in this study. Section 7.4 discusses some extensions to the traditional event study approach. Section 7.5 discusses issues around the data employed. Section 7.6 presents the results, while the Section 7.5 presents a summary to the chapter.

7.2 An overview of the theoretical foundation in an event study

This component of the thesis aims to provide an insight into the relationship between bank credit risk and the equity market. This section provides an overview of the main theoretical arguments on which the empirical analysis in this component of the thesis is based. At the core of the theoretical framework is the assumption that the financial market is efficient and incorporates news information in a timely manner. Further, it assumes that the market participants are rational.

7.2.1 The Efficient Market Hypothesis

The theoretical framework for this component of the thesis centres on the Efficient Market Hypothesis (hereafter referred to as EMH). Howells and Bain (2008) suggest that the term *efficiency* within the context of a financial market investigation can mean one of several things. They argue that efficiency may refer to either operational, allocation or information efficiency. This thesis focuses on answering the question of whether financial markets are informationally efficient in the sense that prices incorporate all available information in a timely manner. More specifically, it investigates whether credit rating agencies possess information not already available to the market (and incorporated in bank stock prices). Price efficiency has a significant effect on operational and allocation efficiency in the sense that markets rely on the release of timely and relevant information to be able to operate at minimal cost and allocate funds and resources in a productive way. In order for the market to be efficient, therefore, security prices must fully reflect all available information. According to the EMH, no information or analysis can provide investors with a superior opportunity to consistently outperform the market. Hence, any 'new' information coming to the market about, say, a change in a bank's creditworthiness, is rapidly incorporated into its stock price. However, one cannot rule out the impact of market expectations on the behaviour of stock returns. If there is information that relates to an expected increase in, say, bank's cash flows (e.g. year-end results are better than expected), or lower risk, then stock prices may increase even before the actual announcement of the event.

There is evidence to suggest that financial markets may not be operating at the strong level of market efficiency (Schwert, 2002; Park and Irwin, 2007). An indication of the non-conformity to the strong level of market efficiency may be seen in the case of rating agencies being able to access non-public information. The announcement of a credit rating news event could thus potentially impact on the market and give rise to an abnormal stock return reaction. Any action by the market upon release of this news announcement by rating agencies can be said to constitute semi-strong form efficiency. Further, there have been several reported cases of insider trading which may suggest that the price at which a bank stock is trading does not incorporate all available information (Seyhun, 1998; Chakravarty and McConnell, 1999; Fernandes and Ferreira, 2009). It is interesting to note that the EMH makes no assertion on whether prices will always be correct, nor does it require agents to use all information in forming rational expectations (Elton and Gruber, 1995).

This thesis examines short event windows for stock returns with the aim of providing more accurate inferences using an appropriate econometric approach. With the level of news releases relating to firms, a short window market efficiency study is, at least theoretically, less susceptible to other contaminating news events. This is consistent with the view of Fama (1991) who suggests that the short-horizon tests represent the cleanest evidence on market efficiency.

7.2.2 The Information Content Hypothesis

It is worth noting that the relevancy of information is a crucial consideration for any financial markets news announcement study. Does the information contained in the news announcements by credit rating agencies constitute relevant information to influence the market, such that changes in bank stock behaviour are triggered? Is the market sufficiently rational to make market agents and the market as whole form a rational expectation about the new information? The EMH maintains that individual agents act rationally; hence one should not expect to record a series of abnormal stock returns around the release of bank credit rating news. If abnormal returns and/or market corrections are observed, then the EMH suggests that these will be nothing more than random disturbances from efficient prices. Thus, stock behaviour in the long run represents an aggregation of short term behaviour (hence making the latter relatively unimportant). Put differently, if there is, say, exactly a zero cumulative abnormal effect in the short term then there will be exactly zero abnormal effects in the long term as well.

The notion of information content draws precedence from agency theory and is connected with information asymmetry and signalling hypotheses. The information content hypothesis assumes that there is information asymmetry between the credit rating agencies and the market (Bruno *et al*., 2011). The implication of this is that rating related news announcements by the agencies should potentially convey additional relevant information to the market about the value of a firm. One may argue that, since rating agencies aim to maintain rating stability, there may be a lag between the time taken to process relevant and significant rating information and when the market actually receives it. Thus, in semi-strong form market efficiency, one would not expect a change in a firm's credit rating to impact on security prices. Similarly, credit ratings may reflect irrelevant or incomplete information, thus not resulting in any significant movement in stock prices. Further, due to the conflicts of interest that may exist between the rating agencies and their clients (the issuers), rating agencies may not act upon price-relevant information in a timely manner (Bai, 2010). The business model within the rating industry is an *issuer-pay model* in which issuers pay rating agencies to assign them credit ratings. Hence, one may argue that in order to maintain this stream of revenue and not lose their clientele, rating agencies may not always act in the best interests of the market. However, credit rating agencies maintain that they have their reputation to uphold and hence are incentivised to act in the interest of investors (Golin, 2001; Langohr and Langohr, 2008). Another factor that might reduce the information relevance of rating agencies is that certain market participants (e.g. institutional investors, banks, insiders) may also have access to private, privileged information. Consistent with this argument, Kaplan and Urwitz (1979), Wakeman (1984) and Holthausen and Leftwich (1986) show that rating agencies merely reflect public information.

However, the major credit rating agencies claim to have access to private information obtained through discussion with their clienteles' top management. Such information, they maintain, is not available to other investors. The process of assigning and monitoring a rating is a costly one, hence the rating agencies, by their actions, potentially provide information to the market at a low cost. Similarly, Micu *et al*. (2006) argue that issuers engage credit rating agencies in confidential discussions about their current and future strategic plans, rather than giving full public disclosure to investors and the market. If rating news announcements convey new and relevant information, then one would expect that negative rating news (e.g. downgrades, reviews of downgrades and negative outlooks) should lead to negative abnormal stock returns around the news announcement date. In the same vein, positive rating news (e.g. upgrades, reviews of upgrade and positive outlook) should lead to positive abnormal stock returns around the announcement date. Goh and Ederington (1999) maintain that the potential impact of a rating news announcement on stock prices depends critically on the reason for the announcement. Announcements relating to fundamental valuation or the financial prospects of a firm (e.g. prospective increase in market share, earnings, or mergers and acquisitions) should have either a positive or negative impact on stock prices of the issuer.

The Information Content Hypothesis is also connected to the Signalling Effects Hypothesis which suggests that a change in a firm's rating not only signals to the market the value, future earnings and cash flows of the firm, but also about the industry in which the firm operates (Akhigbe *et al*., 1997; Caton and Goh, 2003). Akhigbe *et al*. (1997) argue that the downgrade of a rival firm may be good news for other firms in that industry. Further, a downgrade may be expected to be followed by a negative stock price reaction for the firm because this signals negative information about the declining value of a firm and leaves the firm potentially vulnerable to attacks. It may also lead to herding behaviour on the part of the market participants, resulting in negative share price reactions for other firms within the industry. The reverse may be the case for an upgrade.

7.2.3 The Price Pressure Hypothesis

The relevance of a bank credit rating news announcement is important in triggering a market reaction. However, if a rating announcement conveys no new information to the market about the creditworthiness of an issuer (e.g. a bank), there may still be a market reaction due to institutional and regulatory pressure or constraints. Section 2.3 describes the role of credit rating agencies in the financial market and how they perform a delegated monitoring role. Market participants and regulators often delegate these roles to rating agencies due to the reduced cost of doing so and the specialist skills on the part of the agencies. Further, investors may be restricted by the mandate given to them by their clients in buying and selling of securities within certain risk categories, and thus rely on the pronouncements by credit rating agencies on the creditworthiness of an issuer (or issue). Hence, price changes might be effected due to buying or selling pressure from these 'restricted' investors. Investment grade assets are particularly important to institutional investors as they seek to maximize returns and target a higher level of income by utilizing assets issued by higher quality companies (Fabozzi, 2012).

There are several studies in the existing literature (Hand *et al.*, 1992; Kliger and Sarig, 2000) which support the price pressure hypothesis. The studies find that downgrades, particularly those from investment- to speculative-grade ratings result in considerable negative price movement. This may be the result of the price pressure hypothesis which triggers the mutual funds, pension funds or other institutional investors to sell (or buy) if there is a downgrade (or an upgrade) of securities. This ensures consistency with investors' mandates. Similarly, rating announcement effects are greater for firms with higher leverage (many of which are in the speculative-grade) than for firms with lower leverage (typically investment-grade). The threshold rating grade (e.g. the BBB- in the Fitch rating grading) is the lowest investment-grade category, and rating announcements that cross this threshold may contravene an investor's investment mandate. This may cause investors to sell such downgraded assets, hence triggering negative price movement.

Table 7.1 shows a prediction of share price reaction following bank credit rating announcements, assuming that credit rating news possesses information relevant to the market. In general, a positive news announcement leads to a positive price reaction based on the Information Content and Signalling Hypotheses. On the contrary, a negative news announcement will be expected to lead to a negative stock price reaction based on the Information Content and Signalling Hypotheses.

Table 7.1: Prediction of share price direction

Rating action	Information content hypothesis	Signalling hypothesis
Upgrade	Increase	Increase
Positive outlook	Increase	Increase
CreditWatch list (positive)	Increase	Increase
Downgrade	Decrease	Decrease
Negative Outlook	Decrease	Decrease
CreditWatch list (negative)	Decrease	Decrease

The issue of the relevance and timeliness of bank credit rating information, as well as the degree to which market participants react to this rating news announcement, shapes the nature of the hypothesis to be tested. The magnitude of the effects and in particular the potential asymmetry between upgrades and downgrades adds to the dynamic nature of market reactions.

This component of the thesis aims to investigate the significance and magnitude of abnormal returns around bank credit rating news announcements. In order to answer the question of whether there is a systematic relationship between credit ratings announcements and the returns pattern of bank stocks, this thesis postulates the following generalised hypothesis:

H_0: On average, bank credit rating news announcements have no impact on the behaviour of bank stock returns

7.2.4 A review of previous empirical evidence

Credit rating agencies provide information to the market on the credit quality of firms and their issues. At times, this information reflects a change in the creditworthiness or the future direction of the credit qualities of such firms and/or their issues. The relationship between credit ratings and the market prices of assets and other instruments has been the focus of a number of empirical studies which mainly examine the effect new ratings, placements on a credit Watchlist, and rating changes (upgrades and downgrades) on the price of a firm's shares, bonds and derivatives. If credit ratings provide information about the credit quality of firms to capital markets, a change in a firm's rating should trigger abnormal stock price behaviour.

A review of the existing literature indicates the existence of information asymmetry in the way financial markets react to rating related news announcements. The majority of existing studies focus on the stock price impact of rating announcements, particularly for sovereign entities as well as non-financial firms and their issues. A cross section of selected results from existing studies is presented in Table 7.2. Very few of the studies (e.g. Richard and Deddouche, 1994; Apergis *et al.,* 2011; Jones and Mulet-Marquis, 2014; Fieberg *et al*., 2013) employ bank credit rating related data to draw inference on the behaviour of bank stocks around rating news announcements. This thesis focuses specifically on banks due to their importance to the economy, and aims to investigate short-horizon bank stock reactions to rating related announcements.

There have been many studies which examine whether ratings add information to market prices, and most of these studies relate to the US. Early studies such as Katz (1974), Pinches and Singleton (1978) and Griffin and Sanvicente (1982) follow the traditional event study approach developed by Fama, French, Jenson and Roll FFJR (1969), and consistent with other studies around that time employ monthly data in their models, and find little evidence of bond and stock prices responding to bond rating changes. Thus, in general, most of these early studies conclude that the market fully anticipates rating changes.

A seminal study by Hand *et al.* (1992) examines the effect of rating agency announcements on both bond and stock prices in the US between 1977 and 1982. The study includes 1,548 S&P and Moody's rated bonds from 1977 to 1982. They measure bond excess returns for a time period 11 days prior to a rating change announcement to 60 days after that announcement, and report that rating downgrades by Standard and Poor's and Moody's result in a mean excess bond return of -1.27%, with non-investment grade bonds on average losing 3.82% compared to the significantly lower loss of 0.55% for investment-grade bonds.

The evidence on upgrades is weaker since the estimated excess return coefficient is only marginally statistically significant, while the excess return differences between investment-grade and speculative-grade bonds are very small (0.33% versus 0.40%, respectively).

Table 7.2: An overview of existing studies on credit rating news announcements

Market studied		Data	Main Results
Stock	Pinches and Singleton (1978)	1959-1972, Moody's 207 firms, monthly abnormal stock returns [-30,12]	Anticipation before rating changes, no abnormal reactions afterwards.
	Griffin and Sanvicente (1982)	S&P, 180 rating changes, monthly abnormal stock returns [-11, 1]	Significantly negative reaction after downgrades, no significant abnormal performance for upgrades.
	Holthausen and Leftwich (1986)	1977-1982, Moody's and S&P, 1014 rating changes, 256 additions to S&P Credit Watch, daily abnormal stock returns [-300, 60]	Significantly negative reaction after downgrades, no significant abnormal performance for upgrades.
	Glascock *et al*. (1987)	1977-1981, Moody's 162 rating changes, daily abnormal stock returns [-90,90]	Significant negative abnormal stock returns before and around downgrades, reversals after day zero (publication date).
	Hand *et al*. (1992)	1977-1982/1981-1983, Moody's and S&P, 1100 rating changes and 250 additions to S&P Credit Watch, window spanning stock and bond returns.	Significantly negative abnormal returns stock and bond returns for downgrades and unexpected additions to S&P Credit Watch, no significant abnormal returns for upgrades.
	Goh and Ederington (1999)	1984-1986, Moody's, daily abnormal stock returns [-30, 30].	Significantly negative returns for downgrades due to earnings deterioration, positive abnormal returns for downgrades due to increased leverage.
	Followill and Martell (1997)	1985-1988, Moody's, 64 reviews and actual rating changes, daily abnormal stock returns [-5,5].	Significantly negative returns at review for downgrade, negligible abnormal performance around actual downgrades.
	Dichev and Piotroski (2001)	1970-1997, Moody's, 4747 rating changes, daily abnormal stock returns.	Significantly negative returns during the first month after a downgrade, no significant reaction for upgrades.
	Vassalou and Xing (2003)	1971-1999, Moody's, 5034 rating changes, monthly abnormal returns of stock portfolio [-36,36] .	Stock returns in rating event studies should be adjusted by size, book-to-market and default risk, increase of default loss indicator before and decrease after downgrades.
	Purda (2008)	1991-2002, Moody's ratings, daily abnormal returns [29,-29].	Downgrades are easier to predict than upgrades, no evidence that the level of anticipation is related to the stock price reaction to the eventual change
	Feiberg *et al.* (2013)	2000-2012, Moody's, S&P, Fitch ratings, 154 countries, daily abnormal returns, [-20,10]	Bank credit rating upgrades not associated with significant abnormal stock returns, downgrades have significantly negative effects.

Notes: [ ] represents the event window over which the impact of the credit rating news event is studied

Market studied		Data	Main Results
Bond	Katz (1974)	1966-1972, S&P, 115 bonds from 66 utilities, monthly yield changes [-12,5]	No anticipation, abnormal performance during 6-10 weeks after downgrades
	Grier and Katz (1976)	1966-1972, S&P, 96 bonds from utilities and industrials, monthly bond returns [-4,3]	Anticipation only for industrials, price changes after downgrades stronger.
	Hettenhouse and Sartoris (1976)	1963-1973, S&P and Moody's, 46 bonds from utilities, monthly yield changes [-6, 6]	Little anticipation before downgrades, no reaction to upgrades.
	Weinstein (1977)	1962-1974, Moody's, 412 bonds from utilities and industrial, monthly abnormal bond returns [-6,7]	Early anticipation but no abnormal performance during 6 months before the event and no reaction afterwards.
	Wansley *et al.* (1992)	1982-1984, S&P, 351 bonds, weekly abnormal bond returns[-12,12]	Significantly negative returns in the week of downgrades, no significant response to upgrades.
	Hite and Warga (1997)	1985-1984, S&P and Moody's, 1200 rating changes, monthly abnormal bond returns [-12,12]	Significantly negative abnormal returns during 6 months before downgrades.
	Steiner and Heinke (2001)	1985-1996, S&P and Moody's, 546 rating changes, 182 watchlisting, daily abnormal bond returns [-180,180]	Significantly negative abnormal returns starting 90 days before downgrades and downgrades and negative watch listings, evidence for overreaction directly after the event
CDS	Hull et al. (2004)	1998-2002, Moody's rating changes reviews and outlook, adjusted CDS spread changes [-90,10]	Significantly positive adjusted CDS spread changes before negative rating events
	Norden and Weber (2004)	1998-2002, Moody's, S&P, Fitch's actual rating changes and reviews for rating changes (Watchlistings), daily abnormal returns [-90,90]	Strong abnormal pre-announcement performance in both CDS and equity market

Notes: [ ] represents the event window over which the impact of the credit rating news event is studied

The authors also account for confounding contemporaneous news announcements around the time of rating changes and in addition examine the effect of the placement of securities on the Credit Watch list on financial markets. They find significantly negative abnormal bond returns for downgrades already on Watchlist and no significant abnormal returns for upgrades. Further, the results for CreditWatch placement were not significant.

Followill and Martell (1997) use data specifying a press release date not only for rating changes, but also for announcements that a corporation's debt rating is to be reviewed. Their examination of the informational value of rating changes and market efficiency is based on the hypothesis that the higher the efficiency of stock markets, the less informational value a rating change carries, and consequently the smaller the reaction of markets to that change. However, they argue that due to extant empirical evidence suggesting that markets are neither perfectly efficient nor inefficient, an accurate and precise evaluation of the impact of rating changes on share prices is required. In addition, they criticise previous studies for not ensuring that the stock price reactions they intend to measure are caused exclusively by the rating changes that take place, rather than by any 'extraneous, material event[s] occurring at the same time' (p. 76). The results of Followill and Martell show that announcements of the review for the possible downgrading of debt have a significant negative effect on stock prices, while subsequent actual downgrades have a negligible impact. Hence, rating change announcements that are preceded by review announcements, however, provide little unanticipated information to the market place, and share values remain relatively unaffected by the announcement of a bond rating downgrade.

The economic impact of rating announcements varies with the type of rating news, and whether these are anticipated or not. Typically, most upgrade announcements have limited impacts on stock returns, while downgrades are usually associated with greater abnormal returns magnitudes on the news event day (Barron et al., 1997; Kliger and Sarig, 2000).

The performance of emerging market bank stocks around the time of rating changes by major international agencies is examined by Richards and Deddouche (1999). They examine 219 rating changes between 1989 and 1998. The data span 49 different banks in 15 countries (mostly South American and Asian countries). Their weekly data study suggests that downgrades on average have followed periods of negative cumulative abnormal returns, but the same is not true for upgrades. Further, their study examines the cumulative abnormal returns prior to rating changes separate from the announcement-window returns. Stock prices appear to reflect most of the information contained in rating changes, on average a week before the change actually occurs, and do not respond to rating changes, or respond in the opposite direction to that expected if announcements convey value-relevant information about financial health.

Dichev and Piotroski (2001) study long-run stock returns following bond rating changes, employing a comprehensive sample that comprises all of Moody's bond rating changes data during the period 1970 to 1997. Their sample size comprises 4,700 observations, including many small, low credit quality firms where analyst and investor following is expected to be low. The rationale for including this category of firms is that since they are small then there is a high likelihood that rating analysts and investors would ignore them. They examine both cumulative abnormal returns and buy-and–hold returns (for three-month, six-month, first-year, second-year and third-year abnormal stock returns following bond rating changes), and control for size and the book-to-market ratio. They find no reliable abnormal returns following upgrades, whereas there are substantial negative abnormal returns following downgrades. With positive news, there is a trickle effect in the way news information flows in the market. The market tends to react more significantly to negative news. Similarly, investors take a worse-case approach to news information, reacting more to bad news than good news. This is a result of the asymmetry in the way market reacts to upgrades and downgrades. The poor results for downgrade firms are more pronounced for small and low-credit-quality firms. They conclude that downgrades are strong predictors of future deteriorations in earnings, and abnormal returns, hence tend to be more extreme "on the downside".

Choy *et al.* (2006) examine the impact that credit rating revisions have on the stock returns of Australian firms rated by Standard and Poor's and Moody's for the period 1989–2003. They argue that the impact of rating change announcements can be inferred from the market's reaction. In general, significant stock price reactions occur in response to the release of news. A significant reaction to the rating change announcement may occur if the market perceives that the announcement contains information that cannot be obtained from other sources. In addition, the credit rating analysts are assumed to have superior analytical skill and this confers an advantage on them in terms of providing reliable and relevant rating information. They suggest that this effect is studied traditionally by examining whether bond prices (or yield spreads) and stock prices change in response to such an announcement. They show that the reaction is most significant when the downgrade: (i) is unanticipated; (ii) is for an unregulated firm; and (iii) reduces the firm's rating by more than one category. They also study the differential impact of rating changes that involves multiple steps or gradation. This also leads to the proposition that companies that fall below investment grade (BBB or below) will experience greater significant abnormal returns.

In sum, early studies (Pinches and Singleton, 1978; Griffin and Sanvicente, 1982) make use of monthly data and find little reaction of share prices to rating changes and hence conclude that the market is efficient and fully anticipates rating changes. However, other research (such as Holthausen and Leftwich, 1986; Glascock, *et al.,* 1987; Hand *et al.* 1992) uses daily data and finds significant abnormal returns reactions, especially for downgrades. Furthermore, by accounting for confounding contemporaneous news announcements around the credit rating news, studies such as Hand *et al.* are able to observe more security returns reactions. The studies differ on the choice of method for calculating the normal or expected returns and whether or not to use the pre- or post-event date periods to estimate the model for normal returns. Other studies by Dichev and Piotroski (2001) and Choy *et al.* (2006) suggest that downgrades are strong predictors of future deteriorations in earnings and companies that fall below investment grade (BBB or below) will experience greater significant abnormal returns. This thesis focuses on testing for any significant stock return movement over a short event-window. Employing a relatively short event-window horizon ensures a reduction in news contamination.

7.3 A review of the event study methodological approach

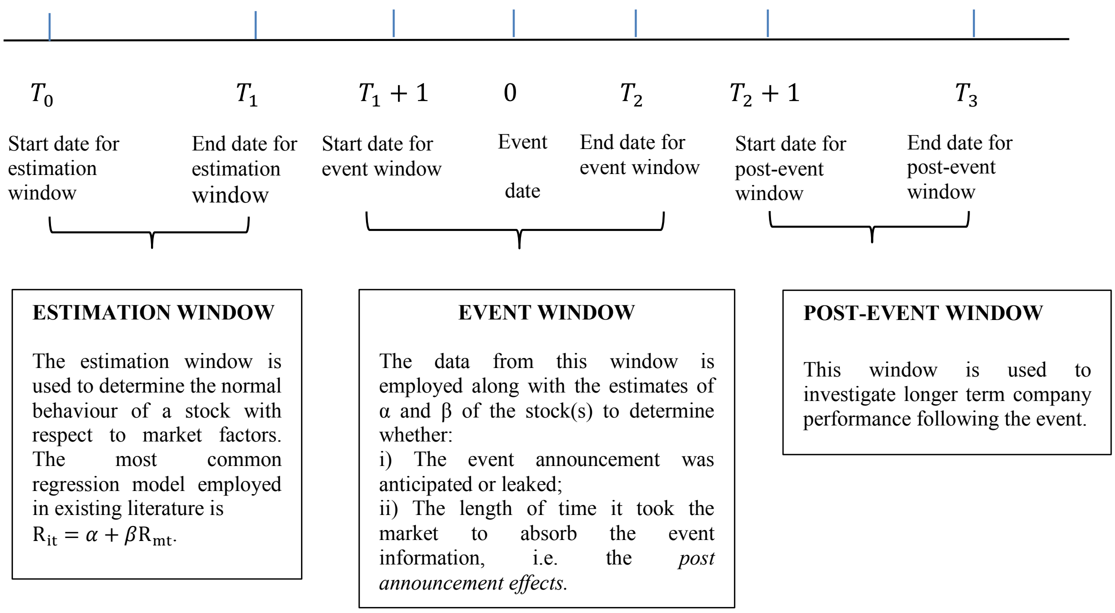
The event study methodology has become the standard approach for measuring security price reaction to an announcement or event. In general, it focuses on announcement effects over a short-time horizon. The methodological approach assesses the effects of information arrival on the prices of stocks (Mackinlay, 1997; Campbell *et al*., 2010). Unlike the majority of existing studies, this thesis applies the event study approach to a multi-country sample in relation to the main market listing of bank stocks in each country and provides additional evidence of the performance of several specifications in such sample. According to Binder (1998), event studies have been employed in empirical finance for two functions: (i) to test the null hypothesis of market efficiency; and (ii) assuming markets are efficient, at least with respect to publicly available information, to examine the impact of some event on the wealth of a firm's security holders. The use of the event study methodology became popular following the seminal paper of Fama, Fisher, Jensen and Roll (1969) (hereafter referred to as FFJR) who examined the adjustment of stock prices to new information (in this case, a stock split).

This section focuses on the design, implementation and statistical properties of the event study methodological approach. An event study starts by establishing a hypothesis concerning the effect of an event on the value of a firm. In specific terms, the hypothesis that this thesis tests is that, on average, bank credit rating news announcement has no effect on the value of bank stocks, across banks with similar information arrival. Persistent abnormal returns after a particular news announcement are inconsistent with market efficiency. Further, an event study provides a measure of the (un)anticipated effect of such an event on the wealth of the firm's claimholders (Kothari and Warner, 2006). If the information in the market is already captured in the share price and investors have already taken this into account, then on average there should not be significant changes in stock returns around the announcement date of an event. It follows that the concept of abnormal returns is central to an event study. The abnormal returns are calculated as the difference between a stock's actual return and its expected return. The expected returns are usually generated using the market model. The total impact of an event through a particular time period is typically captured by summing the abnormal returns, to arrive at the cumulative abnormal returns (CAARs).

7.3.1 The design of an event study

An event study typically aims to examine stock return reaction for a sample of firms experiencing a similar event. This event can be clustered on a particular date or can take place at different times within a calendar year. Mackinlay (1997) argues that there is no unique structure when establishing an event study approach, though there is a general flow of analysis. Following the initial definition of the event, the impact of which is to be gauged (in the case of this thesis, the news event is a bank credit rating announcement), the period over which the bank's returns will be examined is decided. Figure 7.1 presents the timeline for a traditional event study model, showing that an event study typically consists of three windows.

Figure 7.1: An event study timeline



Sources: Benninga (2014) *Used with permission of the publisher

The first of the three windows in the traditional event study approach is the *estimation window*. The *estimation window* represents the period before the event and is included to help capture the ‘normal’ returns of the asset with respect to a market or industry index. The normal return represents the returns of a stock under ‘normal’ circumstances, that is, without conditioning on the event of study. The estimation window and the event window do not overlap in order to ensure that the results of the estimator measurement for the normal returns are not contaminated by the event itself. An estimation model for the normal stock behaviour is defined by, and in most cases it takes the form of, a regression model. The returns of the stock under investigation are regressed against the returns of the corresponding market index. Mackinlay (1997) suggests a minimum of 126 observations (days) in the estimation period, with the normal number of trading days being a maximum of 252 days. This is to ensure that robust results are produced in terms of representing true stock movements. The length of the estimation window is given as T_0 to T_1.

The second of the three windows in the traditional event study approach is the *event window* which is made up of the date of the event at $t = 0$. The event window is usually longer than the specific period of interest. This allows the model to measure the impact of the news announcement in the period surrounding the event. In practice, the specific date of announcement usually includes not only the event day but also the day following the announcement, and according to Campbell *et al.* (1997), this allows for the capture of market movement if the event was announced immediately before the market closed or after market closing. Assuming the event occurs at time 0, the event window is represented as $T_1 + 1$ to T_2. The event window usually starts a few trading days before the actual event day and continues afterwards until a pre-defined number of days. This allows for the capture or investigation of pre-event leakages of information.

The *post-event window* represents the third and final window in the time line. It is sometimes included with the data from the estimation window when measuring the 'normal' return. Campbell *et al.* (1997) argue that using this approach will increase the robustness of the normal market returns measure to gradual changes in its parameter. Further, it allows for a measure of the longer-term impact of an event. The length of the post-event window is given as $T_2 + 1$ to T_3, and could be as short as one month or as long as several years depending on the event in question.

In terms of its practical implementation, the traditional event study approach consists of a two-stage procedure. The first stage involves modelling the 'normal' stock returns and this employs the data in the estimation period. The normal returns may be viewed as the expected returns of the stock without conditioning on the event taking place. The second stage in the process involves the measurement of the abnormal returns in order to gauge the impact of the event on the stock returns. Abnormal returns are the actual *ex post* returns of the security over the event window minus the normal returns of the firm over the estimation period.

Hence, in the traditional event study approach, the abnormal returns may be defined as,

$$AR_{it} = R_{it} - E(R_{it} | X_t) \qquad 7.1$$

where AR_{it}, R_{it} and $E(R_{it} | X_t)$ are the abnormal, actual and normal returns for time period t, respectively. X_t represents the event under consideration, while the normal return is the expected return without conditioning on the event, while i represents the individual firm under investigation.

There are a number of approaches to estimating the normal returns of a given security. Brown and Warner (1985) and Campbell *et al.* (1997) provide detailed descriptions of these models, including the market model, the constant expected returns models, and the Capital Asset Pricing Model (CAPM). The approaches can be classified into statistical and economic models, the most popular of which are the market model (a statistical model) and the CAPM (an economic model). The market model relates the returns of a given security to the returns of the market portfolio. According to Khotari and Warner (2006), the linear specification of the market model follows from the assumed joint normality of asset returns. For a given security *i,*

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad 7.2$$

Where $\mathrm{E}[\varepsilon_{it}] = 0$ and $\mathrm{Var}[\varepsilon_{it}] = 0$.

McKinlay (1997) argues that the benefit of using the market model depends on the R^2 of the model regression, with a higher goodness-of-fit leading to a greater variance reduction in abnormal returns. Binder (1998) argues that the relative ease of application of the market model makes it attractive.

The economic models provide more constrained normal returns by restricting the parameters of the statistical model. The most popular of the economic models is the Capital Asset Pricing Model (CAPM) which controls for security risk in relation to market risk. For a given security i in period t, the *ex-ante* expected return can be stated as:

$$E(\hat{R}_{it}) = (1 - \beta_i)R_{ft} + \beta_i E(\hat{R}_{mt}) \qquad 7.3$$

where R_{ft} is the return on a risk-free security in period t (e.g. Treasury Bills) and β_i is the systematic risk of the security i relative to the market index. The implementation of this involves the estimation of β_i. The predicted abnormal return is given by:

$$\widehat{AR}_{it} = R_{it} - \left(1 - \hat{\beta}_i\right)R_{ft} - \hat{\beta}_i(\hat{R}_{mt}) \qquad 7.4$$

The abnormal return over the event window is interpreted as a measure of the impact of the event on the value of the firm (or its equity). Hence, the assumption is that the event (an exogenous factor) gives rise to a change in the market value of the security. The abnormal return observations are aggregated in order to draw overall inferences for the event of interest (Campbell *et al*., 1997; Binder, 1998). Aggregation is conducted along two dimensions, through time and across securities, in order to provide the mean of the distribution of abnormal returns. Khotari and Warner (2006) argue that the cross-sectional focus on the mean effect or variation (i.e. the first moment of the returns distribution) is appropriate for studying event-induced abnormal returns. The event window is usually an interval spanning more than one day, hence aggregation over the window is conducted over the entire event window to give a single measurement of the abnormal return across securities.

This thesis follows the approach by Campbell *et al.* (2010) in the estimation of the market model. This thesis calculates individual bank stock returns from daily prices obtained from DataStream. The prices on the DataStream database are already adjusted for dividend and stock splits (Ince and Porter, 2006). The market indices and risk free rate employed are also downloaded from DataStream for the period under consideration. DataStream provides information on the daily index prices and traded government securities.

This is followed by a cross-sectional aggregation, the purpose of which is to aggregate the time-series aggregated returns. Average abnormal returns (AAR) are given as

$$\overline{AR}_{it} = (\tfrac{1}{N}) \sum_{i=1}^{\tau} AR_{i\tau} \qquad 7.5$$

The cumulative abnormal return (CAR) is a measure of the total abnormal returns during the event window and is estimated by summing all of the daily abnormal returns from the beginning of the event window. Assuming the event occurs at time 0, the event window is represented as T_1 until a particular day T_2 in the window, i.e.

$$CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} \overline{AR}_i\,(t) \qquad 7.6$$

The next stage involves aggregating the cumulative abnormal returns over the entire sample of events. This involves making the assumption that the abnormal returns are normally distributed and that there is no event window clustering (Karafiath, 2009). The average cumulative abnormal return ($\overline{CAR}$) is given as the arithmetic mean of all *CARs*. Thus,

$$\overline{CAR}_i(T_1 T_2) = \tfrac{1}{N} \sum_{i=1}^{N} CAR_i(T_1 T_2) \qquad 7.7a$$

$$VaR[\overline{CAR}_i(T_1 T_2)] = \bar{\sigma}^2(T_1 T_2) = \tfrac{1}{N^2} \sum_{i=1}^{N} \sigma_i^2\,(T_1 T_2) \qquad 7.7b$$

Equation 7.7b assumes that the event windows of the *N* securities do not overlap, in order to set the covariance terms to zero.

The final step in the event study process involves the computation of a test statistic and then comparing it with the assumed distribution under the null hypothesis that mean abnormal returns equal zero. If the test statistic exceeds a critical value, in general at the

1% or 5% level, then the null hypothesis of no abnormal returns is rejected. Mackinlay (1997) provides several alternatives for test statistics that aggregate standardized abnormal returns. Brown and Warner (1980, 1985) maintain that, empirically, short-horizon event studies are typically not sensitive to the standardization or otherwise of abnormal returns, and thus it makes little difference to the empirical results.

The simple *t* test statistic for the cumulative abnormal return based on average values is given as,

$$t_{T_1 T_2} = \frac{\overline{CAR}_i(T_1 T_2)}{\bar{\sigma}^2(T_1 T_2)} \qquad 7.8$$

7.3.2 Event study tests

One of the most popular parametric test statistics for testing the null hypothesis of zero abnormal returns is the Patell (1976) Z-statistic. Brown and Warner (1980, 1985), Mikkelson and Partch (1998), and Boehmer *et al.* (1991) all applied the Patell. The Patell statistic makes a strong assumption of independence of returns across security-events, and that the event affects only mean returns. The test statistic ignores event-induced variance in the event studies. Brown and Warner (1980, 1985) identify potential testing problems when an event-induced variance is present in an event study. In the presence of event-induced variance, the test statistic leads to rejection of the null hypothesis more frequently than it should. Boehmer *et al*. (1991) propose a variance-change corrected version of the Patell test, the standardized cross-sectional test, which accounts for any event-induced increase in the variance of the returns. Campbell *et al.* (2010) argues that the use of the Boehmer *et al*. (1991) does not harm the performance of the test when there is no variance change.

In order to implement the Boehmer *et al*. (1991) standardized cross-sectional test, it is important to incorporate the information from both the estimation and the event period.

The event-period abnormal returns are first standardized by the estimation-period standard deviation. This gives a test statistic in the form,

$$t_{BMP} = \frac{\frac{1}{N}\sum_{i=1}^{N} SR_i}{\sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}\left[SR_i - \frac{1}{N}\sum_{i=1}^{N} SR_i\right]}} \qquad 7.9$$

where SR_i are the standardized abnormal returns of the *i*th stock, calculated by dividing the event-period abnormal returns on the *i*th stock on day *t* by the standard deviation of the estimation-period abnormal returns. For the estimators of the variance to be consistent, the abnormal returns must be uncorrelated in the cross-section. This requirement is fulfilled by not having clustering of event dates across the securities.

7.4 Extensions of the traditional event study approach

There have been several extensions to the traditional event study (apart from the extension of test statistic by Boehmer), with particular reference to the model's structure and test statistics which now take account of the changing variance of the error term. Several studies account for temporal changes in the returns process during an event period by employing the GARCH approach (e.g. Corhay and Rad, 1994; Chu and Freud, 1996; Brockett *et al.,* 1999; Reyes, 1999). Another strand of the literature employs a one-step approach to modelling abnormal returns by incorporating a dummy variable that captures security returns over the event window within the regression model (Binder, 1998; Karafiath, 2009; Tucker *et al.*, 2012).

7.4.1 The dummy variable approach to event studies

The traditional event study approach has been extended to take account of issues such as the non-normality of daily stock returns as well as the intertemporal and contemporaneous correlation of abnormal returns over time and also along the cross-section of assets. The traditional event study methodology follows a two-step approach in which the normal return is first estimated from the data in the estimation period, and the abnormal return is then obtained as the difference between the actual returns over the event window and the normal return estimates. Salinger (1992) argues that the traditional two-step event study approach ignores both intertemporal and contemporaneous correlations of the residuals of the estimated model. The author's approach makes the assumption that the estimated abnormal returns are intertemporally uncorrelated, enabling the individual variances to be summed when arriving at the variance of the cumulative abnormal returns. However, the estimated abnormal return is a forecast error rather than a true error because it is based on the estimated model parameters. Invariably, the same market model parameter estimates are employed in the calculation of all of the abnormal returns for a bank or set of banks, hence presenting a high probability of correlation between them.

In order to account for any intertemporal or contemporaneous correlation of abnormal returns in the error terms during an event study, a model extension based on a multivariate regression approach including a dummy variable has been employed in a number of studies (Brown and Warner, 1985; Sefcik and Thomas, 1986; Binder, 1998; Karafiath 2009). The model proposed is the standard market model which has the following structure for obtaining abnormal returns:

$$R_{it} = \alpha_i + \beta_i(R_{mt}) + \varepsilon_{it} \qquad 7.10$$

where R_{it} are the actual returns on bank *i* at time *t*, α_i is the intercept of the regression line, β_i is the market beta coefficient for security *i*, R_{mt} is the market return at time *t*, and ε_{it} is a zero mean independent error term in period *t* for security *i*.

Estimating the equation specified in Equation 7.10, the abnormal returns are obtained as

$$AR_{it} = R_{it} - \hat{\beta}_i(R_{mt}) \qquad 7.11$$

The traditional procedure in an event study first involves computing abnormal returns, AR_{it}, using an assumed model for normal returns and then, in the second stage, abnormal returns are averaged and/or cumulated and tested. Salinger (1992) shows that this approach leads to spurious results and suggests the use of a dummy variable approach.

To illustrate Salinger's event study approach, let N be the number of banks in a sample. The returns on bank i's share where $i = (1, \dots, N)$ are R_{it}, $\gamma_{i\tau}$ is the abnormal return for the period τ (i.e. the event window of interest, from T_1 to T_2), and ε_{it} is an error term. Further, a τ-day news event window is defined, where the potential impact on bank returns is captured. $D_{i,\tau,t}$ is a dummy variable that takes a value of 1 for period τ and zero otherwise. The idea of using a dummy variable is to pick up the unanticipated portion of the return, that is, the effects of the bank credit rating news announcement. A dummy variable is employed for each day within the event window (τ). As an illustration, if $\tau = 27$, and assuming a 10-day period before the event date and 15 days after, then, $D_{i,1,t}$ equals 1 ten days before the news announcement, $D_{i,11,t}$ equals 1 on the first day of the bank credit rating related news announcement, and $D_{i,27,t}$ equals 1 on the 15th day of the post-event window, each equalling zero otherwise. Following this procedure, the estimated abnormal returns have the correct standard errors and are distinguished from the residuals. Consistent with previous studies (Hand *et al*., 1992; Goh and Ederington, 1999; Hull *et al*., 2004), the proposed extension typically employs a two-day event window, allowing for the averaging of the abnormal returns on the day of announcement and the following day ($\tau = 11,12$) to get a single value of event day abnormal returns. Using the above illustration, the total number of event 'days' is thus reduced to 26.

The dummy variable (or regression) approach can thus be presented as,

$$R_{it} = \alpha_i + \beta_i(R_{mt}) + \sum_{\tau=T_1}^{T_2} \gamma_{i\tau} D_{i,\tau,t} + \varepsilon_{it}, \quad D_{it} \begin{cases} 1 \; if \; \tau = T_1 \ldots T_2 \\ 0 \quad otherwise \end{cases} \qquad 7.12$$

The primary advantage of the dummy variable approach is that it is a one-step procedure which estimates both the model and the abnormal returns in a single step. Further, both prediction errors and test statistics are conveniently obtained from any standard regression package. Salinger (1992) finds that the standard errors obtained from averaging individually estimated abnormal returns are incorrect. The dummy variable approach encompasses both the intertemporal correlation of individual estimated abnormal returns as well as the contemporaneous correlation of estimated cumulative abnormal returns. Employing the dummy variable approach thus produces estimates with correct standard errors. More importantly, the approach allows for correct estimates of the covariance between successive abnormal returns (Tucker *et al.*, 2012). Unlike the traditional event study approach, the dummy variable approach allows for the correct estimation of standard errors of average cumulative abnormal returns.

The central hypothesis in this component of the thesis is that, on average, bank credit rating announcements have no abnormal impact on the behaviour of stock returns over a short term window. Assume that there are *N* banks within the sample, then, $\tau \times N$ abnormal returns ($\gamma_{i\tau}, i = 1, \ldots N \,;\, \tau = 1, \ldots, t$) are obtained. One dummy variable is used for each day and these are summed across the number of banks in the sample for each day. For the dummy variable model, the specified abnormal return, $\hat{\gamma}_{i\tau}$, has a variance of $\hat{\sigma}_{i\tau}^2$. The estimations of the average abnormal returns, AAR_τ, their variance, and the t-statistics for each event day, τ, are given respectively as,

$$AAR_\tau = \bar{\gamma}_\tau = \frac{1}{N}\sum_{i=1}^{N} \hat{\gamma}_{i\tau} \qquad 7.13$$

$$Var(AAR_\tau) = \frac{1}{N^2}\sum_{i=1}^{N} \hat{\sigma}^2{}_{i\tau} \qquad 7.14$$

$$t_{\tau} = \frac{AAR_{\tau}}{SD(AAR_{\tau})} \qquad 7.15$$

The t-statistic test has the null hypothesis, H_0 that on average bank credit rating announcements have no impacts on the behaviour of bank stock returns around the date of such announcements. The t-test assumes that abnormal returns are independent in cross-section. News announcements by credit rating agencies take place randomly and are rarely clustered. This assumption is therefore realistic and should not negatively impact on the inference drawn from the results.

Consistent with the procedure in the traditional two-step event study approach, the dummy variable approach cumulates the abnormal returns over the event period in order to draw an overall inference on the impact of the news announcement on stock behaviour. Thus, on any given event day, cumulative abnormal returns before and after the announcement are obtained by accumulating the estimates of $\gamma_{i\tau}$. Let $\hat{\gamma}_i = (\hat{\gamma}_{i1}, \hat{\gamma}_{i2}, \dots, \hat{\gamma}_{i3})$ denote the vector of estimated abnormal returns. Further, let $\hat{V}_i$ represent the estimated variance-covariance matrix of these estimates.

So, to test for the significance of the cumulative average abnormal returns in the pre- and post-event periods, the procedure involves defining a τ element vector δ having ones in the pre- or post-event window and zeros elsewhere. As an illustration, to evaluate cumulative returns in the 15-day post-event period, only the last 15 elements (i.e. the returns in the post event period) are set to one. Similarly, for the 10-day pre-event period, only the first 10 elements of δ are set to one.

For any specified window in an event i, Equations 7.16 and 7.17 represent the cumulative abnormal returns and the corresponding variance, respectively:

$$C\hat{A}R_i(\delta) = \delta' \hat{\alpha}_i \qquad 7.16$$

$$\hat{\sigma}_i^2(\delta) = \delta' \hat{V}_i \, \delta \qquad 7.17$$

It is possible to test whether the cumulative abnormal return for the event is, on average, significant across all *N* bank credit rating news events. A simple t-statistic is constructed based on the average values,

$$t(\delta) = \frac{CAAR(\delta)}{\bar{\sigma}(\delta)} \qquad 7.18$$

where,

$$CAAR(\delta) = \frac{1}{N}\sum_{i=1}^{N} C\hat{A}R_i(\delta) \qquad 7.19$$

$$\bar{\sigma}^2(\delta) = \frac{1}{N^2}\sum_{i=1}^{N} \hat{\sigma}_i^2(\delta) \qquad 7.20$$

This further assumes that the standard t(δ) is well specified since the estimation window is large.

7.4.2 The GARCH (1, 1) specification for an event study

A key assumption of the traditional event study approach is that the abnormal returns estimators have an identical event effect on all of the sample firms. Further, event-induced volatility is assumed to be insignificant (i.e. the variance of the error term is assumed to be constant). Bremer and Zhang (2007) argue that the event study approach, assuming constant event-induced abnormal returns and volatility over the event days, potentially inflates Type I error rates and has poor test power. The Boehmer *et al*. (1991) approach using the standardized cross-sectional test (Section 7.3.2) allows for non-constant variance across securities as well as for each security between the estimation and event windows. The Boehmer *et al.* approach however assumes that event-induced volatility is constant over the event window, and thus a change in volatility may result in the test statistics under- or overstating the true event effects.

An extension to the standardized cross-sectional approach to the short-horizon event study scales abnormal returns using conditional variance in one-stage estimation employs a GARCH(1,1) specification to account for heteroskedasticity in the residuals (De Jong *et al*., 1992; Kryzanowski and Zhang, 1993; Bacmann and Dubois, 2003; Bremer and Zhang, 2007). Hilliard and Savickas (2000) argue that following a GARCH(1,1) specification, the test statistics for the error terms in a market model have a higher explanatory power when compared with the traditional event study approach. Further, Corhay and Rad (1996) apply a market model which accounts for GARCH effects, leading to more efficient estimators.

There are various tests to detect the non-linear structure of financial asset returns series (e.g. Ramsey's RESET tests, the BDS test, after the initials of W. A. Brock, W. Dechert and J. Scheinkman) and these conclude that non-linear dependence in financial assets returns series can be best characterised by a GARCH-type process. Therefore, consistent with the De Jong *et al*. (1992), Kryzanowski and Zhang (1993) and Bacmann and Dubios (2003), the market model corrected for GARCH where residuals are conditionally heteroskedastic may be specified as

$$R_{it} = \alpha_i + \beta_i(R_{mt}) + \sum_{\tau=T_1}^{T_2} \gamma_{i\tau} D_{i,\tau,t} + \varepsilon_{it}, \qquad D_{it}\begin{cases} 1 \; if \; \tau = T_1 \dots T_2 \\ 0 \quad otherwise \end{cases}$$

$$\varepsilon_{it} | \; \varepsilon_{it-1}, \varepsilon_{it-2}, \dots \sim N(0, h_{it}) \qquad 7.21$$

$$h_{it} = a_{i0} + a_{i1}\varepsilon_{it-1}^2 + a_{i2}h_{it-1}$$

Where the abnormal return $\gamma_{i\tau}$ is estimated for firm *i* on day τ. The event window is within the range $\tau = T_1 \dots T_2$.

The model in Equation 7.21 is a one-step approach that produces abnormal returns and their standard deviation in a single regression. In order to obtain the cumulative abnormal returns over the event window, the abnormal returns are cumulated over the period ($\tau = T_1 \ldots T_2$) as Γ_i. Brooks (2009) argues that conditional variance changes while the unconditional variance of the residual can be specified as

$$\mathrm{Var}(u_t) = \frac{a_{i0}}{1-(a_{i1}+a_{i2})}, \text{ so long as } a_1 + a_2 < 1 \qquad 7.22$$

To test the null hypothesis that the event has no impact on the behaviour of the mean returns at time τ, so that the average abnormal return is nil, one can specify the following,

$H_{0,t}: \frac{1}{N}\sum_{i=1}^{N} \gamma_{it} = 0$, and thus the cumulative effect of the event is aggregated through time at the firm level. Thus, the cross sectional hypothesis is specified as, $H_{0,t}: \frac{1}{N}\sum_{i=1}^{N} \Gamma_i = 0$.

The test statistic is thus,

$$t_s = \frac{\sum_{i=1}^{N} \widehat{SCAR}_{it}}{\sqrt{N}\hat{\sigma}_{cross\ t}} \qquad 7.23$$

where

$\widehat{SCAR}_{it} = \frac{\hat{\gamma}_{it}}{\hat{\sigma}(\hat{\gamma}_{it})}$ represents the standardized cumulative abnormal returns, and

$\hat{\sigma}_{cross\ t}$ is the standard deviation of $\widehat{SCAR}_{it}$.

Thus, under the null hypothesis of no abnormal returns, the t_s statistic is distributed as a Student-t variable with $N - 1$ degrees of freedom. The estimation of the parameters is obtained using the maximum likelihood technique. The log-likelihood function is formed and the values of the parameters that maximise it are estimated.

7.4.3 The non-parametric approach for an event study

This thesis, in addition to employing parametric tests, reports non-parametric test results for measuring short-run abnormal returns following the announcement of bank credit rating related news. Many event studies employ parametric test statistics where such tests rely on assumptions about the probability distribution of returns. Brown and Warner (1985) argue that an increase in event-induced variance exaggerates the reported price reaction in standard parametric tests. The advantage of reporting non-parametric tests is that they do not require stringent assumptions about returns distributions, and returns variance is not an issue (Cowan, 1992). Some of the popular non-parametric tests include the sign test, the generalized sign test (which is a variation of the sign test), and the rank test (Corrado, 1989). The sign test presents the proportion of positive and negative abnormal returns against an assumed 50 percent split under the null hypothesis of no reaction to the event.

Sanger and Peterson (1990) and Cowan (1992) employ a variant of the sign test referred to as the generalized sign test. This compares the proportion of positive abnormal returns around an event to the proportion from a period unaffected by the event. In so doing, the generalised sign test takes account of possible asymmetry in the returns distribution under the null hypothesis. Evidence suggests that the generalized sign test provides more power in terms of ability to detect abnormal returns than the parametric test based on standard errors from the cross-section of event date abnormal returns (Cowan 1992; Campbell *et al.*, 2010; Kolari and Pynnonen, 2011). Cowan reports the generalized sign test to be well specified and powerful when applied to random samples of NYSE-AMEX and NASDAQ stocks for the period 1972-1990.

The null hypothesis of the generalized sign test is that the fraction of day-zero abnormal returns actually having a particular sign is equal to the fraction expected to have that sign. In sum, the generalized sign test examines whether on average, the number of stocks with positive cumulative abnormal returns in the event window exceeds the number expected in the absence of abnormal returns. Cowan suggests that the number expected is based on the fraction of positive abnormal returns in, say, a 100 day estimation period and this can be represented as,

$$\hat{p} = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{100}\sum_{t=E_1}^{E_{100}} S_{it} \qquad 7.24$$

where, $\hat{p}$ is the observed fraction of the returns computed across stock in one particular event window and $S_{it} = \begin{cases} 1\ if\ AR_{it} > 0 \\ 0\ otherwise \end{cases}$

The test statistic employs the normal approximation and the number of values of abnormal returns is a binomial distribution parameter, $\hat{p}$. If the number of stocks in the event window $(T_1 + 1, T_2)$ for which the cumulative abnormal return $CAR_{j,(T_1+1,T_2)}$ is positive is given as *w,* then the generalized sign test statistic is

$$Z_G = \frac{w - n\hat{p}}{[n\hat{p}(1-\hat{p})]^{\frac{1}{2}}} \qquad 7.25$$

Campbell *et al*. (2010) describe this as the upper-tail alternative hypothesis (i.e. for positive cumulative abnormal returns). For a lower-tailed alternative hypothesis, the positive cumulative abnormal return is replaced by a negative return in the definitions of S_{it} and w.

Similarly, Corrado (1989) proposes another non-parametric test, the rank test, which, as in the case of the generalized sign test, does not require symmetry in the cross-sectional abnormal returns distribution. The rank test transforms each security's time series of abnormal returns into their respective ranks, (k_i), over the combined period that includes the estimation and the event window (T_0, T_2). This is contrary to the generalized sign test which is based on the frequency of positive and negative returns.

The Corrado rank test provides statistics for a one-day event window (i.e. day zero). The rank statistic for day zero is given as,

$$t_{rank} = \left[\left(\frac{1}{N}\sum_{i=1}^{N} k_{i0}\right) - \bar{k}\right] / s_k \qquad 7.26$$

where k_{i0} is the rank of security-event i's day zero abnormal return in security-event i's combined M-day estimation period and τ-day event period time series, $\bar{k}$ is the expected rank, and s_k is the time-series standard deviation of the sample mean abnormal return ranks. Corrado assumes that expected rank is constant across securities. The expected rank ($\bar{k}$) is defined as the empirical mean of the rank of the time-series,

$$\bar{k} = \frac{1}{T}\sum_{i=1}^{T} \frac{1}{N_t}\sum_{i=1}^{N_t} k_{it} \qquad 7.27$$

where N_t is the number of returns on day t and T is the total number of days in the time-series (M + τ). The standard deviation, s_k, for the portfolio of banks in the sample is then given as,

$$s_k = \left\{\frac{1}{T}\sum_{i=1}^{T} \left[\left(\frac{1}{N_t}\sum_{i=1}^{N_t} k_{it}\right) - \bar{k}\right]^2\right\}^{1/2} \qquad 7.28$$

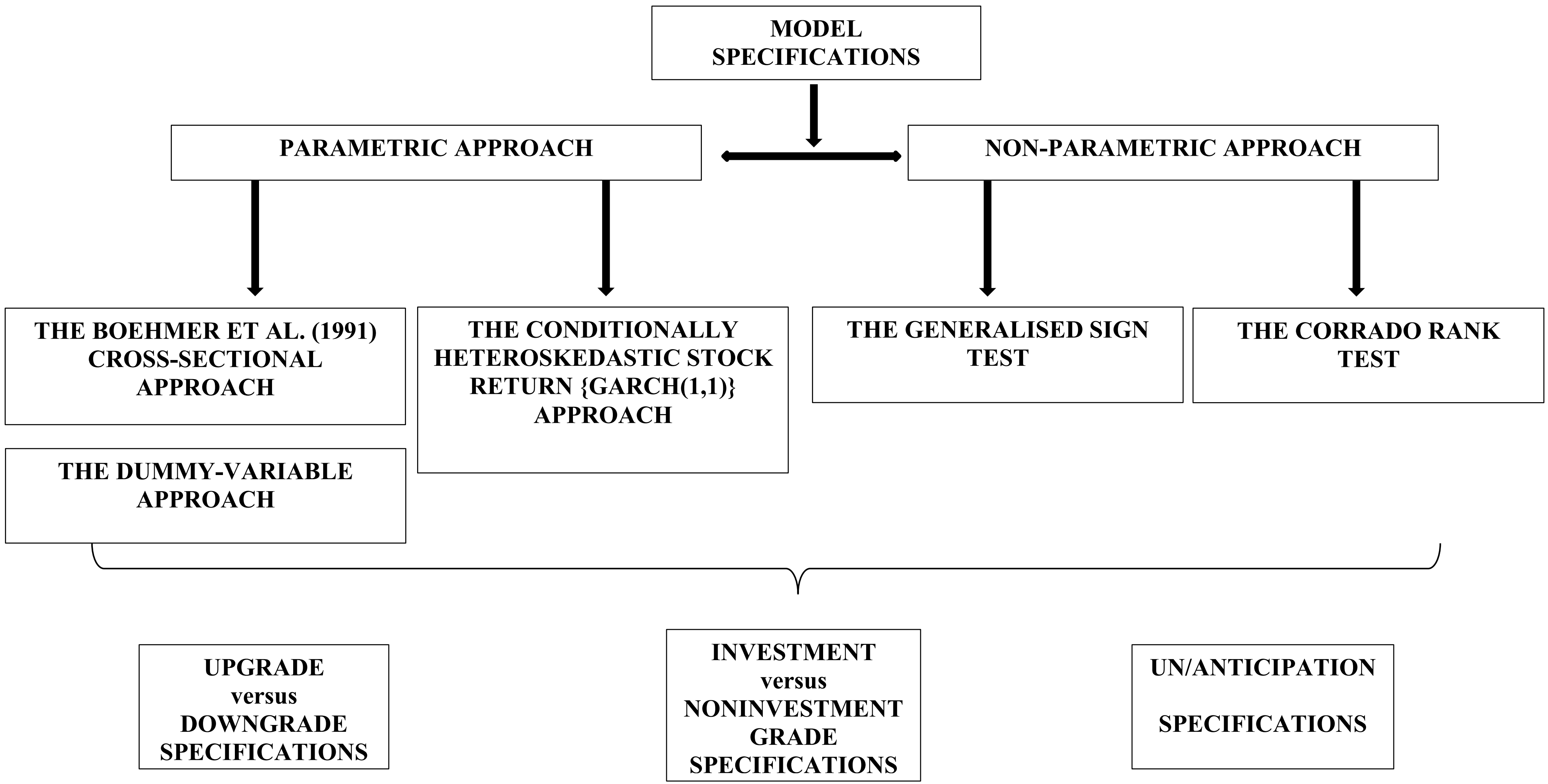
The test compares the ranks in the event period for each firm, with the expected average rank under the null hypothesis of no abnormal returns. Cowan (1992) and Campbell *et al.* (2010) apply the rank test to a multi-day window *CAAR* by substituting security-event i's mean rank across the event windows (τ), in place of k_{i0}, and dividing s_k by the square root of τ. Corrado (1989) shows the rank tests to be well specified and powerful for NYSE stocks. Similarly, Campbell and Wasley (1993) provide evidence to support this for the NASDAQ stocks, even when stock is infrequently traded.

Overall, following the steps in the existing methodological literature (e.g. Campbell *et al.,* 2010), this chapter employs the generalized sign test as well as the Corrado rank test in forming an opinion on whether on average there are no significant abnormal returns around the date of a bank credit rating announcement. This is in addition to the choice of the three parametric tests, the Boehmer *et al.* (1991) test, the dummy variable approach, as well as the GARCH (1, 1) specification. By reporting the results of both parametric and nonparametric test results, this thesis adds to the understanding of the impact of employing different tests in an event study.

7.4.4 The choice of methodological approach in this thesis

This thesis follows the approach suggested in the existing literature, presenting an alternative to the returns (traditional event study) approach (e.g. Thompson, 1985; Salinger, 1992; Kramer, 2001; Karafiath, 2009). The methodological approach in this chapter employs three parametric and two non-parametric approaches to event studies. The methodological approaches used in this component of the thesis are presented in Figure 7.2. The parametric approach includes the Boehmer *et al.* (1991) standardized cross sectional approach, an extension of the traditional event study approach employing the dummy variable approach with a GARCH(1,1) specification to capture the unconditional variance of the error terms, and finally a dummy variable approach without accounting for heteroskedasticity. The choice of model for benchmarking returns is the market model to ensure comparability across the specifications and this is consistent with several existing studies (e.g. Boehmer *et al*., 1991; De Jong *et al.*, 1992; Richard and Deddouche, 1999; Karafiath, 2007). The non-parametric approach includes the generalized sign test and the Corrado rank test. This chapter focuses on a number of different bank rating actions (e.g. upgrades, downgrades). First, the news events are split into good (upgrades) and bad (downgrade) news announcements.

Figure 7.2: Choice of methodological approaches employed in this chapter



The asymmetry between changes in ratings within investment and noninvestment grades is considered by further splitting the sample into investment and noninvestment grade bank stocks for announcement purposes. Lastly, the impact of news announcements relating to reviews and outlooks is considered, particularly in relation to whether or not they trigger any significant reactions prior to an actual rating change.

7.5 Data

This empirical component of the thesis employs bank credit rating data, bank stock prices and market indices. The bank credit rating data consists of actual rating changes, that is, upgrades and downgrades, as well as information on bank credit rating outlooks and Watchlist signals. The latter provides indications of potential upgrades or downgrades or confirmation of the ratings following outlook or Watchlist signals. By employing these different types of bank credit news announcements, the bank credit rating signalling effects are better captured. Thus, the sources of the market reactions to bank credit rating announcements are disentangled between the actual ratings and the signalling announcement (i.e. outlooks and Watchlist). Negative outlook signals contain changes to a negative outlook from a stable/positive outlook, and changes to a stable outlook from a positive outlook. Conversely, positive outlook signals contain changes to a positive outlook from a stable/negative outlook, and changes to a stable outlook from a negative outlook. Negative (positive) watch signals include placing bank *i* on watch for a possible downgrade (upgrade), and the action of confirming the rating of bank *i* after being on watch for a possible upgrade (downgrade).

Thus, bank credit rating outlooks and Watchlists provide indicators of the likely direction and timing of future rating changes (Hamilton & Cantor, 2004). The CRAs have been criticised for their apparent slow reactions in changing ratings. However, it is a useful approach for the CRAs to rate “through the cycle”, considering the sound reasons for stability in ratings (Altman and Rijken, 2006, Löffler, 2004 and Löffler, 2005). In view of this, the Watchlists and outlook signals provide a good outlet for the CRAs to reveal more private information. Bannier and Hirsch (2010) analyse the economic function of the Watchlist, and find that CRAs employ watch signals to improve the delivery of information. Existing studies around the signalling effects of credit ratings suggest that outlook and Watchlist signals have a significant market impact. Hand *et al.* (1992), Hull *et al.* (2004), Hill and Faff (2010) argue that credit rating outlook and Watchlist events are timelier and more informative than rating changes.

Alsakka and ap Gwilym (2012) argue that rating outlooks and Watchlist signals are "designed to signal when risks are imbalanced but a rating change is not certain" (p.46). Evidence suggests that actual rating changes usually follow a non-stable outlook or a creditwatch placements, however a strong or weak rating outlook/watch does not necessarily mean that a rating change will not occur (Hamilton and Cantor, 2004; Klaar and Riley, 2005; Vazza et al., 2005). The information content within these indicator type ratings thus provides a useful insight into the construction of the samples in this thesis.

The data available, particularly those on bank credit rating signalling helps in the construction of the un/anticipated specification within the framework of an event study approach. Markets may anticipate, and not react directly after rating changes because outlooks/placement on a Watchlist may reveal more significant and new information about a bank's creditworthiness. This thesis employs the daily historical share price of the bank stocks in the sample from which the lognormal returns are estimated by the market model. Following Mackinlay (1997), a total of a 252-day estimation window is employed. The market indices corresponding to the sample period are obtained for each of the sample countries, from which market index returns are obtained. To estimate the market model, the returns of the stock are regressed against the market.

7.5.1 Treatment of contaminants

One of the important reasons for conducting a short-run event study test is to reduce the contamination of the event window from other firm or market related news announcements. Following Hand *et al.* (1991) and Richard and Deddouche (1999), this study identifies bank credit ratings that are preceded by anticipated rating actions in the form of rating outlook and placement on a Watchlist. These 'contaminating' events are employed in some of the model specifications within this chapter and help to add to the understanding of the market reactions to rating related news events.

However, this thesis adopts a step-wise approach to eliminate credit rating news events contaminated with other non-bank credit rating related specific news events. For each bank credit rating upgrade and downgrade event day, the study manually checks the global market database using the Reuters news portal, Financial Times, and the Wall Street Journal, as well as country specific financial news portals for both firm and market related news events that could contaminate the event window. The search period for each of the bank credit rating news events is a 2-day period before and after the bank credit rating news event. Bank specific news events such as earnings and dividend announcements, M&A, litigations as well as general market news announcements such as regulatory changes are taken into account. If such an announcement occurs within the specified event window, such bank credit rating events are removed from the sample.

7.6 Results

This section presents the results of the second empirical component of this thesis which relates to testing the hypothesis that, on average, bank credit rating announcements have no impact on the behaviour of bank stock returns. It details the results of different model specifications for capturing abnormal returns around the date of news announcements related to bank credit rating.

This thesis employs models based on parametric and non-parametric approaches. The models employ a 27-day event window, which assumes a 10-day period before the event date and 15 days after. Further, a two-day event day is employed, which allows for the averaging of the abnormal returns on the day of announcement and the following day to get a single value of event day abnormal returns. This is consistent with existing methodological approaches to event studies. For each of the specifications, the thesis investigates the significance of the cumulative average abnormal returns (CAARs) over the trading days -10 to +15.

Thus, the thesis examines the effects of credit rating news announcements across several event windows for each specification within the parametric and non-parametric approach. Hence, the results present a test of significance for CAARs over these windows. The CAARs is quite important in addition to the statistical analysis of the daily average abnormal returns because it provides an idea of the aggregate effect of the abnormal returns over a particular event window. Thus, for this thesis results for CAARs for different event windows including a two-day event day, 11-day and 25-day windows centred on day zero are presented. In addition, the CAARs for the pre- and post-event day windows are examined.

The first part of this section examines the results of positive bank credit rating change, that is, upgrades. In addition, for these upgrades, the results of subsamples within investment and noninvestment grade categories are presented. Further, results of unanticipated upgrades, which take into consideration upgrades not preceded by outlook or placement announcements, are discussed. The news event tests within each specification employ both the parametric and non-parametric approaches in order to show robustness in the modelling of abnormal returns.

7.6.1 Results for bank rating upgrade announcements on bank stock returns

This section commences with three bank credit rating news event tests I–III, based on specifications employing the Boehmer *et al.* (1991), GARCH (1, 1) and the dummy variable approach, respectively. This initial set of news event tests are for all bank credit rating upgrades, irrespective of the news announcements being preceded by anticipated news in the form of outlook information or placement on a CreditWatch list (reviews). The section examines the results of the event study tests by gauging the reaction of bank stocks around the day of announcement of bank credit rating upgrades, that is, the event day reaction. This is followed by a study of the pre-event and post-event returns trends. The three news event tests (I–III) presented in this section are estimated using a 27-day event window covering the pre- and post-announcement dates (10 days before the event day and 15 days after). The estimation window employed is a 252-day period consistent with the suggestion of Mackinlay (1997).

Table 7.3 presents the results of Models I–III. Panel A shows the average abnormal returns and the cumulative average abnormal returns over the 27-day event window period as well as the tests of significance of each day, while Panel B shows the results of cumulative average abnormal returns across a range of pre-defined event windows. In addition, Panel B presents tests of statistical significance for the CAARs across the two broad approaches (parametric and non-parametric). The news event test I (Boehmer *et al.*) shows that there is a positive bank stock return of 0.54% significant at the 10% level on day *t*-6. This is an indication of news leakage. Further, the test shows a positive return reaction to the upgrade announcement (0.38%) significant at the 10% level on the event day.

Table 7.3: Results showing bank stock return reactions to upgrade news announcement

Panel A	Model I				Model II				Model III			
Day	**AAR**	**T-Stat**		**CAAR**	**AAR**	**T-Stat**		**CAAR**	**AAR**	**T-Stat**		**CAAR**
-10	0.02%	0.2341		0.02%	0.05%	1.3347		0.05%	0.04%	1.3574		0.04%
-9	0.06%	0.1503		0.08%	0.04%	0.8216		0.09%	0.10%	1.4883		0.14%
-8	0.03%	0.3854		0.11%	0.01%	0.5117		0.10%	0.07%	0.8471		0.21%
-7	0.01%	0.2257		0.12%	0.08%	0.2987		0.18%	0.04%	0.6694		0.25%
-6	0.54%	**1.8341**	*	0.66%	0.22%	1.5999		0.40%	0.34%	1.1585		0.59%
-5	0.21%	0.8426		0.87%	0.39%	**1.7084**	*	0.79%	0.33%	1.0547		0.92%
-4	0.07%	1.2957		0.94%	0.05%	1.2847		0.84%	0.17%	1.3811		1.09%
-3	0.11%	1.3885		1.05%	0.12%	0.6251		0.96%	0.06%	1.1852		1.15%
-2	0.10%	0.9574		1.15%	0.08%	0.8825		1.04%	-0.07%	-0.8647		1.08%
-1	0.17%	1.4847		1.32%	0.65%	1.3367		1.69%	1.24%	**1.5841**	*	2.32%
0	0.38%	**1.7254**	*	1.70%	0.23%	1.2574		1.92%	0.11%	1.1846		2.43%
+1	0.22%	1.5541		1.94%	-0.11%	-0.2142		1.81%	-0.08%	-0.1547		2.35%
+2	-0.16%	**-1.6999**	*	1.78%	0.02%	0.1847		1.83%	-0.15%	-0.2843		2.20%
+3	0.06%	0.5147		1.84%	0.01%	0.1785		1.84%	-0.10%	-0.1954		2.10%
+4	-0.26%	-1.1251		1.58%	-0.08%	-0.2251		1.76%	-0.06%	-0.1236		2.04%
+5	-0.11%	-0.3211		1.47%	-0.12%	-0.3015		1.64%	-0.11%	-1.2140		1.93%
+6	-0.10%	**-1.8008**	*	1.37%	-0.14%	-0.2159		1.50%	-0.07%	-0.5471		1.83%
+7	0.21%	1.2681		1.58%	0.01%	0.1841		1.51%	-0.14%	**-1.8451**	*	1.69%
+8	0.02%	0.6947		1.60%	0.04%	0.1762		1.55%	-0.22%	-1.3358		1.47%
+9	-0.24%	-0.9214		1.36%	-0.07%	-0.2718		1.48%	-0.02%	-1.1520		1.45%
+10	-0.11%	-1.0225		1.25%	-0.09%	-0.1057		1.39%	-0.17%	-1.2954		1.28%
+11	-0.03%	-1.1324		1.22%	0.02%	0.2941		1.41%	0.03%	0.9547		1.31%
+12	0.08%	1.6611		1.30%	0.01%	0.1516		1.42%	0.06%	1.2141		1.37%
+13	-0.12%	-0.7514		1.18%	-0.13%	-0.2351		1.29%	-0.01%	-0.1557		1.36%
+14	-0.05%	-0.0822		1.13%	-0.04%	-0.1485		1.25%	0.06%	1.1951		1.42%
+15	0.13%	1.3180		1.26%	-0.18%	-0.3471		1.07%	-0.12%	-1.3951		1.30%

N= 862

Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	Boehmer *et al.*	T-Stat	GARCH (1,1)	T-Stat	Dummy Variable	T-Stat	Corrado Rank	T-Stat	Generalized Sign	T-Stat
(-10, +15)	1.26%	1.2221	1.07%	1.0514	1.30%	1.5484	1.62	1.1251	1.55	1.0902
(-10, -1)	1.32%	1.3514	1.69%	1.3821	2.32%	1.1125	2.31	**2.2392** **	2.44	**2.1691** **
(+1, +15)	-0.46%	**-1.8824** *	-0.85%	-0.5482	-1.10%	-0.6646	1.34	**-1.6658** *	-1.01	**-1.7225** *
(-5, +5)	0.79%	**1.7001** *	1.24%	0.6991	1.34%	1.5220	1.09	1.3821	1.32	1.5148
(0, 0)	0.38%	**1.7254** *	0.23%	1.2227	0.11%	0.9954	0.98	1.4472	1.11	1.3232

Notes: Table 7.3 presents the bank stock reactions to upgrade announcements. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 1 days before the event to 15 days following the upgrade news announcements. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

The abnormal return on the event day is much lower than that of the day *t-6,* and this could suggest that the news leakage in the pre-event day period impacted on the magnitude of bank stock return on the news announcement day. The magnitude of the significant abnormal return on the event day is more than twice that of day *t-1*. The market partly corrected itself on day *t+2* with a magnitude of the negative abnormal return of 0.16% which is lower than that of the event day abnormal return. This is significant at the 10% level. A further positive abnormal return of 0.10% was observed on day *t*+6 significant at the at the 10% level. The magnitude of the significant abnormal return following the news announcement (0.26%) partly offset the positive event day bank stock returns of 0.38%.

The results are rather different for news event tests II (GARCH specification) and III (dummy variable specification). These latter models present no event day reaction. In addition, in the news event test II, there is evidence of news leakage with the day *t-5* showing positive abnormal bank stock return of 0.39% significant at the 10% level. The resulting effect of this new leakage is that there is no event day reaction. The test III shows information leakage. There is a positive abnormal return of 1.24% significant at the 10% level on day *t*-1. The result shows a day *t+7* negative abnormal return of 0.14% significant at the 10% level. This suggests market correction to the positive trends in the returns series for the event window period preceding day *t+7*. The estimations for news event tests I to III, employing different empirical model specifications show a differing magnitude of market reaction to bank credit rating upgrades. There is a mixed literature on the market reaction to positive news (in this case a bank credit rating upgrade).

Panel B shows the results of the CAARs across the three parametric and two non-parametric approaches. These test the level of significance for a number of days over which the abnormal returns are cumulated. In terms of the CAAR over the two-day event-day (0, 0), only Model I shows positive abnormal returns of 0.38% significant at the 10% level. The result observed for the partial market correction in Model I is consistent with the CAAR over the period (+1, +15) which shows a negative abnormal return of -0.46% significant at the 10% level. The CAAR (+1, +15) is higher than the event-day abnormal returns for the Boehmer *et al.,* 1991 specification in Model I. This suggests that the market fully corrected for the abnormal returns observed on the event-day over the post event day window. The only other event window specification that produced a significant CAAR is the Model I specification (-5, +5) with a positive CAAR of 0.79% significant at the 10% level. This suggests that for upgrade announcements, there is a significant bank stock return reaction over a relatively short event window spanning both sides of the news event day. This result is consistent with the observed news leakage and subsequent positive significant event day abnormal return.

The non-parametric approach presents another alternative to examining the effects of bank credit rating announcements on bank stock returns. For the purposes of this thesis, the results of the CAARs for the Corrado Rank and the Generalized Sign Test are discussed. Panel B shows similar results for the CAARs in the pre- and post-event day periods for both the non-parametric approaches. The Corrado Rank approach shows a positive CAAR of 2.31% significant at the 5% level over the event window (-10, -1), and a negative CAAR of -1.34% significant at the 10% level over the event window (+1, +15). These results capture the leakage of the good news and suggest the good news trickle effect and its consequence on the event day abnormal return not being significant under this specification. The results present evidence of a weak and partial market correction in the event window (+1, +15).

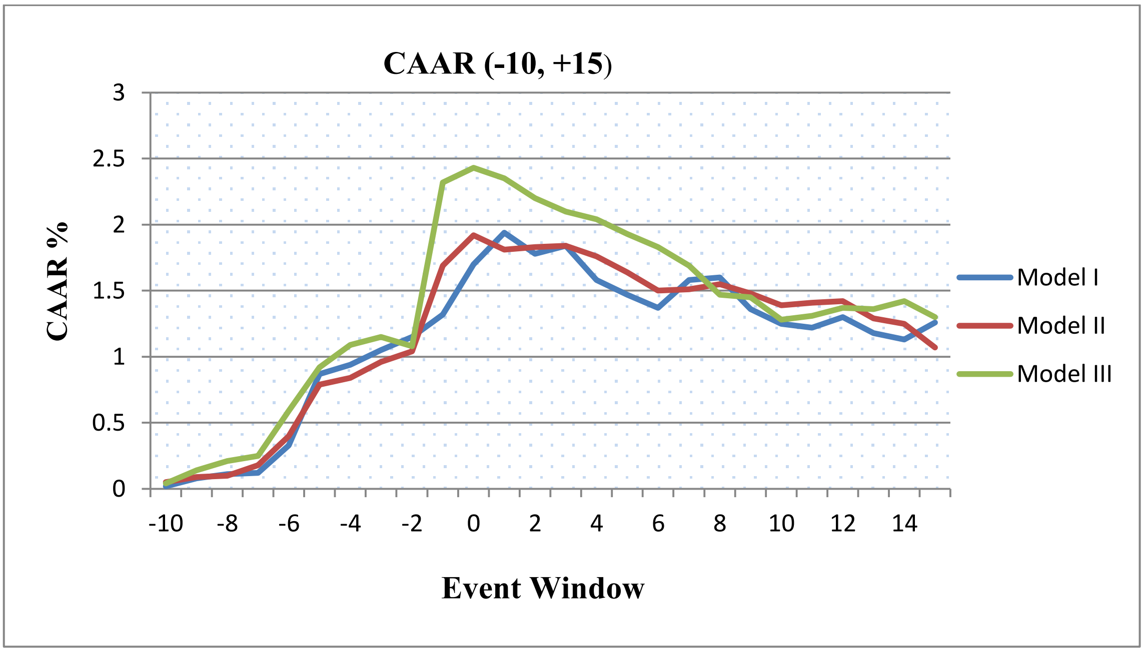
The results from the different specifications and approaches are mixed in their inference regarding market efficiency. There is a strong suggestion from the Boehmer *et al.* (1991) test specification, as well as the two nonparametric approaches of the market anticipating the upgrade announcements for banks. This is particularly evident in the non-parametric approach where the CAARs in the pre-and post-event day windows are significant. Model I shows significant event day abnormal returns, but there is no evidence of information leakage as the CAAR (-10, -1) are not significant. This is however contrary to the day *t*-6 significant abnormal returns of 0.54% at the 10% level. There is however evidence of partial market corrections. Models II and III, show no significant CAARs over the pre-defined event windows. The results are consistent with the semi-strong form market efficiency.

Chan (2001) argues that most of the results of stock returns after specific news items seem to fall on the side of underreaction, which he defines as average post-event abnormal returns of the same sign as event date returns (abnormal or raw). However, Fama (1998) presents a contrary position, arguing that investors do not show abnormal reactions to events. He suggests that the observed patterns present no consensus on investor reactions, and some disappear entirely after accounting for size and book-to-market effects. Several studies that test market reactions to credit rating upgrades (Hand *et al.* 1992; Nayar and Rozeff, 1994; Followill and Martel, 1997; Steiner and Heinke, 2001, Arezki *et al*., 2011; Kanli and Barlas, 2012) find that upgrade announcements generate no significant market reaction on the news announcement day. One can thus argue that the findings are consistent with the literature on rating effects that upgrades do not constitute positive news to stock markets, probably because the market already reflects most the information contained in the information.

Björklund and Sharafuddin (2013) study the impact of credit ratings by Moody's on the Swedish market and find that the Swedish stock market is susceptible to Moody's negative credit ratings but is largely unaffected by the positive credit ratings. Models II and III are consistent with these findings in terms of the event day reaction, however Model I gives weak evidence of positive abnormal returns on event day and subsequent partial correction. The weak evidence in Model I could be linked to the certification role of credit ratings, consistent with the findings by Elayan *et al.* (2003).

Figure 7.3 shows bank stock cumulative abnormal returns for upgrades over the event window (-10, +15). The graph shows a positive (upward) movement in the cumulative returns for the three models in the pre-event day period. Despite being insignificant over most of the event window, Model III shows the highest CAAR around the event day. There are consistent partial market corrections as evidenced by the downward trends across the three models. Further, the graph shows that over the event period *t+6* to *t+15*, the bank stock returns became less volatile as the event information is now reflected in stock prices. This is consistent with Tucker *et al.* (2012) who find that significant post-event reactions are all over-reactions followed by reversal corrections, with the large part of the reversal typically taking place within the first five days. This is similar to the findings of Daniel, Hirshleifer, and Subrahmayam (1998) who investigate investor psychology and security market under- and overreaction behaviours.

Figure 7.3: Bank stock cumulative abnormal returns for upgrades



7.6.2 Results for upgrade announcements for investment-grade bank stocks

This section presents results for bank stock reactions to bank credit upgrade announcements within the investment-grade category. It builds on the specifications in Section 7.4.1 by examining bank stock reactions to positive bank credit rating news announcements (upgrades) for this subsample of banks. By discriminating between bank rating categories (investment- vs noninvestment-grades), this thesis intends to add more to the understanding of market reaction to bank credit rating announcements.

The estimations of the abnormal returns for the event windows are presented in the news event tests IV–VI. These models follow the Boehmer *et al*. (1991), GARCH (1, 1) and the dummy variable approach, respectively. Similar to the approach for Models I–III, the estimations in this section make the implicit assumption that market participants are rational investors and that credit rating news announcements are made available to the public at the same time.

Table 7.4 presents the results for Models IV to VI. Panel A presents the average abnormal returns and cumulative abnormal returns over the 27-day event window period covering the pre- and post- announcement dates. Panel B shows the results of cumulative abnormal returns across a range of pre-defined event windows. Tests of statistical significance for the CAARs employing both the parametric and non-parametric approach are presented in Panel B.

The results for the parametric approach show significant positive abnormal returns on the day of the event announcement. Further, the CAARs for the pre- and post- event day windows are significant across the three news event test specifications (IV–VI). This is contrary to the results in Models II and III where the CAARs are insignificant. The magnitudes of the abnormal returns for the event windows are significantly larger than those in the specifications employed for Models I to III. The news event test IV shows no evidence of new leakages contrary to test I. Further, the results show event day positive abnormal returns of 0.52% significant at the 10% level. The magnitude of the event day abnormal returns for this subsample is greater than that of the entire sample. The higher magnitude in the event day abnormal returns may be linked with the non-leakage of information in the pre-event period in Model IV. Similar to the results in Model I, there is evidence of market correction on day $t+6$. The market correction is partial, with a negative abnormal return of 0.33% significant at the 5% level. Similarly, the estimations for the abnormal returns for Models V and VI show results consistent with Model IV, except for Model VI where there is a weak evidence of news leakage in the pre-event day period.

The news event test V shows event day positive abnormal returns of 0.47% significant at the 10% level. This is contrary to the corresponding result in Model II, where no significant bank stock return is observed. In addition, and consistent with the results obtained for Model IV, there is evidence of market correction on day $t+6$. The correction is partial and shows a negative abnormal return of 0.36% significant at the 10% level. The estimation of the last parametric specification in Model VI shows evidence of news leakage on day $t-2$.

There is a day $t-2$ positive abnormal return of 0.42% significant at the 10% level. It is interesting to note that despite this news leakage, the magnitude of event day abnormal returns is higher than in the other specifications. The news event test VI shows a positive abnormal return of 0.78% significant at the 5% level. The higher magnitude and level of significance observed for this specification (VI) may be as a result of the power of the test approach (a one-step approach) in capturing abnormal bank stock returns around news announcement date.

Table 7.4: Results showing bank stock returns reaction to upgrade news announcement within the investment-grade category

Panel A

Day	Model IV AAR	Model IV T-Stat	Model IV CAAR	Model V AAR	Model V T-Stat	Model V CAAR	Model VI AAR	Model VI T-Stat	Model VI CAAR
-10	0.06%	0.2225	0.06%	0.15%	0.6141	0.15%	0.07%	0.5174	0.07%
-9	0.16%	0.6241	0.22%	0.06%	0.9954	0.21%	0.13%	1.2216	0.20%
-8	0.07%	0.3844	0.29%	0.03%	0.6262	0.24%	0.05%	0.3254	0.25%
-7	0.05%	0.8541	0.34%	0.12%	0.3365	0.36%	0.11%	0.5921	0.36%
-6	0.22%	0.9622	0.56%	0.11%	1.5847	0.47%	0.24%	0.2514	0.60%
-5	0.14%	0.2251	0.70%	0.07%	1.3954	0.54%	0.20%	1.1589	0.80%
-4	0.12%	1.3357	0.82%	0.20%	1.6590	0.74%	0.19%	1.0051	0.99%
-3	0.09%	1.4149	0.91%	0.11%	0.7984	0.85%	0.22%	1.2325	1.21%
-2	0.13%	1.1114	1.04%	0.09%	0.8882	0.94%	0.42%	**1.8990***	1.63%
-1	0.10%	1.0216	1.14%	0.16%	1.4517	1.10%	0.33%	1.2517	1.96%
0	0.52%	**1.6974 ***	1.36%	0.47%	**1.9054 ***	1.57%	0.78%	**2.4854 ****	2.74%
+1	0.04%	1.2254	1.40%	-0.26%	-1.4478	1.31%	0.21%	0.6251	2.95%
+2	-0.10%	-1.5854	1.30%	0.11%	0.2365	1.42%	-0.32%	-0.3511	2.63%
+3	0.03%	1.2256	1.33%	-0.13%	0.9584	1.29%	-0.12%	-0.2658	2.51%
+4	-0.16%	-1.3911	1.17%	-0.15%	-0.4841	1.14%	-0.16%	-0.1514	2.35%
+5	-0.02%	-0.4822	1.15%	-0.09%	-0.6954	1.05%	-0.23%	-0.3229	2.12%
+6	-0.33%	**-2.1157 ****	1.12%	-0.36%	**-1.8566 ***	0.69%	-0.09%	-0.4588	2.03%
+7	0.11%	1.3625	1.24%	0.06%	0.6541	0.75%	-0.66%	**-1.6999 ***	1.37%
+8	0.19%	0.8547	1.43%	0.10%	0.8874	0.85%	-0.13%	-1.3052	1.24%
+9	-0.22%	-1.2529	1.21%	-0.09%	-0.9514	0.76%	-0.08%	-1.3621	1.16%
+10	-0.16%	-1.1171	1.05%	-0.10%	-0.6593	0.66%	-0.11%	-1.0584	1.05%
+11	-0.04%	-1.1005	1.01%	0.12%	0.3954	0.78%	0.07%	0.5847	1.12%
+12	0.01%	1.5471	1.02%	0.05%	0.4458	0.83%	0.03%	1.0225	1.15%
+13	-0.13%	-0.2214	0.89%	-0.03%	-0.3639	0.80%	-0.04%	-0.5584	1.11%
+14	-0.16%	-0.0095	0.73%	-0.08%	-0.2658	0.72%	0.09%	1.1215	1.15%
+15	0.18%	1.2514	0.91%	-0.13%	-0.2269	0.59%	-0.10%	-1.2658	1.20%

N=522

Panel B: **Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches**

Dates	Boehmer *et al.*	T-Stat	GARCH (1,1)	T-Stat	Dummy Variable	T-Stat	Corrado Rank	T-Stat	Generalized Sign	T-Stat
(-10, +15)	1.12%	1.5991	1.23%	1.0514	0.85%	1.5484	1.21	1.0051	0.63	0.2841
(-10, -1)	1.55%	**1.7021***	1.08%	1.7821	1.19%	**1.6995 ***	2.42	**1.5992 ***	2.51	**1.9925 ***
(+1, +15)	-0.94%	**-2.3801****	-1.16%	**-1.7482 ***	-1.68%	**-1.7778 ***	1.65	**-1.7954 ***	-1.26	**-2.0251 ***
(-5, +5)	0.88%	0.8251	1.02%	0.4447	1.04%	1.5220	0.55	1.3821	0.85	1.2141
(0, 0)	0.52%	**1.6974 ***	0.47%	**1.9054 ***	0.78%	**2.4854 ****	1.09	**1.8881 ***	1.23	**2.5846 ***

Notes: Table 7.4 presents the bank stock reactions to upgrade announcements within investment grade. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 1 day before the event to 15 days following the upgrade news announcements within investment grade. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

Consistent with the other parametric specifications, there is evidence of partial market correction. The day *t+7* show a negative abnormal return of 0.66% significant at the 10% level. An examination of Panel B shows results that differ from those obtained for entire (bank upgrade) sample estimates in Table 7.3. The CAARs for Model IV in the event window (-10, -1) and (+1, +15) show significant aggregate effects of bank rating upgrade news on bank stock returns. The aggregate effect of upgrade announcements for investment-grade bank stocks over the pre-event day window (-10, -1) shows positive abnormal returns of 1.55% significant at the 10% levels. There is evidence of partial market correction over the post-event day period (+1, +15) with a negative abnormal return of 0.94% significant at the 5% level. This result is slightly different from the corresponding estimate in Panel B in Table 7.3 which shows an insignificant CAAR over the pre-event day period. The significant positive CAAR in the (-10, -1) window suggest information leakages or anticipation by the market. However, this leakage is not captured in news event test IV in Panel A. Despite this, the significant abnormal returns observed on the event-day point towards the value-added effects of bank upgrade information within the investment-rating category.

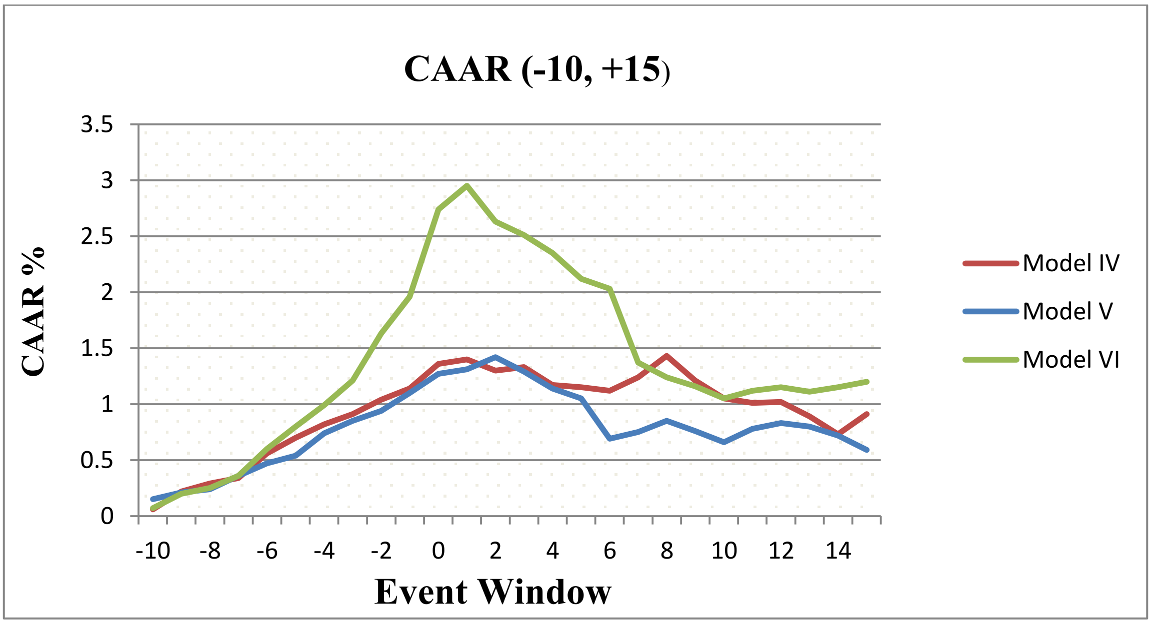
Contrary to the results in Panel B in Table 7.3 for the news event test Models II and III, Models V and VI show significant CAARs in the post-event day period. The news event test Model V shows a negative CAAR of 1.16% significant at the 10% level in the window (+1, +15). Consistent with the earlier results in the full sample (upgrades), there are no significant CAARs in the pre-event day period. For Model VI, there is a positive CAAR of 1.19% significant at the 10% level in the window (-10, -1) and evidence of full market correction in the post-event day window (+1, +15). The magnitude of the negative CAAR in the window (+1, +15) is 1.68%, significant at the 10% level. This is contrary to the corresponding results for the entire sample where there is no evidence of significance CAARs over the various pre-specified windows.

In terms of the results for the non-parametric approach, the estimates for the Corrado rank and generalized sign test both show similar results to the specifications in Figure 7.3. However, for both approaches, the event-day CAARs are positive (1.09% and 1.23% respectively) and significant at the 10% level. The Corrado rank test shows a positive CAAR of 2.42% significant at the 10% level for the window (-10, -1). The post-event day (+1, +15) estimation shows a negative CAAR of 1.65% significant at the 10% level, and suggests partial market correction. For the generalized sign test, the result shows a pre-event day positive CAAR of 2.51% significant at the 10% level and post-event day negative CAAR of 1.26% significant at the 10% level. This gives an indication of partial market correction of the pre-event day CAAR and positive significant event day abnormal return.

Overall, the results of bank stock return reactions to upgrade announcement news within the investment category show higher magnitudes in terms of the observed abnormal returns. Similarly, there are significant abnormal returns across both the parametric and non-parametric approaches for the event-day. The results also suggest market corrections in the post-event-day window (+1, +15) under the various specifications. This specification is an important addition within this thesis and allows for a better understanding of the market dynamics pertaining to bank credit rating upgrades. Hence, despite the general argument in the existing literature that upgrades are seldom associated with significant market reactions around the announcement date, the results within these section are to the contrary. However, within an emerging economy study by Larrain, Reisen and von Matzlan (1997), the authors find that rating actions have a significant impact, even to a degree of market overshooting on investment grades. The strong drive for market reaction to investment grade bank rating upgrades could be associated with the certification role within an investment grade setting (Kiff *et al.,* 2012).

Figure 7.4 shows the bank stock cumulative abnormal returns for upgrades within the investment-grade category over the event window (-10, +15). The graph shows a positive (upward) movement in the cumulative returns for the three models in the pre-event day period. Similar to the results for Model III, Model VI shows the highest CAAR around the event day. In addition, the graph shows that bank stock returns becomes less volatile after day *t+6,* which is the period after the market correction. The cumulative abnormal return for the Model VI is significantly higher than those of Models IV and V. This is consistent with the results in Table 7.4. The figure shows that between days *t*+6 and *t*+15, the prices of the bank stock have incorporated the information contained in the bank upgrade news announcement, hence the observed reduced volatility.

Figure 7.4: Bank stock cumulative abnormal returns for upgrades within the investment category



7.6.3 Results for upgrade announcements for noninvestment-grade bank stocks

This section presents results for bank stock reactions to credit rating upgrade announcements for the noninvestment-grade category. The results presented in this section build on those in Sections 7.5.1 and 7.5.2 by examining the effects of upgrade announcements on bank stock returns for another subsample, the noninvestment grade bank stocks. The results obtained in this section present a good basis for comparison with those on Sections 7.5.1 and 7.5.2. The noninvestment grade category contains bank that are vulnerable to adverse business, financial and economic conditions. The estimations of the abnormal returns for the event windows for the banks within this category are presented in news event test Models VII–IX. These models follow the Boehmer *et al*. (1991), GARCH (1, 1) and the dummy variable approach, respectively. The results are presented in Table 7.5. The results for this subsample contrast those in earlier sections. The event-day abnormal returns for the three parametric approaches models are insignificant.

The insignificant abnormal returns observed in Table 7.5 may be due to the net impact of the sum moderate effect (the full sample) less the subsample strong effect (investment grade subsample), leaving on average the remaining subsample weak effect in Table 7.5. This suggests that news announcements relating to the upgrades of noninvestment-grade banks do not convey any significant information to the market. The results are consistent with the estimation of CAARs for both the parametric and non-parametric approach. This is an indication that there is less information asymmetry in the way market reacts to credit ratings news for banks within the non-investment grade compared to the investment grades. More importantly, it may suggest that investment analysts do not follow these low-rated banks and therefore there are no reactions.

Table 7.5: Results showing bank stock returns reaction to upgrade news announcement within the noninvestment-grade category

Panel A	Model VII			Model VIII			Model IX		
Day	AAR	T-Stat	CAAR	AAR	T-Stat	CAAR	AAR	T-Stat	CAAR
-10	0.03%	0.1247	0.03%	0.01%	0.5547	0.15%	0.02%	0.8612	0.02%
-9	0.05%	0.3119	0.08%	0.03%	0.1299	0.21%	0.03%	1.0251	0.05%
-8	0.10%	0.2514	0.18%	0.02%	0.3258	0.24%	0.02%	0.8862	0.07%
-7	0.09%	0.4842	0.27%	0.04%	0.2325	0.36%	0.01%	1.3625	0.08%
-6	0.03%	0.3321	0.24%	0.02%	1.1254	0.47%	0.06%	0.8454	0.14%
-5	0.06%	1.0084	0.30%	0.05%	1.0325	0.54%	0.04%	1.2366	0.18%
-4	0.05%	1.1517	0.35%	0.01%	1.1540	0.74%	0.03%	1.1254	0.21%
-3	0.07%	0.9514	0.42%	0.06%	0.9951	0.85%	0.01%	0.5477	0.22%
-2	0.11%	1.2288	0.53%	0.02%	1.1222	0.94%	0.04%	1.2514	0.26%
-1	0.08%	0.8474	0.61%	0.04%	0.6547	1.10%	0.03%	1.5888	0.29%
0	0.14%	0.2146	0.75%	0.07%	0.8848	1.57%	0.05%	0.7844	0.34%
+1	0.04%	0.5348	0.79%	0.03%	1.3251	1.31%	0.01%	0.2558	0.35%
+2	-0.05%	-0.1183	0.74%	0.04%	0.6658	1.42%	-0.02%	-0.5111	0.33%
+3	0.08%	1.2235	0.82%	0.01%	1.5254	1.29%	-0.06%	-0.3514	0.27%
+4	-0.12%	-1.3232	0.70%	-0.04%	-0.6695	1.14%	-0.04%	-0.5151	0.23%
+5	-0.06%	-0.1247	0.64%	-0.03%	-1.2597	1.05%	-0.04%	-0.2899	0.19%
+6	-0.03%	-0.2514	0.61%	0.07%	1.1547	0.69%	0.07%	0.8895	0.26%
+7	0.06%	0.5310	0.67%	0.05%	0.7845	0.75%	-0.01%	-1.3371	0.25%
+8	0.01%	0.2215	0.68%	0.03%	1.2588	0.85%	-0.03%	-1.2284	0.22%
+9	-0.04%	-1.2867	0.64%	0.02%	1.4993	0.76%	-0.02%	-1.3390	0.20%
+10	-0.04%	-0.2251	0.60%	0.01%	0.2144	0.66%	0.02%	-1.3254	0.22%
+11	0.06%	1.0864	0.66%	0.03%	0.8471	0.78%	0.07%	0.6647	0.29%
+12	0.03%	1.3599	0.69%	0.06%	0.2365	0.83%	0.02%	1.5825	0.31%
+13	0.07%	0.1417	0.76%	-0.04%	-1.6001	0.80%	-0.02%	-0.2481	0.29%
+14	-0.03%	-1.3399	0.73%	-0.05%	-0.7623	0.72%	0.06%	1.3516	0.35%
+15	0.10%	1.5841	0.63%	0.01%	0.2110	0.59%	-0.03%	-1.0017	0.32%
N=340									

Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	Boehmer *et al.*	T-Stat	GARCH (1, 1)	T-Stat	Dummy Variable	T-Stat	Corrado Rank	T-Stat	Generalized Sign	T-Stat
(-10, +15)	0.13%	1.2478	0.13%	0.8522	0.06%	1.2626	0.21	0.8471	0.19	0.8422
(-10, -1)	0.09%	1.3695	0.06%	0.9963	0.08%	1.3302	0.17	1.1594	0.09	0.7926
(+1, +15)	-0.07%	-1.5541	0.04%	1.0052	0.04%	1.1931	0.11	-1.2627	-0.11	-1.4479
(-5, +5)	0.15%	0.6682	0.09%	0.6658	0.07%	0.7625	0.12	0.6588	0.06	1.0374
(0, 0)	0.14%	0.2146	0.07%	0.5477	0.05%	0.6584	0.18	1.3971	1.01	1.1154

Notes: Table 7.5 presents the bank stock reactions to upgrade announcements within noninvestment grade. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 1 day before the event to 15 days following the upgrade news announcements within noninvestment grade. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

Overall, the results in Sections 7.5.2 and 7.5.3 show that there is an asymmetry in bank stock return reaction to rating upgrade announcement for banks within the investment and noninvestment grades. On the one hand, bank stocks react to upgrade news announcements for investment grade banks, particularly on news event day, however, there is no observed significant abnormal for bank stock returns for the noninvestment grade banks.

7.6.4 Results for news announcements where there are unanticipated upgrades

This section presents results for bank stock price reactions to unanticipated bank credit upgrade announcements. The section is motivated by the argument that the stock price reaction to credit rating announcements is influenced by the market's anticipation or otherwise of the news. Hsueh and Liu (1992) find that the magnitude of abnormal returns is more pronounced when there is no anticipation by the market, that is, when the rating change is a surprise. The failure to control for anticipated credit rating news announcements may indeed have significant effects on the estimation and may bias the test results.

A model that takes into consideration the expectation of the market about possible credit rating changes could be a more powerful test of the effects of rating change announcements. By investigating a subset of the sample, conditioned on anticipated news in the form of outlook announcements or placements on Watchlist, this thesis intends to add more to the understanding of market reaction to bank credit rating announcements.

Here, the assumption is made that upgrades preceded by a positive outlook, as well as placement on the Watchlist, are more anticipated in the market than those preceded by no such announcements. The estimation of the abnormal returns for the event windows is presented in news event test Models X–XII.

Table 7.6: Results showing bank stock returns reaction to unanticipated credit rating upgrade news announcement

Panel A	Model X			Model XI			Model XII		
Day	**AAR**	**T-Stat**	**CAAR**	**AAR**	**T-Stat**	**CAAR**	**AAR**	**T-Stat**	**CAAR**
-10	0.05%	1.3265	0.05%	0.03%	0.5547	0.03%	0.06%	0.7241	0.06%
-9	0.09%	0.8954	0.14%	0.08%	0.1299	0.11%	0.04%	0.5147	0.10%
-8	0.12%	0.6652	0.26%	0.10%	0.3258	0.21%	0.12%	0.8472	0.22%
-7	0.10%	0.4994	0.36%	0.09%	0.2325	0.30%	0.11%	1.4251	0.33%
-6	0.06%	0.3971	0.42%	0.12%	1.1254	0.42%	0.10%	0.8471	0.43%
-5	0.11%	1.2514	0.53%	0.06%	1.0325	0.48%	0.09%	1.3200	0.52%
-4	0.12%	1.6977	0.65%	0.10%	1.1540	0.58%	0.14%	1.2581	0.66%
-3	0.03%	1.2514	0.68%	0.08%	0.9951	0.66%	0.18%	0.8956	0.84%
-2	0.16%	0.8863	0.84%	0.11%	1.1222	0.77%	0.07%	1.3544	0.91%
-1	0.27%	1.4720	1.11%	0.07%	0.6547	0.84%	0.13%	1.7888	1.04%
0	0.74%	**2.2954** **	1.85%	0.82%	**2.3848** **	1.66%	0.88%	**2.4844** **	1.92%
+1	0.22%	0.5348	2.07%	0.14%	1.3251	1.80%	0.18%	0.5547	2.10%
+2	0.16%	-0.1183	2.23%	0.06%	0.6658	1.86%	0.10%	0.3251	2.20%
+3	0.08%	1.2235	2.31%	0.13%	1.5254	1.99%	-0.17%	-0.6284	2.03%
+4	0.11%	-1.3232	2.42%	0.24%	-0.6695	2.23%	-1.01%	**-2.0151** *	1.02%
+5	-0.58%	**-1.8801** *	1.84%	-0.88%	**-1.9597** *	1.35%	0.04%	0.3547	1.06%
+6	-0.32%	**-1.9362** *	1.52%	0.17%	1.1547	1.52%	0.06%	0.4501	1.12%
+7	0.10%	0.5310	1.62%	0.13%	0.7845	1.65%	-0.02%	-1.2475	1.10%
+8	0.06%	0.2215	1.68%	0.09%	1.2588	1.74%	-0.07%	**-1.7284** *	1.03%
+9	-0.07%	-1.2867	1.61%	0.07%	1.4993	1.81%	0.13%	1.2281	1.16%
+10	-0.08%	-0.2251	1.53%	0.03%	0.2144	1.84%	0.10%	1.0954	1.26%
+11	0.06%	1.0864	1.59%	0.04%	0.8471	1.88%	0.08%	0.5595	1.34%
+12	0.04%	1.3599	1.63%	0.05%	0.2365	1.93%	0.20%	1.2514	1.54%
+13	0.02%	0.1417	1.65%	-0.26%	-1.6001	1.67%	0.06%	0.3216	1.60%
+14	-0.03%	-1.3399	1.62%	-0.09%	-0.7623	1.58%	0.06%	1.6668	1.66%
+15	0.09%	1.5841	1.53%	0.02%	0.2110	1.60%	-0.09%	-1.1410	1.57%

N=286

Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	**Boehmer *et al.***	**T-Stat**	**GARCH (1, 1)**	**T-Stat**	**Dummy Variable**	**T-Stat**	**Corrado Rank**	**T-Stat**	**Generalized Sign**	**T-Stat**
(-10, +15)	0.51%	1.5584	0.39%	0.3514	0.40%	1.2626	0.38	0.7882	0.20	0.3514
(-10, -1)	0.12%	1.5992	0.10%	0.6246	0.17%	1.3302	0.20	1.2417	0.37	0.5577
(+1, +15)	-0.62%	**-2.3514** **	-0.55%	**1.9953** *	-0.72%	**2.3931** **	0.65	**-2.4005** **	-0.77	**-2.3218** **
(-5, +5)	0.23%	**1.8812** *	0.10%	0.8920	0.19%	0.7625	0.32	0.7843	0.10	1.2518
(0, 0)	0.74%	**2.2954** **	0.82%	**2.3848** **	0.88%	**2.4844** **	1.41	**2.3514** **	1.03	**2.2990** **

Notes: Table 7.6 presents the bank stock reactions to unanticipated upgrade announcements. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 1 day before the event to 15 days following the unanticipated upgrade news announcement. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

These models follow the Boehmer et al. (1991), GARCH (1, 1) and the dummy variable approach, respectively. The results of the estimations are presented in Table 7.6. Panel A shows the abnormal returns over the 27-day event window, while Panel B presents the results of the CAARs over various event windows.

The results of the bank stock return reactions to unanticipated credit rating news announcements are consistent across the three models. The results of the news event test Models X–XII show significant positive reactions on the announcement day. For Model X, there is a positive average abnormal return on the event-day of 0.74%. This is significant at the 5% level. The event-day abnormal return is higher than that observed in the corresponding full sample (upgrades) in Model I (0.38%). Contrary to the results in Model I, there is no evidence of news leakage in the pre-event window. Further, there is a market correction over a two day period, that is, negative average abnormal returns of 0.58% and 0.32% on days *t+5* and *t+6* respectively. The Model X shows a full market correction following the unanticipated bank rating upgrade news event, however only a partial market correction is observed for the Model I specification.

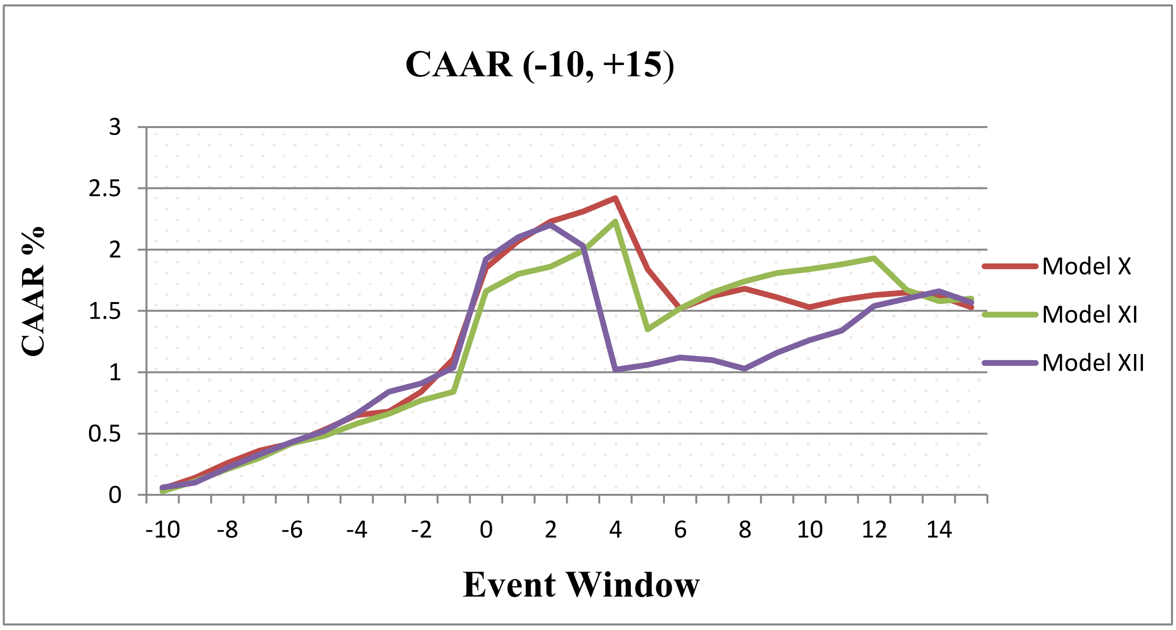
Similarly, Models XI and XII show positive average abnormal returns of 0.82% and 0.88% significant at the 5% level respectively, on the event day. Consistent with the result in Model X, there is no evidence of news leakage and there is full market correction to the observed event-day abnormal reaction. In terms of the CAARs over the pre-defined windows, there is significant stock reaction to unanticipated news credit rating news announcements in bank stocks.

In the post event-day window (+1, +15), there is a negative CAAR of 0.62% which is significant at the 5% level for the Boehmer *et al.* model specification. Similarly, the CAARs for the GARCH and dummy variable approaches are negative at 0.55% and 0.72%, both of which are significant at the 10% and 5% levels, respectively. The results of the CAARs in Panel B of Table 7.6 differ from those of the full sample in Table 7.3. Panel B in Table 7.3 shows no significant abnormal returns over the post-event day window (+1, +15) except for the Boehmer *et al.* specification. The results of the non-parametric approach are presented in Panel B of Table 7.6. There are positive and significant CAARs on the event-day for both the Corrado rank and the generalised sign test. The Corrado rank test shows a positive and significant CAAR of 1.4% at the 5% level. Similarly, the CAAR for the generalised rank test is a positive 1.03% and this is significant at the 5% level. Both of the non-parametric approaches show evidence of market correction in the event window (+1, +15). There are CAARs of -0.65% and -0.77% both significant at the 5% level for the Corrado rank and generalised sign test approach, respectively, in the post-event window.

The results in Table 7.6 suggest that the magnitude and significance of abnormal returns is influenced by the level of un/anticipated news event. This implies that when there is no anticipation of news events, the tendency for news leakage is reduced and this potentially affects the magnitude of bank stock return reaction on the day of the news event. When compared with the results in the full sample (upgrades), estimates for the news event test conditioned on news anticipation are consistent across all the parametric approaches and there is full market correction in the post-event day period. Overall, the results within this section are consistent with the existing literature (e.g. Brooks, Patel and Su, 1998). By focusing on unanticipated events, this thesis provides new and unique evidence on how financial markets process information relating to rating announcements.

Figure 7.5 shows the bank stock cumulative abnormal returns for unanticipated upgrades for the whole sample over the event window (-10, +15). The graph shows a positive (upward) movement in the cumulative returns for the three models in the pre-event day period. This upward movement continued for a couple of days following the news event announcement. The market fully corrected for the unanticipated news between days *t+5* and *t*+8, and this is depicted by the sharp downward movement in bank stock returns around this period In addition, the graph shows that bank stock returns becomes less volatile after day *t+8,* which is the period after the full market correction.

Figure 7.5: Bank stock cumulative abnormal returns for unanticipated upgrades



7.6.5 Results for bank stock return reactions to upgrade news announcements on bank rating reclassifications

This section shows the results of bank stock returns reaction when there is an upgrade from noninvestment to an investment grade, that is, from BB+ to BBB- (Table 7.7). The motivation for investigating this category of rating upgrade is that, theoretically, movement across this noninvestment/investment grade threshold may trigger a response from institutional investors who may typically have mandates to invest only in investment grade bank stocks. Many institutional investors (e.g. pension funds, brokers, investment advisors) may be mandated to purchase assets in certain categories (e.g. investment grades), and this prohibits or restricts their portfolio.

Hence, one may expect such reclassification (from noninvestment to investment grade or vice versa) to trigger greater abnormal returns around the corresponding news announcement date. The thesis allows for a test of whether there is a significantly larger stock price response when a bank is upgraded from noninvestment to investment grade, compared to upgrades that do not result in such reclassification.

The estimations of the abnormal returns for the event windows are presented in Models XIII–XV. These models follow the Boehmer *et al.* (1991), GARCH (1, 1) and the dummy variable approaches, respectively. Panel A in Table 7.7 shows the abnormal returns over the 27-day event window, while Panel B presents the results of the CAARs over various event windows for both the parametric and non-parametric approaches. The results are mixed for this specification across the three parametric approaches employed. Only Model XIII shows significant abnormal returns on the event day. There is a positive abnormal return for day $t=0$ of 0.36% significant at the 10% level. In addition, there is evidence of market correction in the post-event period.

The results show $t+2$ and $t+6$ negative abnormal returns of 0.22% and 0.06%, both significant at the 10% level. Model XIV shows evidence of news leakage. However, there are no significant abnormal returns when the returns are aggregated in the CAAR for the pre-event period. There are significant CAARs for the nonparametric approach over the pre- and post-event periods, though no significant returns are observed on the event day. The Corrado rank approach shows a positive return of 2.31% significant at the 5% level in the (-10, -1) window. Similarly, the generalized sign test shows a positive abnormal return of 2.44% significant at the 5% level over the same window. In the post-event day period, (+1, +15), there are negative abnormal returns of 1.34% and 1.01%, respectively, significant at the 10% level in both the Corrado and the Sign test.

.

Table 7.7: Results showing bank stock return reactions to bank credit rating upgrade reclassification news announcements

Panel A

Day	Model XIII AAR	T-Stat	CAAR	Model XIV AAR	T-Stat	CAAR	Model XV AAR	T-Stat	CAAR
-10	0.12%	0.2341	0.12%	0.10%	1.3347	0.05%	0.04%	1.3574	0.04%
-9	0.08%	0.1503	0.20%	0.06%	0.8216	0.09%	0.12%	1.4883	0.14%
-8	0.06%	0.3854	0.26%	0.05%	0.5117	0.10%	0.11%	0.8471	0.21%
-7	0.10%	0.2257	0.36%	0.06%	0.2987	0.18%	0.08%	0.6694	0.25%
-6	0.07%	**1.8341** *	0.43%	0.12%	1.5999	0.40%	0.30%	1.1585	0.59%
-5	0.09%	0.8426	0.52%	0.22%	**1.7084** *	0.79%	0.13%	1.0547	0.92%
-4	0.08%	1.2957	0.60%	0.09%	1.2847	0.84%	0.11%	1.3811	1.09%
-3	0.08%	1.3885	0.68%	0.11%	0.6251	0.96%	0.07%	1.1852	1.15%
-2	0.13%	0.9574	0.81%	0.13%	0.8825	1.04%	-0.06%	-0.8647	1.08%
-1	0.11%	1.4847	0.92%	0.51%	1.3367	1.69%	0.99%	1.5841	2.32%
0	0.36%	**1.7254** *	1.28%	0.39%	1.2574	1.92%	0.10%	1.1846	2.43%
+1	0.12%	1.5541	1.40%	-0.12%	-0.2142	1.81%	-0.15%	-0.1547	2.35%
+2	-0.22%	**-1.6999** *	1.18%	0.03%	0.1847	1.83%	-0.20%	-0.2843	2.20%
+3	-0.10%	0.5147	1.08%	0.02%	0.1785	1.84%	-0.62%	-0.1954	2.10%
+4	-0.16%	-1.1251	0.92%	-0.10%	-0.2251	1.76%	-0.21%	-0.1236	2.04%
+5	-0.04%	-0.3211	0.88%	-0.16%	-0.3015	1.64%	-0.09%	-1.2140	1.93%
+6	-0.06%	**-1.8008** *	0.94%	-0.17%	-0.2159	1.50%	-0.08%	-0.5471	1.83%
+7	0.18%	1.2681	1.12%	0.09%	0.1841	1.51%	-0.10%	**-1.8451** *	1.69%
+8	0.11%	0.6947	1.23%	0.04%	0.1762	1.55%	-0.18%	-1.3358	1.47%
+9	-0.13%	-0.9214	1.10%	-0.09%	-0.2718	1.48%	-0.03%	-1.1520	1.45%
+10	-0.07%	-1.0225	1.03%	-0.10%	-0.1057	1.39%	-0.13%	-1.2954	1.28%
+11	0.09%	-1.1324	1.12%	0.04%	0.2941	1.41%	0.06%	0.9547	1.31%
+12	0.10%	1.6611	1.22%	0.08%	0.1516	1.42%	0.09%	1.2141	1.37%
+13	-0.11%	-0.7514	1.11%	-0.06%	-0.2351	1.29%	-0.07%	-0.1557	1.36%
+14	-0.03%	-0.0822	1.08%	-0.05%	-0.1485	1.25%	0.03%	1.1951	1.42%
+15	0.10%	1.3180	1.18%	-0.09%	-0.3471	1.07%	-0.10%	-1.3951	1.30%

N=171

Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	Boehmer *et al.*	T-Stat	GARCH (1,1)	T-Stat	Dummy Variable	T-Stat	Corrado Rank	T-Stat	Generalized Sign	T-Stat
(-10, +15)	1.26%	1.2221	1.07%	1.0514	1.30%	1.5484	1.62	1.1251	1.55	1.0902
(-10, -1)	1.32%	1.3514	1.69%	1.3821	2.32%	1.1125	2.31	**2.2392** **	2.44	**2.1691** **
(+1, +15)	-0.46%	**-1.8824** *	-0.85%	-0.5482	-1.10%	-0.6646	1.34	**-1.6658** *	-1.01	**-1.7225** *
(-5, +5)	0.79%	**1.7001** *	1.24%	0.6991	1.34%	1.5220	1.09	1.3821	1.32	1.5148
(0, 0)	0.38%	**1.7254** *	0.23%	1.2227	0.11%	0.9954	0.98	1.4472	1.11	1.3232

Notes: Table 7.7 presents the bank stock reactions to upgrade reclassification announcements. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 1 day before the event to 15 days following the upgrade reclassification news announcement. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

The remaining part of Section 7.4 presents the results of different model specifications for capturing abnormal returns around the date of negative bank credit rating news announcements. The findings so far show that the degree of market reaction differs depending on the type of rating events. Consistent with the analysis for the positive news results, the estimation of the models is based on both the parametric and non-parametric approaches. The models employ a 27-day event window, which assumes a 10-day period before the event date and 15 days after. In addition, the thesis adopts a two-day event day period in order to capture any news announcement that occurs after the close of the market trading. For each of the specifications, the thesis investigates the significance of the cumulative average abnormal returns over the trading days -10 to +15.

Using this approach, separate results for different event windows such as the two-day event day, and 11-day and 25-day windows centred on day zero, as well as the pre- and post-event day windows are examined. In addition, the section examines the results of subsamples within the investment and noninvestment grade categories, the impact of unanticipated downgrades, and downgrades from investment to noninvestment bank rating categories.

7.6.6 Results for downgrade announcements on bank stock returns

Table 7.8 presents the results of Models XVI–XVIII. Panel A shows the average abnormal returns and the cumulative average abnormal returns over the 27-day event window period as well as the tests of significance for each separate day. Panel B shows the results of cumulative average abnormal returns across a range of pre-defined event windows. In addition, Panel B presents tests of statistical significance for the CAARs across the two broad (parametric and non-parametric) approaches.

Table 7.8: Results showing bank stock returns reactions to downgrade news announcements

Panel A	Model XVI			Model XVII			Model XVIII		
Day	**AAR**	**T-Stat**	**CAAR**	**AAR**	**T-Stat**	**CAAR**	**AAR**	**T-Stat**	**CAAR**
-10	-0.06%	-0.0584	-0.06%	-0.08%	-1.0155	-0.08%	-0.05%	-1.2117	-0.05%
-9	-0.05%	-0.6258	-0.11%	-0.03%	-1.2211	-0.11%	-0.07%	-1.3364	-0.12%
-8	-0.04%	-0.6009	-0.15%	-0.06%	-0.9827	-0.17%	-0.02%	-0.6655	-0.14%
-7	-0.06%	-0.6841	-0.21%	-0.12%	-1.1114	-0.29%	-0.10%	-1.2660	-0.24%
-6	-0.22%	**-2.2361** **	-0.43%	-0.07%	-0.4848	-0.36%	-0.12%	-1.4008	-0.36%
-5	-0.25%	**-1.7988** *	-0.68%	-0.30%	**-2.1212** **	-0.66%	-0.09%	-1.2068	-0.45%
-4	-0.12%	-0.9144	-0.80%	-0.18%	**-1.8886** *	-0.84%	-0.33%	**-2.0421****	-0.78%
-3	-0.10%	-1.2008	-0.90%	-0.11%	-0.7762	-0.92%	0.02%	1.8520	0.76%
-2	-0.06%	-1.5547	-0.96%	-0.04%	-1.3548	-0.96%	-0.08%	-0.8871	-0.84%
-1	-0.07%	**-1.7001** *	-1.03%	-0.09%	-1.0877	-1.05%	-0.23%	-1.6001	-1.07%
0	-0.86%	**-2.3544** **	-1.89%	-0.66%	**-2.2219** **	-1.71%	-0.74%	**-2.1846** **	-1.81%
+1	-0.32%	-1.2121	-2.21%	0.08%	1.5580	-1.63%	-0.04%	-0.8471	-1.85%
+2	-0.22%	-0.6384	-2.43%	-0.01%	-0.3658	-1.64%	0.12%	0.2843	-1.73%
+3	0.36%	**1.8112** *	-2.07%	0.16%	1.2760	-1.48%	0.48%	**1.9214** *	-1.25%
+4	0.13%	**2.3944** **	-1.94%	0.07%	0.8832	-1.41%	0.07%	0.2231	-1.18%
+5	0.11%	1.4711	-1.83%	0.11%	1.3265	-1.30%	0.11%	1.0014	-1.07%
+6	0.12%	0.6584	-1.71%	0.59%	**2.2841** **	-0.71%	0.06%	0.6841	-1.01%
+7	0.04%	0.1746	-1.67%	0.12%	1.5947	-0.59%	0.35%	0.7713	-0.66%
+8	0.03%	0.7474	-1.64%	0.07%	1.8264	-0.52%	0.01%	1.3018	-0.65%
+9	0.12%	1.1518	-1.52%	0.03%	0.9863	-0.49%	0.12%	1.5524	-0.53%
+10	-0.06%	-1.2183	-1.46%	0.06%	1.2276	-0.43%	-0.02%	-0.7954	-0.51%
+11	-0.10%	-1.1922	-1.36%	0.08%	1.6251	-0.35%	0.04%	0.8861	-0.47%
+12	0.03%	1.0141	-1.33%	0.03%	1.6682	-0.32%	0.06%	1.3225	-0.41%
+13	0.07%	0.6669	-1.26%	-0.13%	-0.5330	-0.45%	0.03%	1.1507	-0.38%
+14	0.02%	0.7141	-1.24%	-0.10%	-0.8854	-0.55%	0.03%	1.5214	-0.35%
+15	0.03%	1.0216	-1.21%	-0.07%	-0.7921	-0.62%	0.07%	1.2346	-0.28%

N=908

Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	Boehmer *et al.*	T-Stat	GARCH (1,1)	T-Stat	Dummy Variable	T-Stat	Corrado Rank	T-Stat	Generalized Sign	T-Stat
(-10, +15)	-0.32%	-0.8436	-0.59%	-1.2254	-0.44%	-1.3644	0.72	-1.3655	-0.48	-1.1202
(-10, -1)	-0.40%	**-1.8566** *	-0.68%	**-1.8027** *	-0.23%	**-1.8169** *	1.01	**-2.1255** **	-1.12	**-1.9945** **
(+1, +15)	0.55%	**-1.8824** *	0.67%	**1.7221** *	0.36%	**1.8646** *	0.84	**1.8624** *	0.99	**-1.8210** *
(-5, +5)	0.19%	0.9541	-0.39%	-0.8646	0.38%	1.5220	0.66	-1.3821	-1.22	-1.0364
(0, 0)	-0.86%	**-2.3544** **	-0.66%	**-2.2219** **	-0.74%	**-2.1846** **	1.38	**-2.1472** *	-1.41	**-2.0577** **

Notes: Table 7.8 presents the bank stock reactions to downgrade announcements. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 1 day before the event to 15 days following the downgrade news announcement. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N* = rating actions.

The results from the news event test employing the Boehmer et al. approach (Model XVI) show negative abnormal returns of 0.22% (significant at the 5% level), 0.25% (significant at the 10% level) and 0.07% (significant at the 10% level) on day t-6, t-5 and t-1. This may suggest anticipation of the negative (downgrade) news announcement by the market, that is, the existence of news leakage. The economic and statistical significance of the abnormal returns in the pre-event period is higher than that estimated for upgrades (in Table 7.3). The event-day abnormal return shows abnormal return of -0.86%, significant at the 5% level, which is higher in absolute value when compared with the stock market returns movement for upgrade news announcement.

Consistent with the results obtained for upgrade news announcement effects, there is evidence of a partial correction of the abnormal bank returns around the day of the news announcement. The days *t+3* and *t+4* show positive abnormal returns of 0.36% and 0.13% significant at the 10% and 5% levels, respectively. The total magnitude of correction (0.49%) is lower than the event day abnormal returns of -0.86%. This market correction for bank credit rating downgrade is less in relative terms than the corresponding results for upgrades. The other parametric approaches in the news event tests Model XVII and XVIII show consistent results with the existence of news leakage, event day significant reaction, and subsequent market correct.

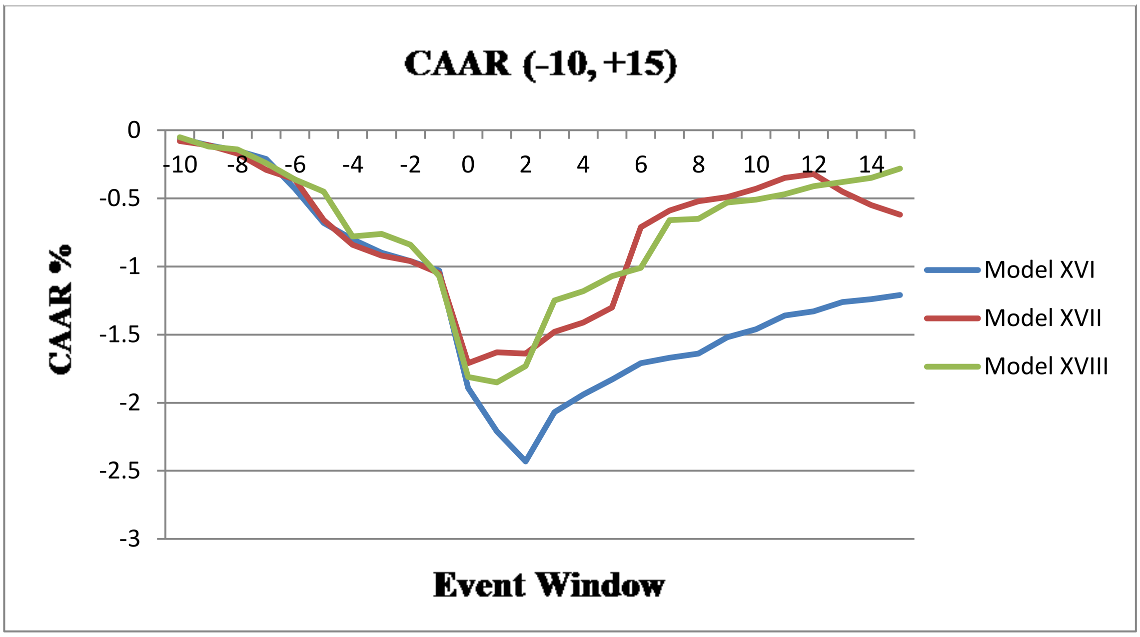
Model XVII shows negative abnormal returns over day *t-5* and *t-4* of -0.30% and 0.18% significant at the 5% and 10% level, respectively. There is an event day abnormal return of -0.66%, and subsequent market correction on day *t+6* of 0.59%, significant at the 10% level. Similarly, Model XVIII shows pre-event day news leakage on day *t-4* of -0.33% significant at the 5% level. Consistent with the other parametric specifications, there is an event day negative abnormal return of 0.74% significant at the 5% level. The market subsequently reversed this partially on day *t+3* with a positive abnormal return of 0.48% significant at the 10% level.

In addition, Model XVI results in Panel B of Table 7.8 show that the cumulative abnormal returns in the pre- and post-event windows are both significant for the parametric and nonparametric specifications. The event window (-10, -1) shows a CAAR of -0.40%, significant at the 10% level. There is an asymmetry in the way market reacts to upgrade and downgrade news information. This is evidence in the results for upgrades where the CAAR is insignificant. Similarly, the post event window (+1, +15) CAAR for downgrades shows a CAAR of 0.55%, significant at the 5% level. This is a higher correction response (in terms of magnitude) than the CAAR for upgrade news announcement for the same window. Further, Panel B shows that the results for Model XVII and XVIII are similar to those of Model XVI, with significant abnormal returns in both the pre- and post-event day periods. There is also strong evidence of partial market correction within the first week after the news announcement day.

The non-parametric approaches, that is, the Corrado and Sign tests, show much higher bank stock reactions to bank credit rating downgrade news announcements than the parametric approaches. For the pre-event day period (-10, -1), there are CAARs of -1.01% and -1.12%, significant at the 5% level for the Corrado and Sign tests, respectively. For the two specifications, there is a weak partial market correction over the post-event day period, with CAARs of 0.84% and 0.99%, significant at the 10% level for both the Corrado and Sign test. Further, for the event day reaction, the results in Panel B show strong negative abnormal returns of -1.38% and -1.41%, significant at the 5% level for the Corrado and Sign test, respectively.

Figure 7.6 shows the bank stock cumulative abnormal returns for downgrades for the whole sample over the event window (-10, +15). The Figure 7.6 shows negative (downward) movement in the cumulative returns for the three models in the pre-event day period. These downward movements continued for a couple of days following the downgrade news event announcements. The market fully corrected for the unanticipated news between days *t+3* and *t+*10, and this is depicted by the sharp upward movements in bank stock returns around this period. In addition, the graph shows that bank stock returns becomes less volatile after day *t+10,* which is the period after the full market correction.

Figure 7.6: Bank stock cumulative abnormal returns for downgrades



Overall, the results in Table 7.8 show that downgrade news announcements result in a greater market reaction (in terms of magnitude) when compared with the results in Table 7.3 for upgrade news announcements. This is consistent with the findings of several existing studies (Hand *et al.,* 1992; Schweitzer *et al*., 1992; Calderoni *et al.*, 2009). However, studies such as Abad-Romero and Roble-Fernandez (2006) find no reaction to downgrades and propose a wealth redistribution hypothesis to support their findings.

7.6.7 Results of downgrade announcements for investment-grade for bank stocks

This section presents the results of an examination of the effects of bank credit rating downgrades for investment-grade bank stocks. It attempts to give more information on whether there is asymmetry in the market reaction to subsamples of rating grades (e.g. investment- versus non-investment-grade).

Table 7.9 shows the results of Models IXX, XX and XXI which are estimates for the abnormal returns using the Boehmer *et al*., GARCH (1, 1) and the Dummy Variable approaches. Panel A shows the average abnormal returns across time and across event banks. Panel B shows the results of cumulative average abnormal returns across a range of pre-defined event windows. Further, it presents tests of statistical significance for the CAARs across the two broad (parametric and non-parametric) approaches.

Model IXX shows negative abnormal returns in the pre-event period. There are abnormal returns of -0.21% and -0.39% on days *t-6* and *t-2*, significant at the 10% level. Further, significant market returns reaction is observed on the event day. An abnormal return of -1.01%, significant at the 5% level, is observed on the event day. This is greater in magnitude than the -0.86% observed for the Model XVI, that is, the estimate of the whole sample. This suggests that downgrades within the investment-grade category result in a relatively higher magnitude of negative abnormal returns. There is an indication of partial market correction within the first week after the news announcement, with day *t+4* showing abnormal returns of 0.55%, significant at the 10% level. The magnitude of the significant abnormal return is higher than that observed for this specification for upgrades, and this implies a greater market reaction to downgrades. The results of the other parametric specifications (Model XX and XXI) are similar to those for Model IXX. Models XX and XXI show abnormal returns of -0.88% and -1.21%, significant at the 5% level.

Table 7.9: Results showing bank stock return reactions to downgrade news announcements within the investment-grade

Panel A

Day	Model IXX AAR	Model IXX T-Stat	Model IXX CAAR	Model XX AAR	Model XX T-Stat	Model XX CAAR	Model XXI AAR	Model XXI T-Stat	Model XXI CAAR
-10	-0.08%	-0.1251	-0.08%	-0.02%	-1.4574	-0.02%	-0.12%	-1.2511	-0.05%
-9	-0.12%	-0.8425	-0.20%	-0.05%	-1.3515	-0.07%	-0.07%	-1.3254	-0.12%
-8	-0.08%	-0.8954	-0.28%	-0.07%	-0.5488	-0.14%	-0.03%	-12565	-0.14%
-7	-0.03%	-0.6583	-0.31%	-0.11%	-1.3690	-0.25%	-0.10%	-1.5582	-0.24%
-6	-0.21%	**-1.8515** *	-0.52%	-0.07%	-1.2551	-0.32%	-0.09%	-0.9871	-0.36%
-5	-0.11%	-1.3001	-0.63%	-0.15%	-0.5472	-0.47%	-0.26%	**-1.8821** *	-0.45%
-4	-0.06%	-0.1583	-0.69%	-0.10%	-1.2221	-0.57%	-0.12%	-1.5991	-0.78%
-3	-0.13%	-1.3251	-0.82%	-0.06%	-0.8783	-0.63%	-0.12%	1.4002	0.76%
-2	-0.16%	-1.5484	-0.98%	-0.08%	-1.2148	-0.71%	-0.10%	-0.2226	-0.84%
-1	-0.32%	**-1.8683** *	-1.30%	-0.14%	-1.0154	-0.85%	-0.42%	**-2.3484** **	-1.07%
0	-1.01%	**-2.2566** **	-2.31%	-0.88%	**-2.3223** **	-1.73%	-1.21%	**-2.2973** **	-1.81%
+1	-0.12%	-1.6663	-2.43%	0.12%	1.2154	-1.61%	-0.12%	-0.5480	-1.85%
+2	-0.15%	-0.9584	-2.58%	-0.22%	-0.7816	-1.83%	-0.06%	-0.1290	-1.73%
+3	-0.06%	-1.2354	-2.64%	0.07%	1.3581	-1.76%	-0.21%	-0.6922	-1.25%
+4	0.55%	**1.9666** *	-2.09%	0.63%	**2.1215** **	-1.13%	0.78%	**2.2231** **	-1.18%
+5	0.12%	1.4052	-1.97%	-0.06%	-1.2214	-1.19%	0.21%	1.2810	-1.07%
+6	0.15%	0.2547	-1.82%	0.12%	1.2657	-1.07%	0.05%	1.3574	-1.01%
+7	0.06%	0.3654	-1.76%	0.07%	0.2191	-1.00%	0.10%	1.4845	-0.66%
+8	0.04%	0.8957	-1.72%	-0.04%	-1.4251	-1.04%	0.08%	1.3651	-0.65%
+9	0.04%	1.0254	-1.68%	0.04%	0.9584	-1.00%	0.11%	1.2828	-0.53%
+10	-0.03%	-1.3354	-1.71%	0.06%	1.3256	-0.94%	-0.07%	-0.8601	-0.51%
+11	0.12%	1.3622	-1.59%	0.04%	1.5547	-0.90%	0.13%	1.2548	-0.47%
+12	0.13%	1.4919	-1.46%	0.10%	1.2183	-0.80%	0.05%	1.2649	-0.41%
+13	0.09%	1.2547	-1.37%	-0.10%	-1.3741	-0.90%	-0.06%	-1.6514	-0.38%
+14	-0.07%	-0.3251	-1.44%	-0.07%	-0.7952	-0.97%	0.09%	1.5214	-0.35%
+15	0.04%	1.0474	-1.40%	-0.12%	-0.5591	-1.09%	0.10%	1.2346	-0.28%

N=771

Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	Boehmer *et al.*	T-Stat	GARCH (1,1)	T-Stat	Dummy Variable	T-Stat	Corrado Rank	T-Stat	Generalized Sign	T-Stat
(-10, +15)	-0.32%	-0.8436	-0.34%	-1.7851	-0.56%	-1.2614	0.62	-1.0214	-0.55	-1.3581
(-10, -1)	-0.22%	**-1.8666** *	-0.54%	**-1.9663** *	-0.35%	**-1.9992** *	0.88	**-2.2651** **	-1.03	**-2.3942** **
(+1, +15)	0.38%	**-1.9881** *	0.72%	**1.8884** *	0.66%	**1.9601** *	0.92	**2.2323** **	0.71	**-1.8927** *
(-5, +5)	0.10%	1.2516	-0.23%	-1.2247	0.40%	1.2841	0.23	-1.5974	-0.64	-1.0214
(0, 0)	-1.01%	**-2.2566** **	-0.88%	**-2.3223** **	-1.21%	**-2.2973** **	1.32	**-2.2666** **	-1.30	**-2.1532** **

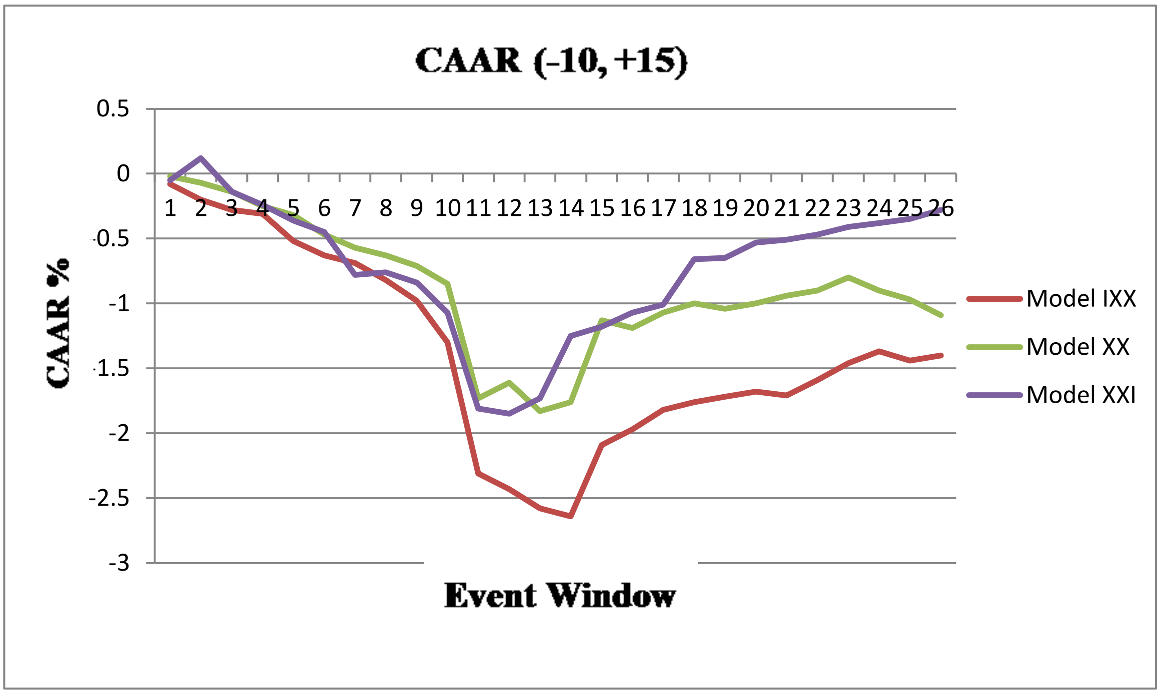
Notes: Table 7.9 presents the bank stock reactions to downgrade announcements within the investment grade. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 1 day before the event to 15 days following the downgrade news announcements within the investment grades. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

Consistent with Model IXX, they both provide evidence of partial market corrections on day *t+4* of 0.63% and 0.78%, significant at the 5% level.

The results of the CAARs over the specified periods are consistent across the parametric and non-parametric approaches. Both the pre-and post-event windows show significant abnormal returns. The result shows a CAAR of -0.22% in the pre-event window (-10, -1), significant at the 10% level. This aggregate abnormal return implies news leakage. There is full market correction as evidenced by the positive CAAR of 0.38%, significant at the 10% level in the (+1, +15) event window. For the Model XX specification, there is a negative CAAR in the pre-event window of -0.54%, significant at the 10% level. In addition, the post-event day period shows positive abnormal returns of 0.72%, significant at the 10% level. Model XXI shows a negative CAAR of -0.35%, significant at the 10% level. Consistent with the CAAR results of the other parametric approaches, there is a positive post-event window CAAR of 0.66%, significant at the 5% level. The Corrado and Sign test show event-day significant negative abnormal returns of -1.32% and -1.30%, respectively, significant at the 5% level. These magnitudes of negative abnormal returns are higher than those observed for the non-parametric approaches specifications in Table 7.8 where the whole sample is employed.

Overall, the results in this section show that downgrades within a subsample of bank investment-grade stocks elicit a greater response from the market than when the entire sample is employed (Figure 7.7). There are generally economic reactions in terms of the abnormal returns in the pre-event period as well as the event-day compared with the corresponding responses for upgrades. There is also evidence of partial market adjustments in terms of the market correcting for the excess significant abnormal returns observed on the event-day within the first few days following the news announcement events. The findings are consistent with Micu, Remolona and Wooldridge (2004). The authors argue that the greater impact of the downgrade news announcements on investment-rated entities possibly reflects investors' aversion to issuers at risk of losing their investment grade status and becoming 'fallen angels' (p. 61).

Figure 7.7: Bank stock return reactions to downgrade news announcements within the investment-grade



7.6.8 Results of downgrade announcements for noninvestment-grade bank stock

This section presents results for the effects of downgrade announcements within the noninvestment-grade. Table 7.10 shows the results for Models XXII, XXIII, and XXIV. These model specifications examine all bank credit rating downgrades within the noninvestment grades. Discrimination between investment and noninvestment-grade banks can potentially provide a better understanding of the way the market reacts to downgrade news announcements. Consistent with the earlier models, the three models presented in this section are estimated based on a 27-day event window. This event window covers the pre- and post-announcement dates (10 days before the event day and 15 days after).

Table 7.10: Results showing bank stock returns reaction to downgrade news announcement within the noninvestment-grade

Panel A	Model XXII			Model XXIII			Model XXIV		
Day	AAR	T-Stat	CAAR	AAR	T-Stat	CAAR	AAR	T-Stat	CAAR
-10	-0.02%	-0.5874	-0.02%	-0.06%	-1.3214	-0.06%	-0.03%	-1.2140	-0.03%
-9	0.03%	0.6595	0.01%	-0.03%	-1.0658	-0.09%	-0.04%	-1.3030	-0.07%
-8	0.06%	1.2651	0.07%	-0.02%	-0.8924	-0.11%	-0.06%	-1.3647	-0.13%
-7	-0.02%	-0.3666	0.05%	-0.04%	-1.3361	-0.15%	-0.01%	-1.0614	-0.14%
-6	0.05%	1.3232	0.10%	-0.03%	-1.2141	-0.18%	-0.09%	-1.2513	-0.23%
-5	-0.04%	-1.0640	0.06%	0.02%	0.2226	-0.16%	-0.07%	-1.3212	-0.30%
-4	0.03%	0.8916	0.09%	0.04%	1.3541	-0.12%	-0.06%	-1.0064	-0.36%
-3	0.09%	1.4594	0.18%	-0.05%	-0.9543	-0.17%	0.05%	1.3325	-0.31%
-2	0.04%	1.3621	0.22%	-0.03%	-1.2514	-0.20%	-0.03%	-0.8941	-0.34%
-1	-0.06%	-1.2620	0.16%	-0.04%	-1.4821	-0.24%	-0.05%	-1.4471	-0.39%
0	-0.10%	-0.8613	0.06%	-0.06%	-1.3228	-0.30%	-0.11%	-1.3364	-0.50%
+1	-0.07%	-1.2397	-0.01%	0.03%	0.8638	-0.27%	-0.09%	-0.7621	-0.59%
+2	0.11%	0.7513	0.10%	-0.04%	-1.2239	-0.31%	-0.03%	-0.6508	-0.62%
+3	-0.06%	-1.0062	0.04%	-0.06%	-1.0551	-0.37%	-0.04%	-0.7921	-0.66%
+4	0.12%	1.3255	0.16%	-0.01%	-1.0084	-0.38%	0.03%	1.3328	-0.63%
+5	0.05%	1.2144	0.21%	0.04%	1.2647	-0.34%	0.02%	1.0844	-0.61%
+6	0.02%	0.6691	0.23%	-0.10%	1.0669	-0.44%	0.05%	1.3721	-0.56%
+7	0.06%	1.2395	0.29%	0.03%	1.2151	-0.41%	0.07%	1.4325	-0.49%
+8	0.07%	0.7732	0.36%	-0.02%	-1.0012	-0.43%	0.03%	0.2151	-0.46%
+9	-0.03%	-1.1212	0.33%	-0.06%	-0.3694	-0.49%	0.10%	1.5959	-0.36%
+10	-0.02%	-1.3934	0.31%	0.02%	1.0627	-0.47%	-0.01%	-0.7621	-0.37%
+11	0.05%	0.2155	0.36%	0.01%	1.3694	-0.46%	0.04%	1.1125	-0.33%
+12	0.04%	1.3397	0.41%	0.02%	1.2265	-0.44%	0.07%	1.3621	-0.26%
+13	-0.06%	-1.0321	0.35%	-0.04%	-1.1122	-0.48%	-0.03%	-1.2252	-0.29%
+14	-0.02%	-0.3666	0.33%	-0.06%	-0.8924	-0.54%	0.09%	1.0258	-0.20%
+15	0.01%	1.1214	0.34%	-0.10%	-1.3658	-0.64%	0.03%	1.3290	-0.17%

N=137

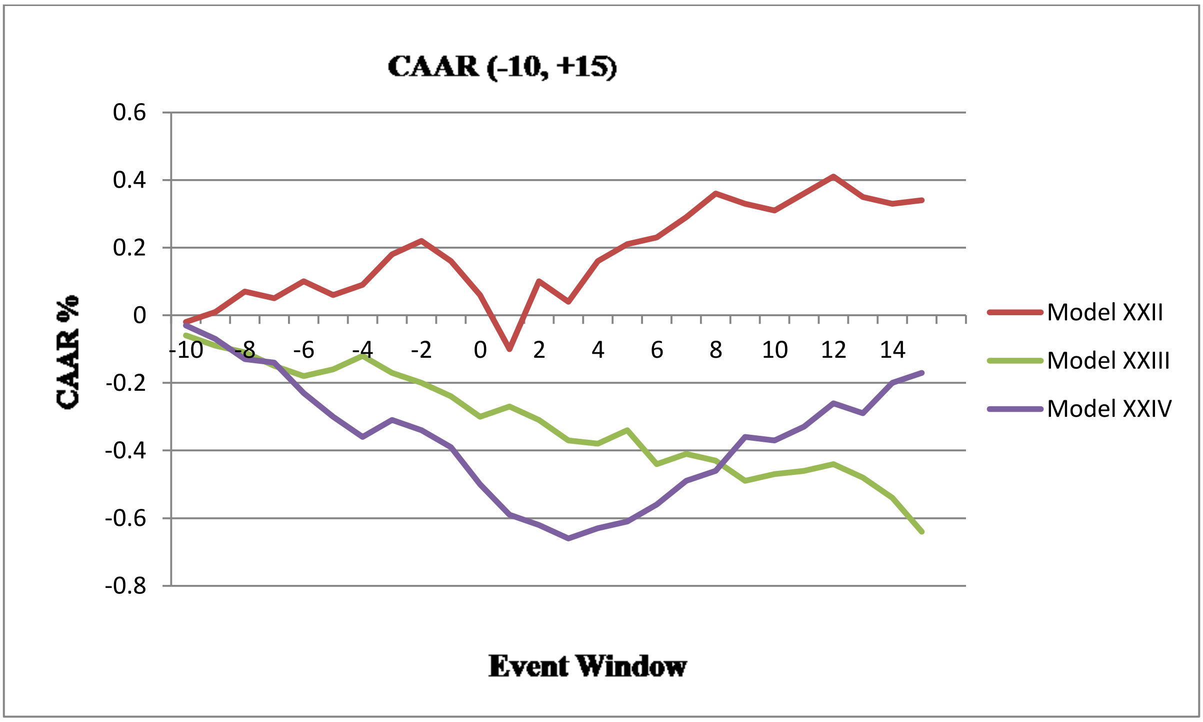
Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	Boehmer *et al.*	T-Stat	GARCH (1,1)	T-Stat	Dummy Variable	T-Stat	Corrado Rank	T-Stat	Generalized Sign	T-Stat
(-10, +15)	-0.02%	-1.2584	-0.11%	-1.0321	-0.13%	-1.2651	-0.12	-1.4453	-0.19	-1.0325
(-10, -1)	0.09%	0.6566	-0.13%	-0.8989	-0.11%	-0.9583	-0.24	-0.7974	-0.33	-1.2254
(+1, +15)	0.10%	1.0512	0.06%	0.5682	0.07%	1.1158	0.13	1.3358	0.21	1.3222
(-5, +5)	0.06%	0.6848	-0.07%	-1.2668	0.12%	1.2383	-0.11	-1.0024	-0.09	-1.0045
(0, 0)	-0.10%	-0.8613	-0.06%	-1.3228	-0.11%	-1.3535	-0.33	-1.4973	-0.42	-0.8642

Notes: Table 7.10 presents the bank stock reactions to downgrade announcements within the noninvestment grade. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 1 day before the event to 15 days following the downgrade news announcements within the noninvestment grades. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

Panel B shows the results of cumulative average abnormal returns across a range of pre-defined event windows. In addition, Panel B presents tests of statistical significance for the CAARs across the two broad (parametric and non-parametric) approaches. Figure 7.8 shows the results of stock cumulative abnormal returns for downgrades within the noninvestment grades. The results across all the model specifications show that there are no observed significant abnormal returns for bank credit rating downgrades within the noninvestment grades. The magnitude of the abnormal returns is lower than that of other downgrade specifications discussed thus far. In terms of the signs of the abnormal returns in the event window, there are no clear patterns. Similarly, the CAARs show no significant abnormal returns in either the parametric or the non-parametric approaches. The results are opposite to those of Ederington and Goh (1998) who find that downgrades within the non-investment category result in greater stock movements than within the investment-category.

Figure 7.8: Bank stock cumulative abnormal returns for downgrades (noninvestment grade)



7.6.9 Results of news announcement bank stock return reactions to unanticipated downgrades

This section presents results for bank stock reactions to unanticipated bank credit downgrade announcements. It investigates a subset of the sample banks, conditioned on anticipated news in the form of outlook announcements or placements on the Watchlist. It makes the assumption that a downgrade not preceded by a negative outlook and/or placement on a Watchlist results in a greater market reaction than the case when there is an anticipation of the downgrade news. The estimations of the abnormal returns for the event windows are presented in Models XXV–XVII. The results of the estimations are presented in Table 7.11. These models follow the Boehmer *et al.*, GARCH (1, 1) and the dummy variable approach respectively. Panel A shows the abnormal returns over the 27-day event window, while Panel B presents the results of the CAARs over various pre-specified event windows. There are no observable significant abnormal returns in the pre-event period, except for day *t-1* in Model XXV where there is a negative abnormal return on 0.12%, significant at the 5% level. The event day abnormal returns are consistently significant across the three Models parametric specifications. The magnitudes of the abnormal returns are higher than those observed in earlier models for downgrades. There are significant negative abnormal returns of -1.33%, -1.42% and -1.55% respectively across the Models XXV, XXVI and XXVII, respectively, all significant at the 5% level. Consistent with the earlier models, there is evidence of partial market correction within the first week after the event day. There is an abnormal return of 0.78%, significant at the 10% level in Model XXV, while Model XXVII shows an abnormal return of 0.12% (significant at the10% level) and 0.66% (significant at the 5% level). It is interesting to note that there are no observed significant CAARs for the parametric approach (Model XXV, XXVI and XXVII).

Table 7.11: Results showing bank stock return reactions to unanticipated credit rating downgrade news announcements

Panel A	**Model XXV**			**Model XXVI**			**Model XXVII**		
Day	**AAR**	**T-Stat**	**CAAR**	**AAR**	**T-Stat**	**CAAR**	**AAR**	**T-Stat**	**CAAR**
-10	-0.02%	-0.5514	-0.02%	-0.03%	-1.0155	-0.03%	-0.01%	-1.0214	-0.01%
-9	-0.04%	-0.6693	-0.06%	-0.02%	-1.2211	-0.05%	-0.03%	-1.3151	-0.04%
-8	-0.03%	-0.6161	-0.09%	-0.04%	-0.9827	-0.09%	-0.06%	-0.8621	-0.10%
-7	-0.03%	-1.2344	-0.12%	-0.08%	-1.1114	-0.17%	-0.03%	-1.3360	-0.13%
-6	0.09%	-0.9547	-0.03%	-0.03%	-0.4848	-0.20%	-0.02%	-1.2125	-0.15%
-5	0.04%	-1.0151	0.01%	-0.06%	-1.3281	-0.26%	-0.04%	-1.0600	-0.19%
-4	-0.03%	-0.6997	-0.02%	-0.03%	-0.9952	-0.29%	-0.03%	-1.2369	-0.22%
-3	-0.07%	-1.2241	-0.09%	-0.05%	-0.7762	-0.34%	-0.01%	-0.9964	-0.23%
-2	-0.02%	-0.2533	-0.11%	-0.03%	-1.3548	-0.37%	0.06%	0.2293	-0.17%
-1	-0.12%	**-2.2214** **	-0.23%	-0.07%	-1.0877	-0.44%	0.02%	1.4932	-0.15%
0	-1.33%	**-2.3952** **	-1.56%	-1.42%	**-2.3314** **	-1.86%	-1.55%	**-2.2355** **	-1.70%
+1	-0.55%	-0.8784	-2.11%	-0.08%	1.5580	-1.94%	-0.06%	-0.6251	-1.76%
+2	-0.04%	-0.3692	-2.15%	-0.02%	-0.3658	-1.96%	0.02%	1.2323	-1.74%
+3	0.11%	0.6692	-2.05%	0.05%	1.2760	-1.91%	0.05%	0.2166	-1.69%
+4	0.22%	1.4682	-1.85%	0.06%	0.8832	-1.85%	0.12%	**1.6925** *	-1.57%
+5	0.06%	1.3913	-1.79%	0.68%	**2.3005** **	-1.17%	0.66%	**2.2251** **	-0.91%
+6	0.78%	**1.8924** *	-1.01%	0.06%	0.3842	-1.11%	0.03%	1.2581	-0.88%
+7	0.23%	0.6584	-0.74%	-0.08%	1.5947	-1.19%	0.07%	0.9324	-0.81%
+8	0.18%	0.9837	-0.56%	0.04%	1.8264	-1.15%	0.03%	1.3318	-0.78%
+9	0.10%	1.0315	-0.46%	0.01%	0.9863	-1.14%	0.08%	1.6262	-0.70%
+10	0.15%	-1.3480	-0.31%	0.03%	1.2276	-1.11%	-0.03%	-1.3235	-0.73%
+11	0.04%	-1.0045	-0.27%	0.05%	1.6251	-1.06%	-0.02%	-0.9937	-0.75%
+12	0.06%	1.1285	-0.21%	0.02%	1.6682	-1.04%	0.03%	1.3236	-0.72%
+13	0.03%	0.9806	-0.18%	-0.06%	-0.5330	-1.10%	0.02%	1.2929	-0.70%
+14	0.04%	1.2240	-0.14%	-0.02%	-0.8854	-1.12%	-0.01%	-0.3621	-0.71%
+15	0.02%	1.3364	-0.12%	-0.03%	-0.7921	-1.15%	0.02%	0.1547	-0.73%

N=233

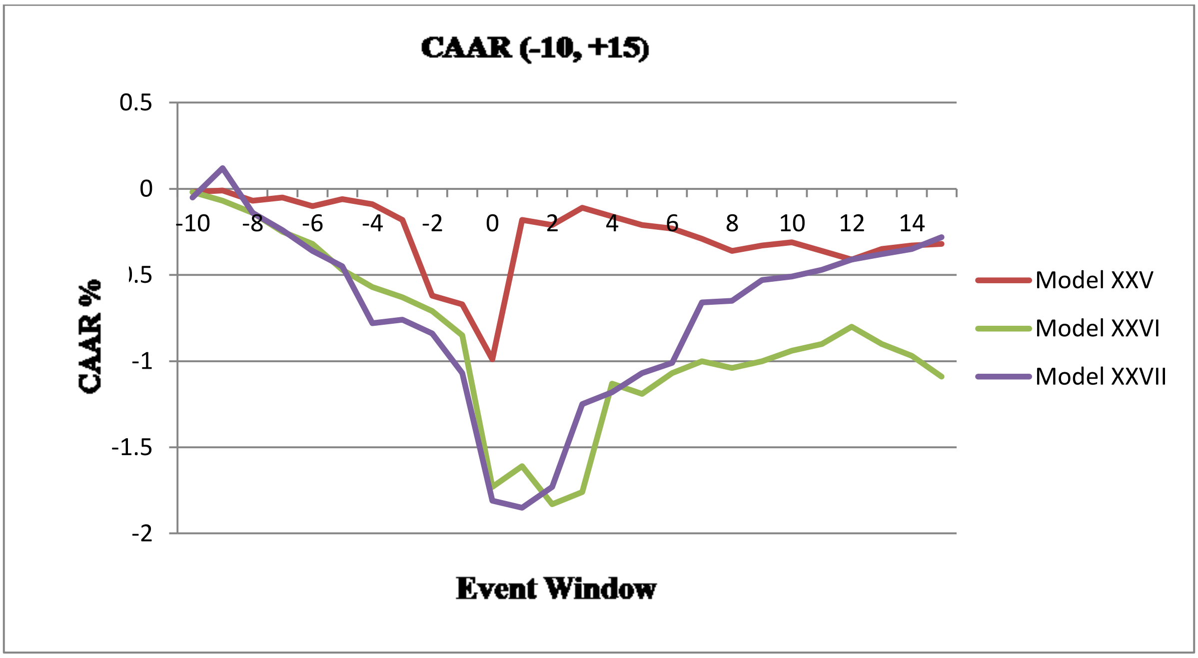
Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	**Boehmer *et al.***	**T-Stat**	**GARCH (1,1)**	**T-Stat**	**Dummy Variable**	**T-Stat**	**Corrado Rank**	**T-Stat**	**Generalized Sign**	**T-Stat**
(-10, +15)	-0.06%	-1.2581	-0.07%	-1.2254	-0.06%	-1.0505	0.09	-1.0021	-0.12	-1.1001
(-10, -1)	-0.12%	-1.0057	-0.04%	-1.1282	-0.10%	-0.6482	1.11	-1.1837	-0.08	-0.8233
(+1, +15)	0.15%	-1.3541	0.10%	0.9932	0.15%	1.1147	0.53	**1.7514** *	0.89	**-1.8211***
(-5, +5)	0.07%	0.5174	-0.24%	-0.6281	0.11%	1.2281	0.11	-1.0051	-0.62	-1.1382
(0, 0)	-1.33%	**-2.3952** **	-1.42%	**-2.3314** **	-1.55%	**-2.2355** **	1.66	**-2.3231** **	-1.77	**-2.3341** **

Notes: Table 7.11 presents the bank stock reactions to unanticipated downgrade announcements. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 15 days before the event to 1 day before the news announcement for unanticipated downgrade. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

The non-parametric approaches, the Corrado and the Sign tests, show an event-day CAAR of -1.66% and -1.77%, both significant at the 5% level. The post-event period CAARs are 0.53% and 0.89%, significant at the 10% level for the Corrado and Sign tests, respectively. Figure 7.9 shows the bank stock abnormal returns for unanticipated downgrades across the different specifications.

Figure 7.9: Bank stock cumulative abnormal returns for unanticipated downgrades



7.6.10 Results for stock return reactions to downgrade news announcements on bank rating reclassifications

This section presents the results of bank stock return reactions to downgrades across the investment threshold, that is, from BBB- to BB+. Again, the investigation of the category of downgrades is motivated by the potential behaviour of institutional investors who may have mandates to invest only in investment grade bank stocks. The estimations of the abnormal returns for the event windows are presented in Models XXVIII–XXX. The results of the estimations are presented in Table 7.12. These models follow the Boehmer *et al*. (1991), GARCH (1, 1) and the Dummy Variable approach respectively. Panel A shows the abnormal returns over the 27-day event window.

Table 7.12: Results showing bank stock return reactions to downgrade news announcements for bank rating reclassifications

Panel A	Model XXVIII			Model XXIX			Model XXX		
Day	**AAR**	**T-Stat**	**CAAR**	**AAR**	**T-Stat**	**CAAR**	**AAR**	**T-Stat**	**CAAR**
-10	-0.03%	-0.3151	-0.02%	-0.05%	-1.3214	-0.03%	-0.03%	-1.4514	-0.01%
-9	-0.06%	-0.7845	-0.06%	-0.03%	-1.0269	-0.05%	-0.05%	-1.2558	-0.04%
-8	-0.07%	-0.8585	-0.09%	-0.10%	-1.1158	-0.09%	-0.06%	-1.0081	-0.10%
-7	-0.12%	-0.3681	-0.12%	-0.05%	-1.3267	-0.17%	-0.04%	-1.1247	-0.13%
-6	0.01%	-0.9547	-0.03%	-0.04%	-0.8471	-0.20%	-0.03%	-1.0014	-0.15%
-5	0.03%	-1.2231	0.01%	-0.05%	-1.0902	-0.26%	-0.06%	-1.2151	-0.19%
-4	-0.12%	-1.2154	-0.02%	-0.09%	-1.5323	-0.29%	-0.10%	-1.0211	-0.22%
-3	-0.09%	-1.0521	-0.09%	-0.01%	-0.8866	-0.34%	-0.12%	-0.8514	-0.23%
-2	-0.11%	-0.8854	-0.11%	-0.03%	-1.4545	-0.37%	0.11%	0.6500	-0.17%
-1	-0.07%	-1.3289	-0.23%	-0.08%	-1.1258	-0.44%	0.09%	1.2647	-0.15%
0	-0.66%	***-2.4999*** **	-1.56%	-0.52%	***-2.4051*** **	-1.86%	-0.61%	***-2.3385*** **	-1.70%
+1	-0.23%	-1.3791	-2.11%	0.12%	1.2214	-1.94%	-0.11%	-0.7814	-1.76%
+2	-0.10%	-0.3254	-2.15%	0.10%	0.8470	-1.96%	0.03%	1.2217	-1.74%
+3	0.07%	0.8201	-2.05%	0.06%	1.1123	-1.91%	0.04%	1.3351	-1.69%
+4	0.19%	0.3624	-1.85%	0.07%	0.8914	-1.85%	0.10%	0.6327	-1.57%
+5	0.08%	1.5591	-1.79%	0.10%	0.6951	-1.17%	0.10%	0.7821	-0.91%
+6	0.23%	0.2516	-1.01%	0.09%	1.3528	-1.11%	0.06%	1.1214	-0.88%
+7	0.11%	0.8513	-0.74%	0.02%	1.6624	-1.19%	0.04%	1.3661	-0.81%
+8	0.06%	0.3593	-0.56%	0.09%	1.2514	-1.15%	0.09%	1.0219	-0.78%
+9	0.11%	1.1154	-0.46%	0.03%	0.8416	-1.14%	0.11%	1.1254	-0.70%
+10	0.07%	-1.2972	-0.31%	0.02%	1.1284	-1.11%	-0.02%	-1.3658	-0.73%
+11	0.03%	0.2141	-0.27%	0.06%	1.5532	-1.06%	-0.06%	-0.4755	-0.75%
+12	0.21%	1.6565	-0.21%	0.05%	1.2316	-1.04%	0.04%	1.3499	-0.72%
+13	0.06%	0.7820	-0.18%	0.03%	-0.6641	-1.10%	0.07%	1.2788	-0.70%
+14	0.03%	1.3051	-0.14%	-0.06%	-1.1473	-1.12%	-0.03%	-1.1143	-0.71%
+15	0.07%	1.0084	-0.12%	-0.04%	-0.8931	-1.15%	0.06%	0.2791	-0.73%

N=108

Panel B: Cumulative abnormal returns (CAARs) results for both the parametric and non-parametric approaches

Dates	**Boehmer *et al.***	**T-Stat**	**GARCH (1,1)**	**T-Stat**	**Dummy Variable**	**T-Stat**	**Corrado Rank**	**T-Stat**	**Generalized Sign**	**T-Stat**
(-10, +15)	-0.10%	-1.2565	-0.15%	-1.0014	-0.18%	-1.1525	0.17	-1.1158	-0.05	-1.1021
(-10, -1)	-0.08%	-1.1579	-0.10%	-1.3586	-0.12%	-0.9232	0.04	-1.3947	-0.12	-0.7514
(+1, +15)	0.13%	1.2158	0.12%	1.0814	0.15%	1.1347	0.17	0.2514	0.19	-1.0089
(-5, +5)	0.07%	0.2514	-0.07%	-0.6851	0.07%	1.2201	0.13	-1.2141	-0.10	-1.2514
(0, 0)	-0.66%	***-2.4999*** **	-0.52%	***-2.4051*** **	-0.61%	***-2.2385*** **	0.81	***-2.2985*** **	-0.88	***-2.3111*** **

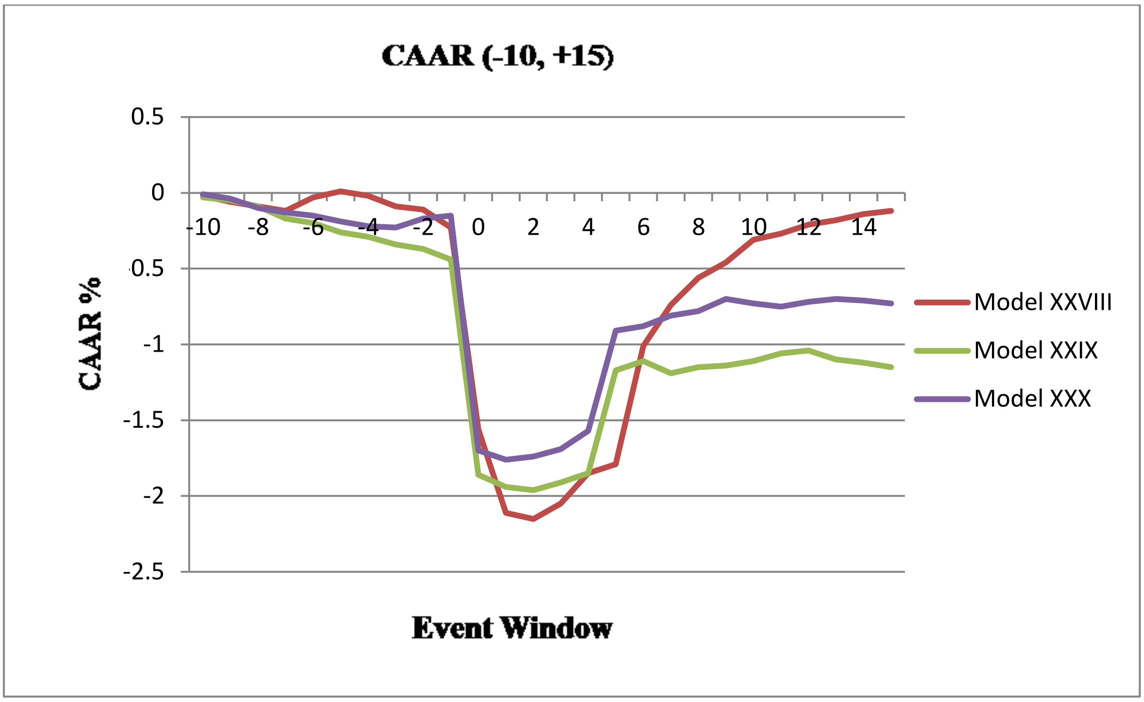
Notes: Table 7.11 presents the bank stock reactions to bank credit rating downgrade reclassification announcements. AAR is the Average Abnormal Return, and CAAR is the Cumulative Average Abnormal Return. Averaging was carried out across time and across event banks. The event window extends from 15 days before the event to 1 day before the news announcement for downgrade reclassification. The event day consists of two trading days. The significance of the t-statistics for the null hypothesis that AAR is zero is indicated by ***, ** and * for the 1%, 5% and 10% levels of significance respectively which are also shown in italicized bold. *N*=rating actions.

Panel B presents the results of the CAARs over various event windows for both the parametric and non-parametric approaches. The results are consistent across the three models and show significant negative abnormal returns on the event day. Model XXVIII shows an abnormal return of -0.66%, significant at the 5% level on day *t=0.* Similarly, the results for Models XXIX and XXX both show abnormal returns of -0.52% and -0.61%, respectively, all significant at the 5% level.

There is no indication of any significant post-event day abnormal returns, which may suggest that the market did not correct for the observed abnormal returns on the event day. The CAARs over the pre-specified event windows do not show significant abnormal returns. Similarly, the results from the nonparametric approach show no significant abnormal returns over the specified period. However, on the event day, the Corrado rank test shows an abnormal return of 0.81%, significant at the 5% level, while the generalized sign test shows an abnormal return of 0.88%, significant at the 5% level on the event day.

Figure 7.10 shows the results of bank stock cumulative abnormal returns for downgrades (reclassifications). The results are consistent with Hand *et al.* (1992) and Kliger and Sarig (2000) who find that downgrades, particularly those from investment- to non-investment categories, result in considerable negative price movements. The results for the rating classification within this section could be linked to the widespread regulatory use of credit ratings. This has the potential of effecting an unintended action since downgrades across thresholds could lead to systemic reactions by a number of regulated market participants. Again, the use of credit ratings in private decision making-rules, e.g. in internal guidelines by institutional investors and private contracts, could result in a rating trigger.

Figure 7.10: Bank stock cumulative abnormal returns for downgrade (reclassification)



7.7 Summary

This chapter presents evidence on bank stock return reactions to bank credit rating news announcements. By examining whether credit rating agencies possess information not already available to the market, it gives a better understanding of the roles of these agencies. The core of the theoretical framework for this component of the thesis is the EMH. Information efficiency is important within the context of an event study where market participants are assumed to be rational. The information content of news events becomes critical in the assessment of the efficiency or otherwise of the market.

This chapter adopts the event study methodological approach in testing for the presence of significant abnormal returns over an event window. The approach adopts three parametric and two non-parametric news event test specifications. This is to ensure robustness in the estimations and specifications. Further, the thesis, apart from investigating broad upgrade and downgrade news effects on bank stock return behaviour, examines subsamples of these news announcements. Thus, the impact of news announcements relating to the effects of upgrades/downgrades of banks within the investment and non-investment categories, and also the effects of unanticipated changes are examined. The general position in the existing studies is that there are asymmetries in the way market reacts to credit rating news announcements. Downgrade results are usually associated with a significant abnormal price movement around the date of news announcement, while for upgrades the reactions are minimal.

This thesis shows that for bank stocks, there are also considerable market price movements for upgrades within certain credit rating notches. For example, upgrade announcements within the investment category show significant abnormal returns on the day of the event across all the specifications (both parametric and non-parametric). There is also some evidence of partial market correction in the post-event day period. Similarly, unanticipated bank credit rating upgrades produce event day significant positive market reactions to the news announcements. Within the sample of banks and different specifications employed in this chapter, the results for the downgrades are consistent with the findings in the literature. The results within the different model specifications show consistent negative abnormal returns on the event day, except for downgrade news announcement for noninvestment-grade bank stock. The magnitude of these abnormal returns varies considerably across the specifications. Downgrades for investment-grade bank stocks and downward reclassification (across rating thresholds) elicited greater negative abnormal returns. This negative reaction may be associated with institutional investors realigning their portfolio to reflect the mandate of clients for investment in top rated bank stocks. There is also evidence of partial market corrections to the negative significant abnormal returns in the full sample estimation following downgrade announcements. Finally, the non-parametric results show a greater level of significance and economic magnitude for the abnormal returns than is the case in the parametric specifications.

CHAPTER 8. AN EMPIRICAL INVESTIGATION OF BANK CREDIT RISK MIGRATION: A RATING TRANSITION ANALYSIS

8.1 Introduction

The subject of credit risk in the banking industry is critically important, especially following the global financial crisis. Credit rating agencies (CRAs) assign ratings to banks (as well as other companies) with the aim of assessing the credit quality of these entities. A change in credit rating reflects an assessment that a bank's credit quality has improved (upgrade) or deteriorated (downgrade). This chapter builds on the empirical work in Chapters 6 and 7 by investigating bank credit rating migration. Chapter 6 presents the results of models of the determinants of bank credit ratings. By incorporating both financial and non-financial information in alternative model specifications, the chapter provides an insight into the joint and individual significance of the variables expected to impact on the way rating agencies assign letter ratings to the credit qualities of banks. Chapter 7 examines the impact of changes in bank credit rating qualities, that is, upgrades and downgrades, as well as other rating related actions on bank stock prices, testing for the significance of abnormal returns around announcements relating to bank credit rating changes.

This chapter deals with an equally important aspect of bank credit ratings by investigating credit rating dynamics, focusing on rating migration based on the historical pattern of ratings and ratings changes. The global financial crisis has given rise to a global review of the credit rating methodologies employed by rating agencies as well as the reclassification of rating notches, especially for banks. The post-crisis period witnessed an unprecedented number of downgrades and perhaps an overall decline in bank creditworthiness globally. Further, one might suggest that credit rating agencies have become more conservative in their assessment criteria, methodologies and reviews of bank creditworthiness in the period following the global financial crisis years. Perhaps the need to err on the side of caution and atone for the apparently generous rating notches assigned to issuers and their issues in the boom period prior to the crisis, as well as the focus of regulators on their activities led to this tightening of requirements by the CRAs. This chapter employs various empirical models including those developed in earlier empirical components of this thesis to analyse changes in the credit rating quality of banks for the period 2000-2012.

This chapter considers the estimation bank credit rating transition matrices based on the migration of ratings from one notch or rating category, i, at the beginning of a period to another notch, j, at the end of the period. Specifically, the chapter explores the two approaches to measuring and estimating transition matrices as suggested in the literature (e.g. Lando and Skodeberg, 2002; Jafry and Schuermann, 2004). These are: (i) the *discrete-time cohort* method; and (ii) estimators based on *continuous observations* (*duration or hazard approach*). In both the cohort and the hazard approach, the estimates of the transition probabilities constitute the entries of the transition matrix. In addition, the chapter tests for the presence of non-Markovian behaviour.

Following Lando and Skodeberg (2002), this thesis sets up a framework to test whether bank transition intensities are dependent on certain covariates. The covariate here refers to an indicator that keeps track of an influence on a bank's transition intensity. One of the objectives of this component of the thesis is to test for non-Markovian effects on transition, such that the covariate will be a variable describing whether the previous move was an upgrade or a downgrade or the duration in the present state for each bank. The thesis recognises that these bank rating transitions could be influenced by macroeconomic variables or other factors capturing the business cycle (Nickell *et al*., 2000). Thus, the framework model is constructed to capture any of these fluctuations via baseline intensity as suggested by Lando and Skodeberg (2002). The thesis does not model the influence of bank financial and non-financial information within the transition matrix framework.

The organisation of the rest of this chapter is as follows. Section 8.2 presents the theoretical framework around the basic approach to rating migration – the Markov process. A review of related literature and methodological approaches for the various empirical approaches within this chapter is presented in Sections 8.3 and 8.4, respectively. Section 8.5 discusses the results, focusing on the descriptive statistics for the data as well as the main empirical results. Section 8.6 summarises the findings.

8.2 Theoretical framework – The Markov chain approach

One strand of the credit risk modelling literature employs the use of a matrix of transition probabilities to explain the change in the credit quality of an entity. The accurate estimation of these transition matrices is very important. Banks, as well as other rated entities, take on letter ratings which measure their relative creditworthiness. A bank can stay in a particular grade or rating category as long as its credit assessment remains relatively stable and within the bounds of that category. The survival or otherwise of a bank in a particular rating grade can be observed by examining a transition matrix. Transition matrix reports, particularly those published by the major CRAs, form the basis of most credit risk management techniques such as McKinsey's Credit Portfolio View and Credit Metrics developed by J.P. Morgan. The importance of bank credit rating migration is also crucial in portfolio risk assessment and assessments of regulatory capital. For the purpose of the analyses within this component of the thesis, the transition matrix gives an indication of the distance that rating downgrades/upgrades migrate, the average survival or duration within a particular rating notch, and hence the overall trends of credit rating during the sample period. So, given a bank credit rating today, say A+,[10] the letter rating of that bank one year from now will depend, among other things, on the probability that it will remain at A+, migrate to a higher or lower credit grade category, or even default at the year-end.

According to Jarrow *et al.* (1997), the rating migration process is underpinned by two major assumptions:

i) *Markovian behaviour*. This assumes that the probability of transiting from a current state i to a future state j (i.e. the transition intensity) depends only on the credit quality information contained in the current state *i,* and is independent of the rating history (Gallati, 2003). This implies that all information needed to predict the future rating direction of an entity is contained in the current rating.

ii) *Time homogeneity*: Following from the above assumption, that is, when a one-step transition over a specified time horizon ($t\ to\ \ t + \Delta t$) is time independent, then, the Markov chain process is assumed to be stationary (time-homogenous). The bank credit migration matrices depict the dynamic evolution of the credit quality of banks over time. These transition matrices are constructed by mapping the historical ratings of say, a bank, on to their transition probabilities.

The traditional transition probability matrix follows the first-order, time-homogeneous Markov model, which is based on the two assumptions, (i) and (ii) above. A bank is rated in d categories ranging from 1 (i.e. AAA rating), the best rating category, to the category d (the worst rating), and ratings can transit between this finite set of categories. The raw data consists of a collection of migration events, which are rating movements (upgrades, downgrades or in most cases no change). Let $N_i(t)$ denote the number of banks at the beginning of year t rated i and $N_{ij}(t, t+1)$ the subset of banks observed to

[10] The letter is based on the Fitch fine grading nomenclature employed in this thesis.

have migrated to rating j by year beginning $t+1$. The relative frequency, that is, probability of migration from state i to j can be denoted by,

$$\hat{q}_{ij}(t, t+1) = \frac{N_{ij}(t,t+1)}{N_i(t)} \qquad 8.1$$

in years $t = 1, \ldots, T$.

If one assumes a time-homogeneous Markov rating process, the maximum likelihood (ML) estimator of the one-year credit risk migration is

$$\hat{q}_{ij} \equiv \hat{q}_{ij}(1) = \frac{\sum_{t=1}^{T} N_{ij}(t,t+1)}{\sum_{t=1}^{T} N_i(t)} = \frac{N_{ij}}{N_i} \quad j \neq i \qquad 8.2$$

Thus, the total numbers of annual bank ratings migrating from state i to *j,* i.e. $\hat{q}_{ij}$ is simply the total number of annual migrations between these two states divided by the total number of banks in state *i* at the state of the period (Fuertes *et al.*, 2011). Hardle *et al.* (2005) suggest that to obtain an *n-cohort* migration matrix, $\widehat{Q}(n) = \widehat{Q}^{\,n}$, where $\widehat{Q}$ is obtained from 8.2, the Markov process must conform to the time-homogeneity assumption. A consequence of the above is that if a transition from *i* to *j* does not occur in a given period, then the estimate of the corresponding rate is 0.

Therefore, the distribution of the ratings is independent over time and across banks and the probability of transition is constant over time. The method described thus far is the traditional *discrete-time cohort* approach, which is very popular with most of the major CRAs. It assumes a specific time horizon, typically 1, 2, 5 or 10 years. A major weakness of the *cohort* approach is that it neglects rating changes within a particular specified time horizon, and also the duration of a firm staying at that particular rating. One of the ways around this is the use of a *continuous-time* maximum likelihood (CTML) framework which presents the best way to capture all bank credit rating transition probabilities as it encompasses all necessary historical rating information. This latter approach is discussed in section 8.4.

There is empirical evidence, however, to support the presence of rating momentum or drift (Altman and Kao, 1992; Carty and Fons, 1994; Lando and Skodeberg, 2002; Christensen *et al*., 2004). These studies support the position that future directions of transition probabilities are not only conditional on the current state, but are influenced by rating history. In particular, Lando and Skodeberg show that a downgraded issuer is prone to further subsequent downgrades (downward momentum). Generally, this suggests that consecutive rating changes in the same direction are likely to be more frequent than in the opposite direction. Others argue that over a short time horizon (say 1 or 2 years) the first-order Markov assumption seems to hold. Similarly, empirical evidence suggests that different transition matrices should be considered in boom and contraction periods (Arvanitis *et al*., 1999; Bangia, *et al*., 2002; Lando and Skodeberg, 2002; Mahlmann, 2006). Several previous studies also specify non-homogeneity in their models by arguing for cyclicality considerations in the treatment of credit rating migration (Nickell *et al*., 2000; Kiefer and Larson, 2004). They argue that the business cycle and other external variables (e.g. geographical location, the state of the economy) exert an impact on the probability of transiting from one state to the next.

8.3 A brief literature review

A measure of the credit rating of an entity or its issues is a key indicator of the inherent credit risk associated with such as an entity or its issues. The information provided on rating constitutes an important aspect for the calculation of the capital requirement of banks in light of the recommendation of the Bank for International Settlement that banks can employ a standardized approach for assessing the risk-weighted assets of their portfolio, thus reflecting the changes in the market yield spread charged. The possibility that CRAs will change the rating of a bank may also have repercussions for investment managers whose mandate may be restricted to banks or their issues that are of certain rating categories. This section reviews existing literature in the area of credit rating transition, focusing on issues around measurement, estimation and the stability of rating transition.

Since the seminal work of Jarrow *et al.* (1997), the use of credit rating transition matrices as key components in credit risk modelling has become more prominent. The major credit rating agencies (Fitch, Moody's and Standard and Poor's) adopt a system of averaging the annual transition frequency matrices, $\boldsymbol{P}$, representing transition probabilities, with $\boldsymbol{P}_{ij}$ being the probability that a firm rated i at the beginning of the year is rated j at the end of the year. An implicit assumption here is that transition probabilities are constant over time. This time-homogeneity (which may also be referred to as stationary transition probabilities) means that the determination of an issuer's credit risk (including that of transiting to a new rating state) is dependent only on the issuer's current rating. Stationary transition probabilities thus refer to a situation whereby such probabilities are independent of the time variable, that is, historic states do not affect the current state. This assumption forms the basis of the Markov chain framework discussed in Section 8.2. This *cohort* approach to estimating rating transition matrices is still very popular with major rating agencies due to its simplicity. Under this assumption, the reported transition frequencies are only averages, and are not conditional on all available information.

Fei *et al*. (2012) maintain that if the effects of cyclical considerations are ignored, a one-year transition migration rate may not be constant over the age of a bond. There is possible dependence of transition probabilities on the duration that an entity spends in a rating category, which is referred to as *the aging effect* by Cathy and Fons (1994). Empirical evidence (e.g. Kavvathas, 2001; Lando and Skodeberg, 2002) finds that for firms in certain ratings, the prior rating is an important determinant of the likelihood of a downgrade versus that of an upgrade over a given time horizon. This argument relates to an aspect of rating transition referred to as momentum or rating drift. Despite two firms having the same rating, their credit quality may be different. Put differently, a given entity with fixed ratings has a credit quality that changes over time. In light of the above, there is growing empirical evidence (Lando and Skodeberg, 2002; Keifer and Larson, 2004; Jafry and Schuermann, 2004; Jones, 2005; Frydman and Schuermann, 2008) that supports non-Markov characteristics for credit migration matrices, and further proposes alternative treatments for such rating transitions.

Lando and Skodeberg (2002) argue for the use of a continuous time approach (as opposed to a discrete-time setting). They estimate credit rating transition based on Standard and Poor's data, while applying a semi-parametric regression technique to test for two types of non-Markovian effects in rating transition (rating drift or momentum, and duration dependence). The momentum or rating drift refers to the tendency for a higher likelihood of a downgrade if the current state was reached through a downgrade. They employ data covering 17 years of rating history based on S&P ratings from 1 January 1981 and ending 31 December 1997. They find that the use of a maximum-likelihood estimator to estimate the generator and transition matrices (assuming time homogeneity, i.e. the Markov framework) is still valid for a one-year transition matrix. However, they propose a non-parametric method which replaces the cohort method for longer time periods (say, 5-year or 10-year transition matrices). Further, when testing for duration dependency, their study employs an exponential form model as this keeps the transition intensity[11] positive. The study neglects industry effects which have been shown by Nickell *et al.* (2000) and Kavvathas (2001) to be significant. Lando and Skodeberg find that there is a strong non-Markov effect for downgrades in the aggregated data set. Similarly, both the time taken to remain in a given state (duration) and the direction from which the state was reached have significant effects on the

[11] The transition intensity represents the rate of moving from a current state *i* to a new state *j*.

downgrade transition intensity. However, the effect is less pronounced when they examine a subcategory of financial firms.

The simple, time-homogeneous Markov model, even though restrictive, is still considered useful for describing short-run changes in portfolio risk. Evidence of this Markovian behaviour is also present in issue ratings. Keifer and Larson (2004) consider testing the time-homogeneity assumption of the Markov approach over the short-run, that is, whether the transition from an initial state i to the next state j is constant over a short-time period (i.e. 1 and 2 years). They employ three sets of data, municipal bonds (obtained from S&P, from 1986 to 2000), commercial paper (from a study by Moody's in 2000, covering the period1972-1999), and sovereign debt (from S&P, covering the period 1975-2002). Their study is set against the backdrop that a given credit ratings change in reality exhibits 'momentum'. Put differently, rating change is conditional on the current rating level such that a future credit downgrade (upgrade) is perhaps likely if the entity had experienced a downgrade (upgrade) in the previous period than if it had experienced an upgrade (downgrade). They argue that since rating changes do not occur often, the transition rates reported are essentially estimators of very small probabilities. The method employed follows the basic Markov estimation framework, involving the use of the likelihood ratio test for hypothesising the time-homogeneity of rating transition. Their results indicate that municipal bond ratings as well as commercial paper ratings can be adequately described as time-homogeneous over as much as five-years. With respect to the sovereign ratings, Markov specifications are rejected, possibly due to the very small sample size.

In a similar study, Jafry and Schuermann (2004) attempt to compare two approaches to the measurement and estimation of credit rating migration matrices. They explore the cohort and two variants of duration (i.e. one imposing, and the other relaxing, time homogeneity). They further develop a testing procedure based on the bootstrap technique to statistically assess the differences between migration matrices. Despite the cohort method being the industry standard due to its straightforward approach, it ignores any rating activity which occurs within the period. The variant of duration the authors propose follows a strand of literature on survival analysis applied by Lando and Skodeberg (2002). The idea underlying the duration approach is to be able to account for the time a rating spends in a particular notch and its contribution to estimating the transition probability. They maintain that for a time-homogeneous Markov chain, the transition probability matrix is a function of the distance between dates (time), but not the dates themselves.

The case for the non-Markov property of credit rating dynamics is further examined by Frydman and Schuermann (2008), particularly as it relates to the future distribution of a firm's ratings and how two firms with identical current ratings can have substantially different transition probability vectors. They propose a model consisting of a mixture of two independent continuous time homogeneous Markov chains. The assumption of the model is that the two Markov chains differ only in the speed at which they transit into a new state. The model they propose consists of two populations of firms, each moving in accordance with its own Markov chain. A continuous time homogeneous Markov chain assumes that duration in a particular state follows an exponential distribution with a constant hazard function. They employ two subsamples (independent, and moving according to their own Markov chain). They argue that the duration in a particular state is generated by one or other chain following two exponential distributions so that the observed durations in a given state come from a mixture of two exponential distributions. The implication of this is that the model's framework does not restrict firms, but rather allows them to migrate at their own speed, thereby allowing them arrive at future ratings in different ways. Employing a set of corporate credit rating histories from S&P spanning the period 1998 to 2002, they show that the mixed model not only statistically dominates the simple Markov model but that the differences in the two models is economically meaningful. They maintain that future ratings depend on the historical ratings of entities and that unlike the Markov model; all firms with a particular current rating are not assigned the same future distribution of ratings. There is also a case for heterogeneity in credit rating dynamics as firm-specific transition probabilities can vary significantly, which is a position not supported by the Markov framework.

The test for non-Markovian behaviour has also been conducted using a dataset from the finance industry. Employing credit rating histories for Columbian commercial banks, Gomez-Gonzalez and Kiefer (2009) show that the process of rating migration exhibits significant non-Markovian behaviour. Their study considers all ratings of commercial banks and financial companies from December 1996 to November 2005, including macroeconomic and bank-specific variables. The rating categories are in four categories based on the perceived riskiness of the banks. Following the traditional Markov chain approach and the approach employed by Lando and Skodeberg (2002), they find that the process of rating migration in Colombian banks exhibits significant non-Markovian behaviour, in the sense that the transition intensities are affected by macroeconomic and bank-specific variables. The study employs macroeconomic and bank specific variables including the monthly average interest rate on loans, the real production index, as well as bank capitalization ratios. As with earlier studies, they find that the continuous time framework improves the estimation of transition probabilities, and information provided by migrations alone is not enough to forecast the future behaviour of ratings.

8.4 A review and choice of the methodological approach

Section 8.2 presents the Markovian chain process and focuses on the *cohort* approach based on a discrete-time setting. It forms the basis of estimates presented by most of the rating agencies and in several academic studies, and it has become the industry standard. Hence statistical assessments using this approach seem to be appropriate. As a reminder, the transition rates are estimated as follows: For a given set of firms N_i in a certain rating category i at the beginning of the year, out of this set N_{ij} migrate to the category *j,* then one can estimate the one year transition rate as:

$$\hat{q}_{ij}(\Delta t) = \frac{N_{ij}}{N_i} \; j \neq i \qquad 8.3$$

where Δt is the time horizon (or sampling interval), say, 1 year.

This simply shows the proportion of firms at the end of the period, say, at the end of the year for an annual matrix, with rating *j* having started out with rating *i.* Equation 8.3 implies that if there is no transition from a state *i* to *j* in a given period, then the estimate of the transition rate is 0. The rating change events that occur within this period are not captured and are unfortunately ignored. Hence, there is a need to employ continuous-time data on rating transition to capture events such as multiple rating changes within a year. Under the condition of equation 8.3, Carty and Fons (1997) suggest that firms whose ratings are withdrawn or migrated to the *Not Rated* (*NR*) status are removed from the sample. The cohort method treats the *NR* state as non-informative. Similarly, the cohort method neglects what Jafry and Schuermann (2004) refer to as *censoring* and *truncation*, both linked with using rating histories. The *censoring* refers to situations where the approach does not take into account what happens to the firm after the sample window closes; and *truncation* is where firms only enter into the sample if they have survived long enough or have received a rating.

Building on the traditional Markov (1-year discrete-time) process described in Section 8.2, the first part of this section explores the hazard-rate or duration approach which comes under the class of empirical study referred to as survival analysis. Consider an *N*-

state homogenous Markov chain where the rating notch with the highest rating 'AAA' is assigned 1, and notch d is the worst denoting say, the default state. Following Jafry and Schuermann (2004), for a time homogeneous Markov chain, the transition probability matrix is a function of the distance between dates (i.e. *time*) but not of the dates themselves (i.e. the current state in time). The specification estimation method employed depends on accepting or relaxing the time homogeneity assumption.

Assuming time-homogeneity, a collection of transition probabilities of the Markov chain for a given horizon in an N x N matrix $\mathbf{P}(t)$ can be described by an N x N generator or intensity matrix $\boldsymbol{\lambda}$. Lando and Skødeberg (2002) present the N x N transition probability matrix $\mathbf{P}(t)$ in the form:

$$\mathbf{P}(t) = \exp(\boldsymbol{\lambda}t), \qquad t \geq 0 \qquad 8.4$$

where $\boldsymbol{\lambda}t$ is the matrix $\boldsymbol{\lambda}$ multiplied by t on every entry and the exponential is the matrix exponential. This framework assumes that an estimation of maximum-likelihood (ML) of the transition probability matrices can be evaluated by first obtaining the ML estimate of the generator and then applying the matrix exponential function on the estimate (Bangia *et al*., 2002). The entries of the generator $\boldsymbol{\lambda}$ satisfy:

$$\lambda_{ij}(t) \geq 0 \qquad \text{for all } i \neq j \qquad 8.5$$

$$\lambda_{ii}(t) \equiv \lambda_i(t) = -\sum_{j \neq i} \lambda_{ij}\,(\mathrm{t}) \qquad 8.6$$

The equation (8.6) refers to the on-diagonal elements which ensure that the rows sum to zero. Further, Lando and Skødeberg argue that the entries describe the *probabilistic behaviour* of the *holding time* in notch *i* as exponentially distributed with parameter λ_i, where $\lambda_i(t) = -\lambda_{ii}(t)$, and the probability of jumping from notch i to j over an arbitrarily small time horizon τ is given by.

$$P\big[R(t+\tau) = j \mid R(t) = i\big] = \lambda_{ij}(t)\tau\big] \quad \text{for } i \neq j \qquad 8.7$$

The final task is to obtain estimates of the elements of the generator matrix $\boldsymbol{\lambda}$. Under the assumption of time-homogeneity ($\lambda_{ij}(t) = \lambda_{ij}$), the elements are estimated using the maximum likelihood estimator:

$$\hat{\lambda}_{ij} = \frac{N_{ij}(T)}{\int_0^T Y_i(s)ds} \qquad \text{for } i \neq j \qquad 8.8$$

where $Y_i(s)$ is the number of banks in rating class i at time s and $N_{ij}(T)$ is the total number of transitions over the period from i *to j,* where $i \neq j$. $D_i \equiv \int_0^T Y_i(s)ds$, the denominator, is effectively the number of '*bank years*' spent in state i. Thus any period spent by a bank in this state is captured through the denominator (rating duration). The implication of this is that, given a time horizon say, one year, even if a bank spends a short duration in transiting from, say 'AAA' to 'AA' before ending up in 'A' at the end of the year, the portion of time spent in 'AA' will contribute to the estimation of the transition probability, i.e. $\mathrm{P}_{AAA \to A}$.[12]

The transition risk-matrix estimator is therefore

$$\hat{Q}(\Delta T) \equiv \hat{Q}(T + \Delta_t) = e^{(\Delta t)\lambda} \qquad 8.9$$

Where the transition matrix $P(T) = e^{(\Delta t)\lambda}$ can be derived from the generator matrix as follows:

$$P(T) = e^{(\Delta t)\lambda} = \exp(\boldsymbol{\lambda}T) = \sum_{k=0}^{\infty} \frac{\boldsymbol{\lambda}^k T^K}{k!} \qquad 8.10$$

[12] Firms rated as NR within the year are still counted as part of the denominator and contribute to explaining the rating migration.

where $\boldsymbol{\lambda}$T is the generator matrix multiplied by the scalar T and exp() is the matrix exponential function. The advantage of equation 8.9 is that allows for the measurement of bank credit risk migration over any arbitrary time horizon, Δt. It makes use of rating transitions that occur at any point within the sample as well as rating duration.

8.4.1 Covariates and bank rating transition intensities: The empirical framework

This section provides the framework for investigating the impact of covariates on the transition intensities of a Markov model specification. This allows for a test of the non-Markovian behaviour, that is, rating drift (dependence on previous rating) and the waiting-time effects as suggested by Lando and Skodeberg (2002). The main assumption here is that the transition intensity for each category of rating migration is influenced by the pathway taken to arrive at the current state. Further, Lando and Skodeberg (2002) argue that "an external, time varying covariate" (p. 433) influences the transition intensity for each type of rating migration.

Assuming that Y_{ik} (Y being a dummy variable), denote an indicator process, which is 1 when the process is in state *i*, and 0 otherwise, one can present the intensity of transition from state *i* to state *j* for bank *k* in the form:

$$\lambda_{ijk}(t) = Y_{ik}(t)\alpha_{ijk}(t, Z_k(t)), \qquad 8.11$$

where $\alpha_{ijk}(t, Z_k(t))$ has the multiplicative form

$$\alpha_{hji}\big(t, Z_I(t)\big) = \alpha_{hj0}(t)\exp(\beta_{hj}Z_k(t)). \qquad 8.12$$

Equation 8.11 is a semi-parametric specification employed to estimate and test for influence of the covariate process Z_k on the transition intensity from state h to *j*.

Following Lando and Skodeberg, the base-line intensity[13] $\alpha_{ij0}(t)$ is left unspecified, and thus a full likelihood function cannot be employed. As an alternative, the regression parameter β_{hj} (the parameter of interest here) is estimated by maximising a partial likelihood:

$$L(\beta_{ij}) = \prod_t \prod_t \frac{\exp(\beta_{ij} Z_k(t)}{S_{ij}^0(\beta_{ij}, t)} \qquad 8.13$$

where

$$S_{ij}^0(\beta_{ij}, t) = \sum Y_{ik}(t) \alpha_{ijk}(t, Z_k(t)) \qquad 8.14$$

The maximization is undertaken by setting the (partial) score function of $L(\beta)$ equal to zero. The covariate Z_k tracks the influence on k's transition intensity. Lando and Skodeberg argue that the non-zero values of the product of covariates and the parameter cause the intensities to deviate from the baseline hazard. It therefore means that if the process of rating transition exhibits non-Markov behaviour, the regression coefficients will be significantly different from zero.

Thus, the above specification allows for a test of whether the last rating change influences the transition probability of moving away from the present category. The covariates are defined as:

$$Z_k(t) = \begin{cases} 1 & \text{individual } k \text{ was upgraded to the present rating class} \\ 0 & \end{cases} \qquad 8.15$$

Hence, the statistical test for the hypothesis of no rating drift is $H\colon \beta = 0$, and is equivalent to no serial correlation in any class of previous up- and downgrades. In other words, this thesis tests for non-Markov effects of transition by specifying covariates as

[13] Any fluctuations in macroeconomic influences or business cycles are absorbed through the baseline intensity. This thesis recognises that macroeconomic variables (and business cycles) influence rating intensities (Bangia *et al.*, 2000; Nickell *et al*., 2000). However, the test within this component focuses more specifically on examining the deviations from Markovian behaviour due to the last rating change as well as duration dependencies.

variables describing whether the previous move was an upgrade or a downgrade, as well as the waiting-time in the present state for each bank *k*.

Further, the specification allows for a study of the duration dependence, by defining the duration covariates Z_k as:

$$Z_k\,(t) = \text{'time since last entry into the present state'} \qquad 8.16$$

Following Lando and Skodeberg, the model employed in this thesis follows an exponential form which keeps the transition intensity positive as well as allowing the effect to 'die out' as the duration increases when the regression parameter is negative. In order to ensure enough data, only transition from the current state, R, to a neighbouring state is considered. In addition, all of the possible ways of reaching a particular current state are considered, though all downgrades into this current state, R, are grouped together and assigned the same value of the covariate for banks in this category. Similarly, all upgrades into the current state *R* are grouped together.

The next section presents the various results on bank credit rating migration. Section 8.5 starts by presenting the descriptive statistics to show the number and movements of banks in each rating grade for each year. This facilitates an initial view of the broad pattern of changes within the sample size. Further, the section present the results of a number of specifications of transition matrices based on both the cohort and the duration approach. In order to account for sampling errors, the confidence intervals for the estimated transition probabilities within each matrix are presented. In addition, this section presents the results of the ratings drift, and seeks to answer the question of whether the transition intensity of a bank being upgraded from a state depends on the current state being reached through a downgrade or an upgrade. Similarly, for downgrades: is there a tendency for a downgrade to be more likely if the current state was reached through a downgrade? Finally, an ordered probit model estimate is presented to show the relative importance of the drivers of rating transition.

8.5 Results

8.5.1 Descriptive statistics

Table 8.1 presents the credit rating distribution and relative frequencies per year across ratings classifications for the banks in the sample. The sample of banks employed in this study consists of 322 international commercial banks from 70 countries across the world. The ratings for these banks consist of Fitch's Long Term bank credit ratings over the period 2000–2012. Panel A shows the actual number of ratings per category, while Panel B presents the relative frequencies for each rating category over time. The categories employed for this purpose are AA and above ('very good rating'), A ('good rating'), BBB ('Fair rating') and BB+ and below ('Poor rating'). The study employs these four 'coarse' rating granularities in order to examine the transition of bank ratings across a shorter spectrum compared with say 9 categories. Further, it helps provide more rating data within each coarse category. Table 8.1 shows evidence of a shift in the distribution of credit ratings over time. The results provide a visual indication of the trends in changes in the credit quality of international banks over the sample period. An initial observation of the top rating class shows that 'AA and above' ratings have progressively increased up until 2007 when there was a global financial crisis. Conversely, the threshold rating category (BBB) and the speculative grades have been on the rise throughout the sample period, especially following the financial crisis. This trend is also evident in Figure 8.1, which displays a monotonic decrease in the proportion of banks in the higher investment-grade rating categories, as opposed to the increase in the number of banks in the lower rating categories.

Table 8.1: Banks credit rating distribution and relative frequencies per year

Panel A: Fitch Ratings, 2000-2012

Rating	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
AA and above	32	36	39	39	41	43	46	47	43	33	34	24	21
A	48	51	62	74	82	85	95	97	106	103	100	102	98
BBB	37	49	64	80	81	81	77	82	81	92	97	104	114
BB+ and below	33	43	68	84	90	101	100	96	92	94	91	92	89
Total	*150*	*179*	*233*	*277*	*294*	*310*	*318*	*322*	*322*	*322*	*322*	*322*	*322*

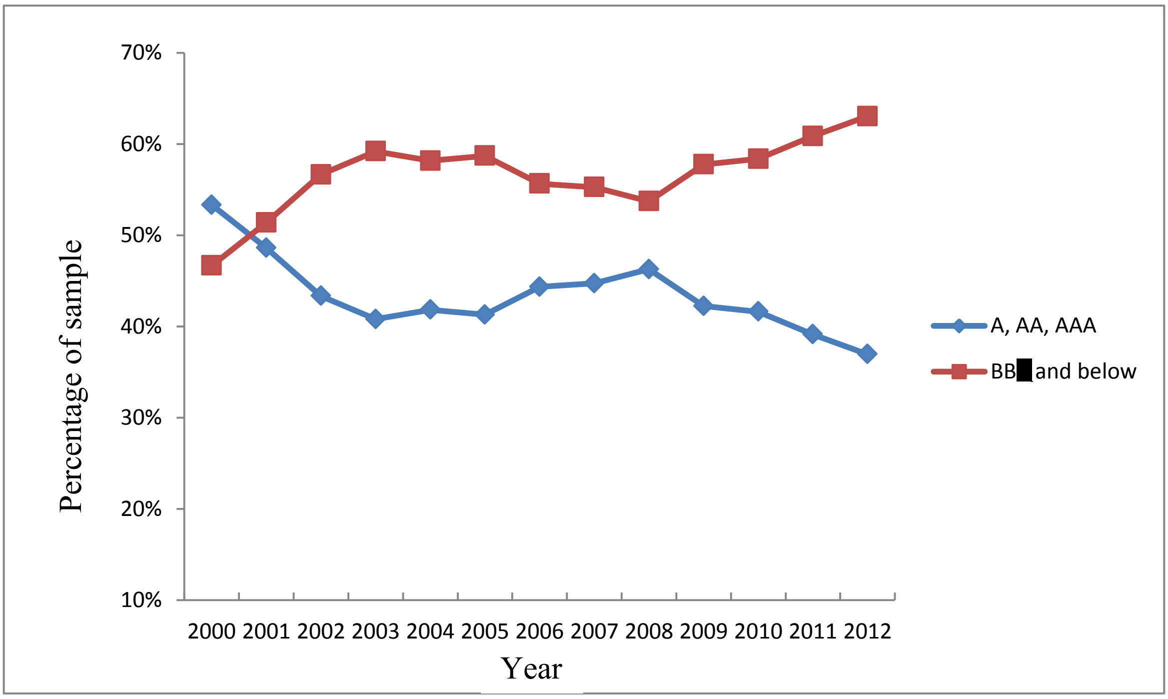
Panel B: Fitch Ratings, 2000-2012 (relative frequencies in %)

Rating	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
AA and above	21	20	17	14	14	14	14	15	13	10	11	7	7
A	32	28	27	27	28	27	30	30	33	32	31	32	30
BBB	25	27	27	29	28	26	24	25	25	29	30	32	35
BB+ and below	22	25	29	30	30	33	32	30	29	29	28	29	28
Total (%)	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*

Note: Rating distribution per rating category for each year for the 322 rated banks in the sample. The figures represent the bank ratings in the different categories at the end of the calendar year. The 322 banks employed within this study are from the Bankscope database. The banks in the sample consists of listed banks commercial banks operating across the world for the period 2000-2012. Further, the banks employed are those rated as Long Term ratings by Fitch credit rating for the sample period.

The distribution shows that there are more banks in the lower rating categories (BBB and below) than the higher ones after the year 2000. An examination of the investment-grade ratings (i.e. ratings in the category AA and above) shows a decline by 34% in the number of bank ratings in this category over the observed time period. Interestingly, the A-rated banks in the sample increased by 50% over the sample period. The lowest rating category (BB+ and below) experienced a 178% increase in the number of banks rated in this category between the start and end of the sample period.

Figure 8.1: Yearly credit rating movements for investment- and speculative-grade banks



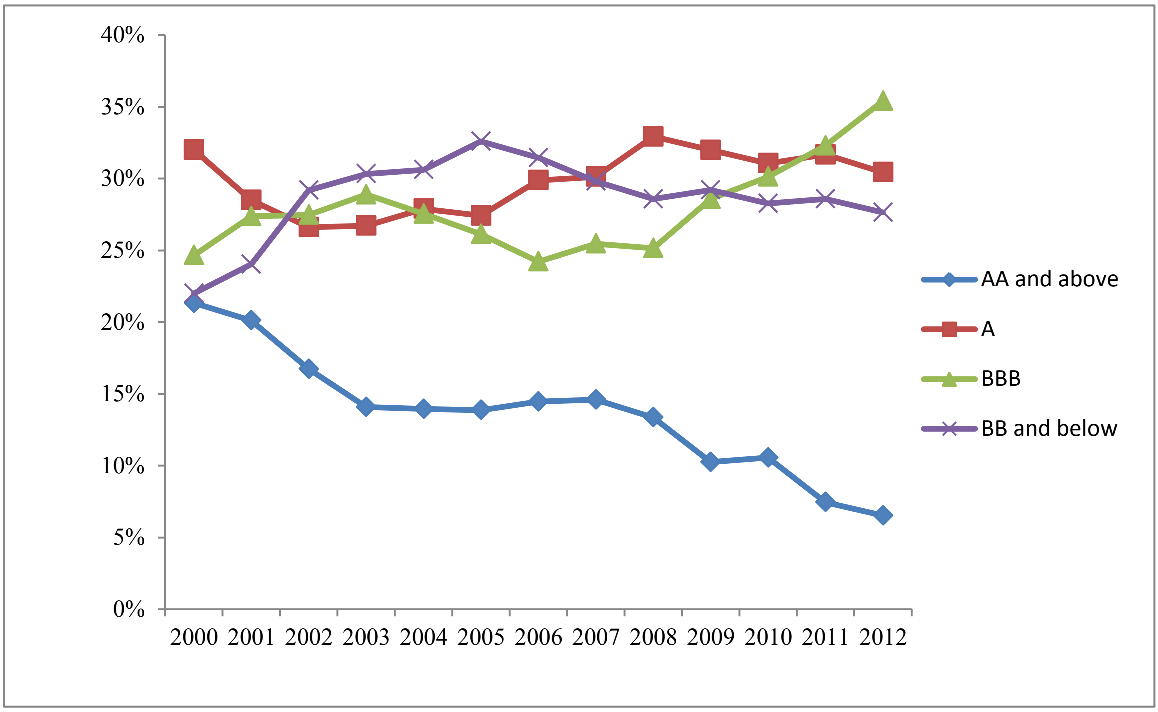
Note: Yearly rating movement of the 322 speculative- and investment-grade banks in the sample.

Figure 8.2 shows a downward sloping curve for the top investment rating grades (AA and above) and the speculative grade (BB+ and below), whereas the low investment-grade is represented by upward curves particularly after the financial crisis of 2007/08. Table 8.2 shows the movement in bank credit ratings for the sample period. There are 831 year-end rating changes from 2000 through to 2012 for the 322 banks in the sample.

These rating changes only reflect transitions at the beginning and year end and ignore changes during the year. The Table shows an increase in the number of rating changes between 2000 and 2012. The transition to a higher rating category (upgrade) is more prevalent in the period leading up to the financial crisis, while in the post crisis period, there were relatively more downgrades. For example, over the period the end of 2008-2009, 69 banks were downgraded relative to 27 banks that had their ratings upgraded.

Year

Figure 8.2: Yearly credit rating movements for investment- and speculative-grade banks



Note: Yearly rating movement for 4 broad rating categories of the 322 rated banks in the sample

Table 8.2: Year-on-Year bank credit rating movement

Panel A: Fitch Ratings Bank Rating Movement, 2000-2012

Rating movement	1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012
Downgrades	15	16	18	17	15	12	9	18	28	69	30	47	45
Upgrades	8	10	13	37	51	51	82	51	48	27	43	33	34
Total	*23*	*26*	*31*	*54*	*66*	*67*	*91*	*69*	*76*	*96*	*73*	*80*	*79*

Panel B: Fitch Ratings, 2000-2012 (relative frequencies in %)

Rating movement	1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012
Downgrade	65	62	58	31	23	20	10	26	37	72	41	59	57
Upgrades	35	28	42	69	77	80	90	74	63	28	59	41	43
Total (%)	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*

Note: Credit rating movement per year for the 322 rated banks in the sample. It represents movement in rating at the end of each year.

8.5.2 The Transition Matrix

Table 8.3 shows an unconditional one-year matrix for the 322 banks in the sample based on the cohort approach. The matrix displays the migration probabilities for international bank credit ratings over the period 2000-2012. In constructing the matrix, each year is weighted according to the number of ratings for that year in relation to the total of ratings for the whole period. Each row shows the ratings at the start of the period, while each column represents the final rating at the end of the period (in this case of the cohort approach, the year-end). The sum of the probabilities for each row is 100%. Based on the transition matrix in Table 8.3, an AA- rated bank has a 4% probability of being downgraded to A+, a 2% probability of being downgraded by two and three notches to A and A- respectively, and a 4% probability of an upgrade to AA rating. Although, the cohort approach is the traditional technique and is widely established, it does not make full use of the available data. The estimates within each cell do not take account of the timing and sequencing of a transition within a year. This is a major drawback as the approach only accounts for the beginning and end rating of the 13 year period, thus reflecting more long-term dynamics, without capturing the short-term dynamics. Another consequence is that the transition to low grade notches is often zero for high-quality issuers (Loffler and Posch, 2011).

Generally, credit risk migration matrices are said to be diagonally dominant, with most of the probability mass residing along the diagonal (Bangia *et al*., 2002). Table 8.3 shows the large values that lie along the diagonal denote the probability of no change or migration. The next large entries are the *one-step* off diagonal entries. The Table shows that the chances of experiencing downgrades are more prevalent for the investment-grade banks.

Table 8.3: Unconditional one-year transition matrix of 322 International rated banks (2000-2012) - Cohort approach

	AAA	**AA+**	**AA**	**AA-**	**A+**	**A**	**A-**	**BBB+**	**BBB+**	**BBB-**	**BB+**	**BB-**	**BB**	**B+**	**B**	**B-**	**CCC+**	**CCC**	**D**
AAA	67%	33%																	
AA+		100%																	
AA		2%	89%	5%	2%	1%	1%												
AA-			4%	88%	4%	2%	2%												
A+				1%	91%	5%	2%	1%											
A					8%	80%	8%	3%	1%										
A-						2%	93%	5%											
BBB+							15%	81%	4%										
BBB-							2%	11%	84%						2%				
BBB-								3%	6%	88%	3%								
BB+									5%	9%	68%	18%							
BB-												100%							
BB										5%	15%	13%	45%	12%	10%				
B+													15%	62%	8%	15%			
B													3%	22%	44%	31%			
B-															35%	65%			
CCC+																29%	71%		
CCC																		100%	
D																			100%

Notes: The blank spaces on the diagonals are due to no observations. The matrix is unconditional, i.e. does not reflect the impact of previous ratings on current ratings. The weightings for each year are on the basis of the number of observations that each year contributes to the total number of observations. The shaded cells along the diagonal show the probabilities of a bank staying within the rating category. The values to the left of the shaded cells indicate upgrades, while those to the right of the shaded cells indicate rating downgrades. Following Hu et al. (2002), if there are no observations in a particular category, such as CCC and D, 100% is placed in the corresponding diagonal position in the matrix

Similarly, banks within this classification are more likely to experience further downgrades, and hence may be said to *travel a greater distance*. For example, this can be observed in the case of AA- rated banks. This finding is consistent with earlier studies (DeServigny and Renault, 2004; Gonzalez et al. 2004; Ali and Zhang, 2008). Table 8.3 indicates that AA-rated banks have a 4%, 2% and 2% chance of being downgraded by one, two, and even three notches respectively, which constitute rather substantial rating changes. Conversely, there is a relatively higher probability of upgrades for the banks in the speculative rating categories than downgrades.

The results are interesting when the sample is split into an expansion and contraction period. The thesis takes the period 2000-2007 as an expansion (or boom period), while the period 2008-2012 is assumed to be a contraction due to the impact of the global financial crisis and associated economic slowdown. The transition matrices for these two periods are presented in Tables 8.4 and 8.5. Table 8.4 shows that during the time of expansion, the values of the default diagonal probabilities are higher, with relative low level of movements in the investment grades. The banks in the speculative grades show more movement in their transition to higher rating notches during the expansion period. Table 8.5 which displays the transition matrix during a contracting period shows a higher likelihood of downgrades, especially in the investment rating categories. Banks tend to experience subsequent downgrading particularly in the investment categories during the contraction periods. In addition, Tables 8.3 and 8.5 show significant volatility in bank ratings for investment grades, biased in particular towards the right of the diagonal. Further, the Tables show that rating upgrades for investment categories involve single rating notch improvement. For the lower rating categories (speculative-grades) in the two tables, there is a higher likelihood of upgrades, while in Table 8.5, despite the contraction period, the level of downgrades is relatively lower than those experienced for upgrades.

Table 8.4: Unconditional one-year transition matrix of 322 International rated banks (2000-2007) - Cohort approach

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB+	BBB-	BB+	BB-	BB	B+	B	B-	CCC+	CCC	D
AAA	67%	33%																	
AA+		100%																	
AA		1%	92%	2%	3%	2%													
AA-			2%	91%	4%	3%													
A+				4%	85%	5%	4%	2%											
A					8%	80%	8%	3%	1%										
A-						2%	93%	5%											
BBB+							15%	81%	4%										
BBB+							2%	11%	84%						2%				
BBB-								3%	6%	88%	3%								
BB+									5%	9%	68%	18%							
BB-												100%							
BB										5%	15%	13%	45%	12%	10%				
B+													15%	62%	8%	15%			
B												10%	3%	12%	44%	31%			
B-														13%	22%	65%			
CCC+																29%	71%		
CCC																		100%	
D																			100%

Notes: The blank spaces on the diagonals are due to no observations. The matrix is unconditional; i.e.it does not reflect the impact of previous ratings on current ratings. The weightings for each year are on the basis of the number of observations that each year contributes to the total number of observations. The shaded cells along the diagonal show the probabilities of a bank staying within a rating category. The values to the left of the shaded cells indicate an upgrade, while those to the right of the shaded cells indicate rating downgrades. Following Hu et al. (2002), if there are no observations in a particular category, such as CC and C, 100% is placed in the corresponding diagonal position in the matrix

Table 8.5: Unconditional one-year transition matrix of 322 International rated banks (2007-2012) - Cohort approach

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB+	BBB-	BB+	BB-	BB	B+	B	B-	CCC	CC	C
AAA	100%																		
AA+		100%																	
AA		3%	81%	10%	3%	2%	1%												
AA-			6%	78%	7%	6%	4%												
A+				4%	85%	5%	4%	2%											
A					8%	80%	8%	3%	1%										
A-						2%	93%	5%											
BBB+							15%	81%	4%										
BBB+							2%	11%	84%						2%				
BBB-								3%	6%	88%	3%								
BB+									5%	9%	68%	18%							
BB-												100%							
BB												13%	75%	12%	10%				
B+													15%	62%	8%	15%			
B													3%	22%	44%	31%			
B-															35%	65%			
CCC																29%	71%		
CC																		100%	
C																			100%

Notes: The blank spaces on the diagonals are due to no observations. The matrix is unconditional, i.e. it does not reflect the impact of previous ratings on current ratings. The weightings for each year are on the basis of the number of observations that each year contributes to the total number of observations. The shaded cells along the diagonal show the probabilities of a bank staying within a rating category. The values to the left of the shaded cells indicate an upgrade, while those to the right of the shaded cells indicate rating downgrades. Following Hu et al. (2002), if there are no observations in a particular category, such as CC and C, 100% is placed in the corresponding diagonal position in the matrix

Table 8.4 shows that banks rated in the speculative grade mostly benefit from an expansion period compared to banks in the investment grades. The latter are relatively more stable and show higher values along the diagonal entries of the transition matrix.

Overall, the results show that there are adverse effects of downgrades between 2008 and 2012, particularly for banks in the investment grades. There is an element of rating drift or momentum as depicted by the 'distance travelled' by ratings over time. This is in contrast to Johnson (2003) who finds a tendency for downgrades to travel more grades for lower investment categories than for higher categories. Splitting the sample into expansion and contraction periods is also informative in the sense that the directions (upgrades/downgrades) can be more clearly examined. In an expansion regime, there is greater stability for investment grade banks, while banks in the speculative grades benefit more from movement to the higher notches. However, in a contraction period, there is more prevalence of downgrades for investment rated categories than in the lower grades. Further, banks in the investment grades appear to *travel* a longer distance than is the case for the speculative grades.

This next section presents the results of the maximum-likelihood estimator of the generator of bank credit rating transition based upon the continuous-time observation over the sample period. The one-year transition matrix estimated from continuous-time data over the period 2000-2012 as the matrix exponential of the transition of the maximum likelihood estimator of the generator is presented in Table 8.6. The results of the one-year transition matrix are based on the continuous-time duration approach.

Table 8.6: Conditional one-year transition matrix of 322 International rated banks (2000-2012) - Duration approach

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB+	BBB-	BB+	BB-	BB	B+	B	B-	CCC	CC	C
AAA	52%	48%																	
AA+		68%	26%	6%															
AA	1%	5%	72%	13%	4%	3%	2%												
AA-		2%	6%	69%	10%	5%	4%	4%											
A+				4%	80%	4%	4%	6%	2%										
A				3%	5%	81%	8%	3%	1%										
A-					1%	2%	82%	6%	5%	4%									
BBB+						6%	10%	77%	4%	3%									
BBB+						1%	3%	5%	88%	2%					1%				
BBB-								2%	6%	89%	3%								
BB+									5%	14%	69%	10%	2%						
BB-									3%	4%	8%	82%	1%	2%					
BB									1%	5%	5%	9%	70%	6%	4%				
B+											1%	3%	10%	66%	8%	12%			
B													8%	16%	52%	11%	13%		
B-															35%	65%			
CCC																33%	77%		
CC																		100%	
C																			100%

Notes: The blank spaces on the diagonals are due to no observations. The matrix is conditional, i.e. it reflects the impact of previous ratings on current ratings. The weightings for each year are on the basis of the number of observations that each year contributes to the total number of observations as well as the duration of the ratings on each grade. The shaded cells along the diagonal show the probabilities of a bank staying within the rating category. The values to the left of the shaded cells indicate an upgrade, while those to the right of the shaded cells indicate rating downgrades. Following Hu et al. (2002), if there are no observations in a particular category, such as CCC and D, 100% is placed in the corresponding diagonal position in the matrix.

The approach takes into consideration the duration spent on each rating grade, before transiting (either to a lower or higher grade[14]).

The initial observation shows that the diagonal values are much lower when compared to the corresponding results for the cohort approach in Table 8.3. This suggests that the duration approach presents a dynamic view to rating transition, enabling the capture of more movement within each rating category. There is a greater tendency for downward movements (downgrades) within the investment category. This might be related to the concept of downward momentum. Ratings also tend to *travel* greater distance within the higher investment grades, particularly towards the right of the matrix. For banks that are within the non-investment grade categories, there is an observed movement towards the left of matrix; however, the distance travelled within this category is much smaller than that observed for the investment category. Overall, the increase in rating movements could be attributed to the ability of the duration approach to capture ratings within periods, and account for the impact of duration of the shift in rating gradation.

When taken together, these descriptive statistics show an interesting pattern in the behaviour of bank credit rating agencies in the pre and post crisis periods. The pre-crisis period shows a progressive increase in the proportion of banks assigned top ratings. One may argue that there were high levels of complacency in the rating industry, particularly with the over reliance of the market on ratings. The oligopoly nature of the credit rating industry, where only three CRAs dominate, results in reduced marketplace competition. With very minimal threats to competition, these agencies are likely to be more complacent in their methodologies. Further, the regulatory reliance on credit ratings,

[14] The first entry is via a generator matrix λ, and the elements of the matrix are estimated using the maximum likelihood estimator given in Equation 8.10. The generator matrix is then multiplied by the scalar T and expressed as an exponential function (see Equation 8.12).

particularly the Nationally Recognised Statistically Rating Organisations (NRSRO), suggests that regulations may have artificially boosted the demand for ratings. One also cannot rule out the lack of investors' due diligence and monitoring of the credit rating agencies on the complacency in the industry. This may also be attributed to the pressure by the market on the CRAs and their need to err on the side of caution whilst (re)assigning ratings to banks.

8.5.3 Results of the test for non-Markovian behaviour in bank credit rating migration

This section presents the findings of the tests for non-Markovian behaviour, i.e. rating drift. This is based on the argument that the history of the rating migration process, and not just the current state, provides information about transition probabilities. In addition, it presents the results of the waiting-time effects, i.e. the effects of the duration that a bank stays on a particular rating on its transition to another state.

The analysis thus examines if the transition intensity of being upgraded from a particular state depends on whether the current state was reached through a downgrade or an upgrade. Similarly, it considers whether downgrades are more prevalent if the current state was reached through a downgrade[15]. Table 8.7 presents the results of the effects of a previous downgrade on the transition intensities of a downgrade to a neighbouring rating state. The Table shows an estimate of the parameter of interest $\hat{\beta}$ as well as the hazard ratio, exp($\hat{\beta}$). To recall, the statistical test is for the hypothesis of no rating drift ($H\colon \beta = 0$), i.e. no serial correlation in any rating class of previous upgrades and downgrades. The findings show strong evidence of downward momentum or drift

[15] This thesis follows Lando and Skodeberg (2002) by considering different ways of reaching the current.

in the upper investment categories (i.e. rating class AAA to A-). The estimates of the beta coefficients for the investment grades are statistically significant at the 1% level. In contrast, the lower investment rating categories and speculative grades have beta estimates that are insignificant; hence the hypothesis of no rating drift is accepted for these categories. In addition, the magnitude of this drift increases as one move down the rating categories, from a higher to a lower rating. The rating drift diminishes once the speculative grade category is crossed.

This result in Table 8.7 is consistent with Lando and Skodeberg (2002) who find no evidence of rating momentum in their subsample of financial institutions within the speculative categories. The finding suggests that there is a strong tendency for banks to lose their competitive edge in the market once their ratings cross the BBB- threshold. In such a case, the bank may be forced to merge or be acquired by a bigger financial institution. Hence, the likelihood of finding a significant downward drift within the speculative grade for bank diminishes.

Table 8.8 presents similar results for rating upgrades, where the intensity of an upgrade is estimated on the basis of the pathway into the current state being an upgrade. In contrast to the results obtained in Table 8.7, there are no significant beta estimates except for categories A+ and BBB+. Hence, the results presented in Tables 8.7 and 8.8 are consistent with those found in literature (Lucas and Lonski, 1992; Carty, 1997; Lando and Skodeberg, 2002; Guettler and Raupach, 2007) for the existence of rating drift for downgrades.

Table 8.7: Results showing the effects of a previous downgrade on the transition intensities of a downgrade to a neighbouring state

Ratings							
From	To	$\hat{\beta}$	$\exp(\hat{\beta})$	$\mathrm{std}(\hat{\beta})$	n_1	n_2	p
AA+	AA	0.714	2.042	0.221	25	23	<0.01
AA	AA-	0.822	2.275	0.254	107	18	<0.01
AA-	A+	0.802	2.230	0.209	347	36	<0.01
A+	A	0.839	2.094	0.185	324	42	<0.01
A	A-	1.005	2.732	0.339	380	46	<0.01
A-	BBB+	1.154	3.711	0.286	400	58	<0.01
BBB+	BBB	1.099	3.001	0.299	645	63	<0.01
BBB	BBB-	0.867	2.380	2.256	357	59	<0.01
BBB-	BB+	0.684	1.981	2.015	336	53	0.66
BB+	BB	0.154	1.166	0.083	196	36	0.89
BB	BB-	0.264	1.302	0.025	268	43	0.20
BB-	B+	0.361	1.435	0.116	310	55	0.42
B+	B	0.514	1.672	0.108	175	42	<0.01
B	B-	0.551	1.734	0.126	148	23	<0.01
B-	CCC+	3.214	24.878	16.141	166	9	0.36
CCC+	CCC	5.551	257.495	6.611	15	3	0.49

Notes: The first column in Table 8.7 shows the type of transition being examined. The estimate of β is presented in the second column. The sign of the β coefficient shows the direction of the downgrade intensity. A positive (negative) β means that the downgrade intensity is increased (decreased) by a factor of $\exp(\beta)$ compared to the case of a previous upgrade. $\mathrm{std}(\hat{\beta})$ shows the standard deviation of the estimate. n_1 represents the number of times a bank is rated and exposed to the given rating type of transition at the start of the year, i.e. the total number of observations in the 'From' rating category. n_2 shows the actual number of transitions observed. The p-value is the test statistic and a result <0.01 is significant at below the 1% level.

Tables 8.9 and 8.10 show the results of the waiting-time effects (duration) in the initial rating grade (labelled 'From') on the transition intensity of a downgrade to a neighbouring state. Again, these aim to test whether the time a bank rating stays on a particular rating grade influences downgrade or upgrade intensity. The hypothesis being tested in this case is that duration has no influence on bank rating transition intensity.

Table 8.8: Results showing the effects of a previous upgrade on the transition intensities of an upgrade to a neighbouring state

Ratings							
From	To	$\hat{\beta}$	$\exp(\hat{\beta})$	$\mathrm{std}(\hat{\beta})$	n_1	n_2	p
AA+	AAA	-0.237	0.789	0.514	25	0	0.75
AA	AA+	-0.106	0.900	0.318	107	13	0.36
AA-	AA	-0.098	0.907	0.295	347	19	0.29
A+	AA-	-0.384	0.681	0.254	324	38	<0.01
A	A+	-0.216	0.806	0.236	380	26	0.11
A-	A	0.254	1.299	0.594	400	32	0.26
BBB+	A-	0.609	1.839	0.397	645	44	<0.01
BBB	BBB+	0.554	1.740	0.484	357	39	0.22
BBB-	BBB	0.235	1.265	0.398	336	40	0.31
BB+	BBB-	-0.627	0.534	1.214	196	38	0.18
BB	BB+	-0.189	0.828	0.192	268	22	0.32
BB-	BB	0.226	1.254	0.354	310	44	0.66
B+	BB-	-3.647	0.026	11.647	175	23	0.49
B	B+	-2.214	0.109	5.251	148	31	0.53
B-	B	0.506	1.659	0.268	166	49	0.18
CCC+	B-	-2.661	0.070	4.581	15	6	0.26
CCC	CCC+	-6.524	0.001	19.515	20	2	0.94

Notes: The first column in Table 8.8 shows the type of transition being examined. The estimate of β is presented in the second column. The sign of the β coefficient shows the direction of the upgrade intensity. A positive (negative) β means that the upgrade intensity is increased (decreased) by a factor of $\exp(\beta)$ compared to the case of a previous downgrade. The estimate, $\mathrm{std}(\hat{\beta})$ shows the standard deviation of the estimate. n_1 represents the number of times a bank is rated and exposed to the given rating type of transition at the start of the year, i.e. the total number of observations in the 'From' rating category. n_2 shows the actual number of transitions observed. The p-value is the test statistic and a result <0.01 is significant at below the 1% level.

Table 8.9: Results from a test of the effect of duration (waiting-time effects) in an initial rating category ('From') on the transition intensity of a downgrade to a neighbouring state

Ratings							
From	To	$\hat{\beta}$	$\exp(\hat{\beta})$	$\text{std}(\hat{\beta})$	n_1	n_2	p
AAA	AA+	-0.401	0.669	0.195	0	0	<0.01
AA+	AA	-0.395	0.674	0.151	25	23	<0.01
AA	AA-	-0.255	0.775	0.028	107	18	<0.01
AA-	A+	-0.613	0.542	0.147	347	36	<0.01
A+	A	-0.224	0.799	0.209	324	42	<0.01
A	A-	-0.509	0.601	0.072	380	46	<0.01
A-	BBB+	-0.457	0.633	0.093	400	58	<0.01
BBB+	BBB	-0.358	0.699	0.138	645	63	<0.01
BBB	BBB-	-0.251	0.778	0.051	357	59	<0.01
BBB-	BB+	-0.361	0.696	0.064	336	53	<0.01
BB+	BB	-0.284	0.753	0.107	196	36	<0.01
BB	BB-	-0.368	0.692	0.039	268	43	<0.05
BB-	B+	-0.254	0.776	0.074	310	55	<0.01
B+	B	-0.528	0.590	0.118	175	42	<0.01
B	B-	-0.351	0.704	0.261	148	23	<0.01
B-	CCC+	-1.624	0.197	0.681	166	9	<0.01
CCC+	CCC	-0.821	0.440	0.021	15	3	<0.01

Notes: The first column in Table 8.9 shows the type of transition being examined. The estimate of β is presented in the second column. The sign of the β coefficient shows the direction of the downgrade intensity. A positive (negative) β means that the downgrade intensity is increased (decreased) after duration of t by a factor of $\exp(\beta t)$ compared to the case where the duration has no effect. $\text{std}(\hat{\beta})$ shows the standard deviation of the estimate. n_1 represents the number of times a bank is rated and exposed to the given rating type of transition at the start of the year, i.e. the total number of observations in the 'From' rating category. n_2 shows the actual number of transitions observed. The p-value is the test statistic, and a result <0.01 is significant at below the 1% level. There is a high level of significantly negative effects of duration in all rating grades.

Table 8.9 shows that in all cases of downgrade transition, the hypothesis that the waiting-time effects (duration) has no influence on downward drift are rejected. The estimate of beta ($\hat{\beta}$) shows a negative sign, which suggests that the intensity is negatively affected by a change in duration. In other words, the longer a bank stays in a particular rating grade, the lower the chances of it being further downgraded. It is observed that the $\exp(\hat{\beta})$ function is less than 1[16], and this supports the explanation of a negative effect of waiting-time.

Similar to the results obtained for downgrades in Table 8.9, the results in Table 8.10 show highly significant negative effects of waiting-time for transition intensity of an upgrade to a neighbouring state. In Table 8.10, the longer a bank stays in the particular

[16] When the $\exp(\hat{\beta})$ function is 1, then the hypothesis that duration has no effect on transition intensity is accepted. However, a value of more than 1 shows a positive influence, while a value of less than 1 shows a negative influence. If β is negative, the $\exp(\hat{\beta})$ function is less than 1. Thus, the intensity $\alpha_{ji}(t) = \alpha_{j0}(t)\exp(\beta Z(t)_{ji}$ is negatively affected by a change in duration (the longer a bank stays on a rating class, the lower its likelihood of transiting to a downgrade category).

grade of interest (labelled ‘From’ in the table), the lower its chances of being upgraded. Taken together, the findings in Tables 8.9 and 8.10 show that the longer a bank stays on a particular (current) rating, the lower the probability of moving to a neighbouring rating.

It should be noted that this thesis only tests the duration relating to downward and upward drifts. The results are also consistent with the position of most of the major credit rating agencies in terms of maintaining *rating stability*. In addition, existing studies (e.g. Altman and Rijken, 2004) argue that rating information shows a high level of stability over time.

Table 8.10: Results of a test of the effect of duration (waiting-time effects) in an initial rating category (‘From’) on the transition intensity of a upgrade grade to a neighbouring state

Ratings							
From	To	$\hat{\beta}$	exp($\hat{\beta}$)	std($\hat{\beta}$)	n_1	n_2	p
AA+	AAA	-0.124	0.883	0.021	25	0	0.91
AA	AA+	-0.328	0.720	0.084	107	13	<0.01
AA-	AA	-0.147	0.863	0.066	347	19	<0.01
A+	AA-	-0.267	0.766	0.102	324	38	<0.01
A	A+	-0.443	0.642	0.118	380	26	<0.01
A-	A	-0.254	0.776	0.038	400	32	<0.01
BBB+	A-	-0.548	0.578	0.069	645	44	<0.01
BBB	BBB+	-0.638	0.528	0.110	357	39	<0.01
BBB-	BBB	-0.251	0.778	0.054	336	40	<0.01
BB+	BBB-	-0.333	0.717	0.039	196	38	<0.01
BB	BB+	-0.235	0.791	0.061	268	22	<0.01
BB-	BB	-0.284	0.753	0.055	310	44	<0.01
B+	BB-	-0.355	0.701	0.101	175	23	<0.01
B	B+	-0.284	0.753	0.183	148	31	<0.01
B-	B	-0.506	0.603	0.324	166	49	0.21
CCC+	B-	-0.847	0.427	0.515	15	6	0.32
CCC	CCC+	-6.524	0.001	19.515	20	2	0.94

Notes: The first column in Table 8.10 shows the type of transition being examined. The estimate of β is presented in the second column. The sign of the β coefficient shows the direction of the upgrade intensity. A positive (negative) β means that the upgrade intensity is increased (decreased) after duration of t by a factor of exp(βt) compared to a case where the duration has no effect. The estimate, std($\hat{\beta}$) shows the standard deviation of the estimate. n_1 represents the number of times a bank is rated and exposed to the given rating type of transition at the start of the year, i.e. the total number of observations in the ‘From’ rating category. n_2 shows the actual number of transitions observed. The p-value is the test statistic and a result <0.01 is significant at below the 1% level. There is a high level of significantly negative effects of duration in most ratin g grades.

The direction, from which a rating grade is attained, as well as the duration in the previous state, has considerable influence on the downward intensity. However, for upgrades, the results show that the pathway to the current rating grade is insignificant in most cases. Further, consistent with the results for downgrades, the waiting-time effects appear to be very prominent, and significantly affect the transition intensity for a neighbouring rating state.

8.6 Summary

This chapter presents an examination of bank credit rating migration. It seeks to investigate trends in bank credit quality over time by examining the movements of banks in each rating grade for each year. By constructing transition matrices on the basis of both discrete and continuous observations, as well as presenting separate matrices for boom and contraction periods, this study provides an insight into the distance that rating downgrades/upgrades travel. Put differently, the chapter provides more explanation of the nature of the overall trend of bank credit ratings during the period of the study. In addition, data on global banks is employed to address the question of rating drift and duration effects on transition migration, as well as the influence of covariates. The study employs the ordered probit model specifications developed in the previous chapter (and employed in Blume *et al*., 1998), and extends these to include year dummy variables for both investment grade and non-investment grade banks in order to test whether there exists downward rating momentum or simply a convergence towards the investment grade threshold.

The initial results from the 831 year-end rating changes from 2000 through to 2012 for the 322 banks in the sample show a downward sloping curve for the top investment rating grades, while the lower grades are represented by upward curves. This suggests one of three things: (1) a simple convergence towards the investment threshold; (2) an observed downward rating drift for the top rated banks; and (3) the presence of duration effects. Both the cohort and duration approach to the transition matrix are further explored to investigate bank credit rating transition. The unconditional one-year transition matrix based on the cohort approach shows more stability than the duration approach that employs continuous rating data. This is evidenced by the higher value observed along the diagonal of the matrices. This suggests that the duration approach is more appropriate in capturing the behaviour of bank ratings over time. Further, the distance travelled within the different rating grades, particularly those in the top investment grades, is higher than for lower grades.

In order to test for ratings drift, this thesis follows the approach by Lando and Skodeberg (2002) and finds strong evidence of a downward momentum or drift in the top investment categories. In contrast, the hypothesis of no rating drift is accepted for those rating in the lower rating categories. For upgrades, insignificant results are observed, suggesting no rating drift for upgrades within the sample. In addition, the thesis presents the results of the impact of duration on rating transition. The general conclusion is that the longer a bank stays on a particular (current) rating, the lower the probability of moving to a neighbouring rating. The results are consistent with the position of most major CRAs in terms of maintaining rating stability.

CHAPTER 9. CONCLUSION

9.1 Introduction

Company credit ratings and the agencies that issue them have become a critical component of financial markets. The spotlight on credit rating agencies has become very intense, particularly following the 2007/08 financial crisis. The primary role of a credit rating is to serve as a benchmark for the likelihood of default for companies and their issue. For rating agencies, there exists a trade-off between rating stability and rating accuracy. Langohr and Langohr (2008) argue that this trade-off aims to achieve the maximum accuracy for a given level of stability, or, reflecting the maximum stability for a given degree of accuracy. Due to the complexity of the rating process and the many issues around the role of ratings in financial markets, this study sets out to investigate empirically three important aspects of bank credit ratings.

Following the establishment and application of several testable frameworks and models, this study achieved its main objectives of empirically investigating the determinants and impact of bank credit ratings. The first main objective of this thesis is to examine the variables driving the assignment of ratings to banks. The thesis identifies the main determinants of international bank credit ratings by employing a unique data set over the period 2000-2012. Further, it employs various model specifications, both parametric and non-parametric, within an event study methodological approach to investigate the impact that bank credit rating news announcements have on the behaviour of bank equity returns. In addition, the thesis investigates bank credit rating growth and dynamics, focusing on rating migration, that is, the historical pattern of ratings, and examines the presence of non-Markovian behaviour in bank credit rating transition.

One of the main motivations of the thesis is to provide an in-depth understanding of the issues surrounding bank credit ratings in the face of a paucity of empirical studies in this area. Whilst studies by Poon (2003), Poon *et al*. (2009), Poon and Chan (2010) focus on the determinants of bank unsolicited ratings, others, e.g. Bissoondoyal-Bheenick and Treepongkaruna (2009) examines solicited ratings. In addition, whereas, Jafry and Schuermann (2004) employ financial data as part of their study, no single study investigates the issue of non-Markovian behaviour, particularly rating drift or momentum within a bank rating transition setting.

This thesis employs a sample of listed international banks over the period 2000–2012. The sample consists of 322 Fitch rated banks. Further, it employs further secondary data from a variety of sources. The financial and market data are taken from BANKSCOPE database. Most of the non-financial data are manually collected from bank annual financial statements. Finally, the bank credit ratings are themselves collected from BANKSCOPE and Fitch long-term credit rating database.

9.2 Main findings

The discussion of the main findings of this thesis focuses on the three areas investigated. Chapter 6 presents the empirical results of the determinant models for international bank credit ratings. The study finds that across all the specifications employed, the *CAMELS* framework components, that is, capital adequacy, asset quality, earnings, liquidity and sensitivity to the market are all statistically significant determinants of international bank credit ratings. The measure of the capital adequacy, *TIER 1,* shows a positive relationship with a bank's credit rating. The quality of bank assets, as measured by, *LLR/GL,* is negatively related to bank credit ratings. The variable measuring bank earnings (*ROA)*, and liquidity (*INTER)*, both have a positive relationship with bank credit ratings. The results obtained within this empirical component of the thesis broadly support the hypotheses stated and are consistent with the limited number of existing studies employing bank data. These findings reinforce the importance of a bank-specific, quantitative measure of balance sheet strength in the assigning of a credit rating to a bank. Langohr and Langohr (2008) argue that in the determination of a bank's probability of default, the financial strength rating evaluation comes first. The importance of financial strength ratings on banks further highlights the importance of the *CAMELS* system in the rating process.

This thesis makes a significant contribution to the body of knowledge in the area of bank credit rating determination, by employing variables that capture the *too-big-to-fail* notion as well as corporate governance factors related to this. It indicates that the variable *too-big-to-fail* is consistently significant across all model specifications. Credit rating agencies perceive the propensity to receive external support by banks as beneficial, and reward banks based on their size and connectedness within the financial system and economy at large. The coefficient of the variable, *too-big-to-fail,* shows a positive relation with bank credit ratings. This result is important since it confirms the necessity of initiatives to reduce systemic risk *'too-big-to-fail'* banks pose Following the financial crisis of 2007/08, there has been a global response on tackling the *too-big-to-fail* issue in banking. The efforts in the EU are led by the UK government following the recommendation of the Vickers Commission and the subsequent passing into law of the UK Banking Reform Act (2013). One of the key sections relates to the proposed implementation of the ring-fencing, which has a significant implication for the structure and business model of banks in the UK. Within the EU, the Liikanen Report (2012) draws from the Vickers and makes recommendations similar to those in the UK. These regulatory changes have significant implications for the rating processes and the way credit rating agencies assign ratings to banks. A move away from the ‘size’ factor, towards a ‘smaller’ and more efficiently run banking institutions presents an interesting development, not just for the rating agencies, but for the market as whole.

In addition to the *too-big-to-fail* impact on the rating framework, the results from the thesis confirm the importance of a range of corporate governance measures (directors’ shareholdings, institutional ownership and the proportion of independent directors on the board of directors) as important factors in determining bank ratings, thereby supporting the hypotheses stated. Directors’ shareholdings, institutional ownership and the proportion of independent directors all exhibit a significant and positive relationship with bank credit ratings.

With the continued efficiency in the way financial markets are run, Chapter 7 investigates the information relevance of bank credit ratings, and conducts an event study over a short horizon. It tests the hypothesis that, on average, bank credit rating announcements have no impact on bank stock returns around the announcement date. This empirical component of the study is based on the theoretic framework that the financial market operates in an efficient manner and all available information is incorporated rapidly into security prices. There is, however, strong existing evidence that financial markets may not be operating with strong-form market efficiency (Schwert, 2003, Park and Irwin, 2007). The claims of major credit rating agencies to possess private information, reported cases of insider trading, and the sophistication of institutional investors in accessing non-public information support this position. The general results from the existing literature are that upgrade announcements are not associated with any significant stock price movement, whereas downgrade announcements produce significant negative abnormal returns around the date of the news announcement.

The results of the news events tests provide evidence of asymmetric reactions in bank stock returns to credit rating news announcements across announcement types. For the full sample of bank upgrades, the parametric approaches show significant (positive) news leakage and partial correction in the market following the date of a bank rating upgrade announcement. Overall, the results for the bank stock reactions for upgrades are consistent with the existing literature. This thesis adds to the body of knowledge by investigating subsets of rating announcements within both upgrade and downgrade settings. For upgrades within the investment grades, the results show significant positive event-day reactions for both the parametric and non-parametric approaches. This is an interesting finding considering that most of the existing studies on the effects of 'positive news' provide evidence of no significant market reactions.

Contrary to the results for bank stocks within the investment-grades, the bank upgrade announcements within the speculative-grade show neither significant daily abnormal returns, nor cumulative average abnormal returns in either the parametric or nonparametric approaches. This asymmetry in market reaction may be due to investors (and in particular institutional investors) paying less attention to speculative grade bank stocks. In addition, the major credit ratings agencies may be more interested in actively monitoring bank stocks in the investment-grades. The results of bank stock reactions to unanticipated news show no evidence of news leakages, and the magnitude of event day reactions are higher across all the parametric and nonparametric approaches than in the other specifications. The bank stock downgrade news announcements are studied using the same specifications as for the upgrades. The general results for the downgrade specifications are consistent with existing studies and suggests that 'bad' news in the form of downgrades triggers significant market reactions. Hence, the market pays more attention to downgrade announcements than it does to upgrades.

Chapter 8 examines the trends in credit rating transition for the sample of international banks. The bank credit rating migration matrices are more diagonally dominant in the cohort approach than in the duration approach. This implies that the duration approach presents a more dynamic view of rating transition by allowing for the capture of more movement within each rating category. Generally, the probability of experiencing downgrades is higher for investment-grade banks than for speculative-grade banks. In addition, during a period of economic expansion the values of the diagonal probabilities are more dominant relative to periods of economic slowdown.

The chapter goes on to discuss the results of the tests for the presence of non-Markovian behaviour in bank credit rating transition. The results of the two non-Markovian behaviour tests, the rating drift and the waiting-time effect tests, show very strong evidence of downward momentum or drift in the top investment-grades (AAA to A-). In contrast, the hypothesis of no rating drift is accepted for banks in the lower investment-grade and speculative-grade ratings. Further, the magnitude of the rating drift increases from higher to lower rating categories, diminishing once the speculative-grade category is crossed. With regard to the hypothesis that duration has no influence on bank rating transition intensity, the results show that the longer a bank stays in a particular rating grade, the lower the chances of it being further upgraded or downgraded. In addition, the pathway direction from which a rating grade is attained and the duration it was situated in the previous state have a significant impact on downgrade intensity, but not on upgrade intensity.

9.3 Policy implications and recommendations of the thesis

The three empirical issues around international bank credit ratings which this thesis addresses have significant policy implications for both the credit rating and the banking industry. The 2007/08 financial crisis shows that the decision by credit rating agencies to assign ratings to banks has important systemic consequences. This is driven by the strong link between the credit rating actions and the continued over-reliance on credit ratings by regulators, banks and investors, as well as market reactions to ratings. This thesis further reinforces the current policy debates around the reliability and over-reliance of credit ratings, the need for regulatory reforms and oversights of the credit rating industry and the need to hold credit ratings accountable for their rating actions. With regulatory reforms already initiated in the US (the Dodd-Frank Act, 2010) and the EU (with the emergence of the European Securities and Market Authority - ESMA in 2011) to tackle the issues of disclosure, transparency and conflicts of interest, this thesis presents empirical evidence of the continued importance of ratings in the financial market.

9.4 The contributions of the thesis

This thesis contributes to the existing body of knowledge on credit ratings in many different ways. Firstly, the thesis employs a novel and rich dataset of international banks from the period 2000–2012. By employing this dataset, it is able to update the empirical literature on bank credit ratings, and enables a comparison with existing studies. It provides a detailed insight into the main determinants of bank credit ratings, and as such contributes to the formulation of a conceptualised framework for modelling rating determinants. Most of the earlier studies of rating determination employ a contemporaneous specification where credit rating agencies effect rating actions following the review of the financial and non-financial position of a bank within the same period. This thesis employs both responsive and predictive time-specifications in addition to the contemporaneous specification, modelling the exact time dynamics concerning the determinants of international bank credit ratings.

Secondly, this thesis extends the current literature by employing several new non-financial variables that are hypothesised to influence international bank credit ratings. It employs sovereign rating information to capture the diverse operating environment of banks across countries within the different model specifications. Another important extension to the existing literature is the incorporation of a variable that measures the propensity of a bank to get external support, that is, Fitch's *too-big-to-fail* index. This is an important addition, particularly against the backdrop of the 2007/08 global crisis.

Thirdly, the thesis provides a detailed insight into the behaviour of bank stock returns around the period of bank credit rating news announcements. The thesis contributes in several respects to the existing literature. The general position in the extant literature is that rating upgrades are not associated with stock market reactions, while rating downgrades elicit significant negative reactions. This thesis employs several specifications in modelling bank stock behaviour by examining subsamples of bank upgrades and downgrades. More specifically, it examines bank credit rating changes within subsamples of bank stocks rated in the investment-grade, speculative-grade, across investment thresholds, as well as unanticipated rating actions. This study is among the first, to the author's knowledge, to test for bank stock reactions to credit rating change announcements. The reported results are insightful and indicate that market reactions vary significantly by rating category.

Fourthly, the thesis extends the bank credit rating literature by employing a robust news event testing technique using both parametric and non-parametric approaches. It adopts an extension of the traditional two-stage event-study parametric approach, by employing a one-stage dummy variable approach within the testing framework. In addition, the thesis accounts for changing variances of abnormal returns across the banks by employing two other variants of the traditional event study approach, that is, the Boehmer *et al.* (1991) specification and the GARCH (1,1) specification. To the author's best knowledge, this is the only study that does so for a sample of international banks.

Fifthly, by investigating the behaviour of international bank credit ratings over time, this thesis addresses two major issues: testing for the presence of non Markovian behaviour in bank credit rating transitions and issues around the evident downward trend in bank ratings, particularly following the 2007/08 financial crisis. These are important considerations because the major credit rating agencies adopt transition frameworks that make the strong assumption of the existence of Markovian behaviour in bank stock credit rating transition. In addition, the major credit rating agencies have reviewed their rating methodologies following the credit crisis due to pressure from regulators, particularly in the US and Euro zone. Thus, the thesis allows for a test of the level of impact this tightening has had on rating assignments for international banks.

9.5 Limitations of the thesis

The limitations of this thesis can be summarised as follows. First, the sample of international banks is taken from the period 2000–2012. The sample of international banks is reduced significantly by the data requirements of this study. Second, the study employs international bank credit ratings obtained from Fitch over the period 2000–2012. The credit rating industry is assumed to be oligopolistic in structure, being controlled by the three major credit rating agencies: Fitch, Moody's and Standard and Poor's. Hence, their outputs (ratings), as well as the empirical results acquired using rating data from any of the agencies are argued to be homogenous and representative of the entire credit rating industry. Pottier and Sommer (1999) argue that the assumption of homogeneity of the credit rating industry is restrictive and works well only for investment grades, while it is more difficult to compare ratings across the rating agencies for speculative grades. It may be argued that the results of this thesis can be applied directly to Fitch ratings and it would be interesting to see whether this is the case by comparing them with results obtained from other rating agencies. The use of Fitch rated bank data is consistent with several existing studies: Poon (2003), Poon and Firth (2005), Van Roy (2006), which employs bank rating data from Fitch. However, one would not expect the results to vary significantly across the credit rating agencies because the parameter inputs to these models are a reflection of the variables that the rating agencies and academic researchers collectively consider as important in the credit rating process, as well as other market data relevant to testing rating news announcement impacts.

9.6 Opportunities for further research

This thesis models the determinants of credit ratings of international banks and confirms the importance of the *CAMELS* framework in the rating process. In addition, it establishes the individual, as well as joint, significance of a number of non-financial variables. Further, it provides an empirical investigation of the effects of credit rating news announcements on bank stock returns. By examining the historical transition of bank credit ratings, it tests for the presence of non-Markov behaviour in the form of rating drift and rating momentum. Following the presentation of several empirically testable conceptual frameworks within the three empirical components, its contribution to the existing body of knowledge can be extended further as follows.

Firstly, the analyses can be extended to bank issue ratings. This thesis focuses on long term issuer (international bank) credit ratings. By analysing international bank bond issues, it would be possible to develop a model that could predict bond ratings and hence enable international banks take actions to reduce the perceived risk and lower their cost of borrowing. For investors, "ratings are the principal source of information about the "quality" and marketability of various bond issues" (Pinches and Singleton, 1978, p. 29). Hence, international investors seeking to invest in international bank bonds can be better informed about the level of inherent risks in these issues. In particular, further research employing bank data from emerging economies may be viewed as valuable by investors because financial information in these markets is much less transparent than in developed markets.

Basel II and III Accords both place emphasis on stress testing banks, and this has implications for international bank credit rating. In particular, the supplemental Pillar II of the Basel III Accord framework stresses the need for regular stress testing of banks. This thesis can be extended to study the impact of stress testing credit risk for banks on the stability of the financial system. Despite stress testing being part of the banks' risk management toolkit for a long time, it has received special attention from regulators following the 2007/08 financial crisis. According to Foglia (2009), stress testing allows for an assessment of the vulnerabilities of financial systems to credit risk, focusing in particular on methods used to link macroeconomic drivers of stress with bank-specific measures of credit risk. By introducing a macroprudential approach to the analysis of credit risk for banks, the empirical investigation on bank stress testing can help assess the resilience of international banks to adverse economic developments.

Thirdly, the framework of this thesis presents an opportunity to examine credit risk interdependence between large financial institutions within the Eurozone area. The financial crisis has shown that the credit risk of large financial institutions is higher due to the linkages between entities and exposures to one another. These linkages bother on cross shareholdings, inter-bank, loans, subsidiary structure, to mention a few. This offers an opportunity to examine the nexus of credit risk exposure interdependence, typically brought about by common exposure of banks to systemic shock, and dependence between the idiosyncratic shocks of individual financial institutions.

Fourthly, the empirical components within this thesis offer a chance to develop more econometric innovations in extending the research. In the modelling of international bank credit rating, the artificial neural network analysis (ANN) offers an alternative to the modelling of the determinants of bank credit ratings. The ANN are particularly appropriate for modelling the determinants of ratings, as they do not require prior specification of theoretical models (Trigueiros & Taffler, 1996; Nazari, 2013).The efficiency of neural network and logistic regression in forecasting credit risk shows that both models have similar efficiency (Salehi and Mansoury, 2011). This approach has already been applied in modelling sovereign ratings (Bennell *et al.,* 2006). The authors show that ANN offers a superior technology for calibrating and predicting sovereign ratings relative to ordered probit modelling, which has been considered by the previous literature to be the most successful econometric approach. Extending the econometric approach (from the more established ordered probit/logit) by employing the ANN can produce improvements on the classification of credit rating accuracy within the context of bank ratings.

Further, another potential extension of this study is to analyse the lead-lag relationships in bank credit ratings across the three largest CRAs. The motivation for this is that CRAs would rationally treat a rating adjustment by another agency as a trigger for reviewing their own ratings, and it could be viewed as cost-effective to follow up a competitor's rating action (Güttler and Wahrenburg, 2007). Alsakka and ap Gwilym (2010) argue that an issuer experiencing a permanent credit quality improvement desires this to be reflected in its ratings as quickly as possible in order to benefit from reduced borrowing costs and/or enhanced capital inflows. Thus, an agency's credibility is enhanced by prompt rating actions (or rating leadership) following any permanent change in an issuer's creditworthiness (Ellis, 1998 and Güttler and Wahrenburg, 2007).

This thesis conducts an event study that captures the impact of bank credit rating news announcements on the bank stock returns. This empirical component of the thesis offers an opportunity to extend some of the econometric discussions and analyses around the area of news event impact modelling. An important aspect of the modelling of an event study framework is the capture of the correct stock return patterns. The Fama and French (2014) five-factor asset pricing model provides a different approach to capturing the returns pattern of banks' stocks. By employing a measure of bank size, value, profitability, book-to-market ratio and investment patterns, the Fama and French (2014) approach provides a better capture of the average stock returns across a pool of banks. However, one of the problems that this approach faces is its failure to capture the low average returns on small stocks whose returns behave like those of firms that invest a lot despite low profitability (Fama and French, 2014).

Within the bank credit risk migration component, this thesis can be extended by modelling the influence of macro-economic variables and business cycle on the transition intensities of banks' credit ratings. A bank's credit risk is influenced by certain macro-economic factors and these have the likelihood of impacting of the (re)assigning of credit ratings. Since the earlier empirical works of Nickell *et al.* (2000) and Bangia *et al.* (2002) which have demonstrated the link between credit rating movements and business cycle (as characterized by the NBER index, the GDP growth rates, the issuer's industry and country), numerous studies have focused on the dependence between the credit quality and the business, financial and economic environments (e.g. Hu *et al*., 2002; Chava and Jarrow, 2004; Duffie *et al.,* 2007;

Figlewski *et al.,* 2012; Fei *et al*., 2012). However, due to the cross-country nature of the bank credit ratings, the macroeconomic factors displaying the state of the economy might not be evenly report across the different countries. This thesis can also be extended by incorporating bank specific information in the context of transition probabilities.

REFERENCES

Abad-Romero, P. and Robles-Fernandez, M. D. (2006) Risk and Return Around Bond Rating Changes: New Evidence From the Spanish Stock Market. *Journal of Business Finance & Accounting.* 33(5-6), pp. 885- 908.

Accenture (2013) *Counterparty Credit Risk and Basel III A Framework for Successful Implementation.* Accenture.

Acharya, V. V. and Mora, N. (2013) *A Crisis of Banks as Liquidity Providers*. Working Paper.

Acharya, V. V., Shin, H.S. and Yorulmazer, T. (2010) Crisis Resolution and Bank Liquidity. *Review of Financial Studies*. 24(6), pp. 2166–2205.

Acharya, V. V. and Viswanathan, S. V. (2011) Leverage, Moral Hazard, and Liquidity. *Journal of Finance.* 66(1), pp. 99–138.

Acharya, V. V. and Yorulmazer, T. (2007) Too Many to Fail—An Analysis of Time-Inconsistency in Bank Closure Policies. *Journal of Financial Intermediation.* 16, pp. 1–31.

Adams, M., Burton, B. and Hardwick, P. (2003) The Determinants of Credit Ratings in the United Kingdom Insurance Industry. *Journal of Business Finance and Accounting.* 30(3&4), pp. 539–572.

Adelino, M. and Ferreira, M. A. (2014) *Sovereign Rating Downgrades and Bank Lending Supply.* ECGI working paper.

Aebi, V., Sabato, G. and Schimd, M. (2012). Risk Management, Corporate Governance, and Bank Performance in the Financial crisis. *Journal of Banking and Finance*. 36, pp. 3213–3226.

Agrawal, A. and Knoeber, C. R. (1996) Firm Performance and Mechanisms to Control Agency Problems between Managers and Shareholders. *Journal of Financial and Quantitative Analysis.* 31(3), pp. 377–398.

Akerlof, G. A. (1970) The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics.* 84(3), pp. 488–500.

Akhigbe, A. and Martin, A. D. (2008) Influence of Disclosure and Governance on Risk of US Financial Services Firms Following Sarbanes-Oxley. *Journal of Banking and Finance.* 32, pp. 2124–2135.

Akhigbe, A., Madura, J. and Whyte, A. M. (1997) Intra-Industry Effects of Bond Rating Adjustments. *Journal of Financial Research*. 20, pp. 545–561.

Alfonso, G., Santos, J. and Traina, J. (2014) Do 'Too-Big-to-Fail' Banks Take On More Risk? *Federal Reserve Bank of New York Economic Policy Review*, Vol. 20, No. 2.

Ali, A. and Zhang, W. (2008) *Proximity to broad credit rating change and earnings management. Working* paper, University of Texas at Dallas and Cheung Kong Graduate School of Business.

Allen, F. and Carletti, E. (2006) Credit Risk Transfer and Contagion. *Journal of Monetary Economics.* 53, pp. 89–111.

Allen, F. and Gale, D. M. (2006) *Systemic Risk and Regulation: The Risks of Financial Institutions*: Editors: Stulz, C. Chicago: Chicago University Press.

Allen and Overy (2013) Credit Rating Agencies Regulation, CRA III *Publication* July 15 2013

Allen, L. and Saunders, A. (2003) *A Survey of Cyclical Effects in Credit Risk Measurement Models.* Basel: Bank for International Settlements, Working Paper No 126.

Alsakka, R. and Ap Gwilym, O. (2012) Rating Agencies' Credit Signals: An Analysis of Sovereign Watch and Outlook. *International Review of Financial Analysis*, 21. pp. 45-55.

Alsakka, R. and Ap Gwilym, O. (2010) Leads and Lags in Sovereign Credit Ratings, *Journal of Banking and Finance*, 34 (11), 2614-2626.

Altman, E. (1968) Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*. 23(4), pp. 589–610.

Altman, E., Brooks, B., Resti, A. and Sironi A. (2002) *The Link Between Default and Recovery Rates: Implications For Credit Risk Models and Procyclicality.* BIS: Bank for International Settlements, Working Paper, No. 113.

Altman, E. and Kao, D. L. (1992) Rating Drift of High Yield Bonds. *Journal of Fixed Income.* 2(1), pp. 15–20.

Altman, E. and Rijken, H. (2004) How Rating Agencies Achieve Rating Stability. *Journal of Banking and Finance*. 28(11), pp. 2679–2714.

Altunbas, Y., Manganelli, S. and Marques-Ibanez, D. (2011) Bank Risk During the Financial Crisis: Do Business Models Matter? *ECB Working Paper Series* No 1394

Amato, J. and Furfine, C. (2004) Are Credit Ratings Procyclical? *Journal of Banking and Finance.* 28(11), pp. 2641-2677.

AMF (2005) *AMF 2005 Report on Corporate Governance and Internal Control.* Autorité Des Marchés Financiers.

Ammer, J. and Packer, F. (2000) How Consistent are Credit Ratings? A Geographic and Sectoral Analysis of Default Risk, Board of Governors of the Federal Reserve System *International Finance Discussion Papers* Number 668

Apergis, N., Sorros, J., Artikis, P. and Zisis, V. (2011) Bankruptcy Probability and Stock Prices: The Effect of Altman Z-Score Information on Stock Prices Through Panel Data. *Journal of Modern Accounting and Auditing.* 7(7), pp. 689–696.

Arellano, M. and Hahn, J. (2006) A Likelihood-Based Approximate Solution to the Incidental Parameter Problem in Dynamic Nonlinear Models With Multiple Effects. *Unpublished Manuscript.*

Arping, A. (2004) *Credit Protection and Lending Relationships.* EFA 2004 Maastricht Meetings Paper No. 4551.

Arvanitis A., Gregory, J. and Laurent, J. P. (1999) Building Models for Credit Spreads. *Journal of Derivatives.* Spring, pp. 27–48.

Asmussen, J. (2005) Rating-Agenturen und Finanzaufsicht. *Betriebswirtschaftliche Forschung und Praxis.* 57, pp. 246–55.

Ashbaugh-Skaife, H., Collins, D. and LaFond, R. (2006) The Effects of Corporate Governance on Firms' Credit Ratings. *Journal of Accounting and Economics*. 42 (1&2), pp. 203–243.

Ávila F., Flores E., López-Gallo F. and Márquez J. (2013) *Concentration Indicators: Assessing the Gap Between Aggregate and Detailed Data.* IFC Bulletin, No 36, Statistical issues and activities in a changing environment, Proceedings of the Sixth IFC Conference, Basel.

Bacmann, J. and Dubois, M. (2003) *Event Studies with Conditionally Heteroscedastic Stock Return.* National Centre of Competence in Research Financial Valuation and Risk Management Working Paper No. 60.

Baghai, R., Servaes, H. and Tamayo, A. (2013) Have Rating Agencies Become More Conservative? Implications for Capital Structure and Debt Pricing. *Forthcoming Journal of Finance*.

Baker, H. K, and Mansi, S. A. (2002) Assessing Credit Rating Agencies by Bond Issuers and Institutional Investors. *Journal of Business Finance and Accounting*. 29(9&10), pp. 1367–139.

Bai, L. (2010) *The Performance Disclosures of Credit Rating Agencies: Are They Effective Reputational Sanctions?* New York University Journal of Law and Business, Fall 2010, University of Cincinnati Public Law Research Paper No. 11-03.

Balling, M., Holm, C. and Poulsen, T. (2005) Corporate Governance Ratings as a Means to Reduce Asymmetric Information. *Working paper, Aarhus: Aarhus School of Business.*

Baltagi, B. H. (2009) *Econometric Analysis of Panel Data*. 4th ed. West Sussex: John Wiley and Sons Ltd.

Baltagi, B. H. and Wu, P. X. (1999) Unequally Spaced Panel Data Regressions With AR(1) Disturbances. *Econometric Theory.* 15: pp. 814–823

Bandyopadhyay, A. (2010) *Understanding the Effect of Concentration Risk in the Banks' Credit Portfolio: Indian Cases.* MPRA Paper No. 24822.

Bangia, A., Diebold, F., Kronimus, A., Schagen, C. and Schuermann, T. (2002) Ratings Migration and The Business Cycle, With Applications to Credit Portfolio Stress Testing. *Journal of Banking and Finance*. 26, pp. 445–474.

Bank for International Settlements (BIS) (2009) *The International Financial Crisis and Policy Challenges in Asia and the Pacific*. BIS Papers No 52.

Bank for International Settlements (BIS) (2010) *Basel III: International Framework for Liquidity Risk Measurement, Standards and Monitoring*. BIS.

Bank for International Settlements (BIS) (2010b) *Countercyclical Capital Buffers: Exploring Options*. BIS Working Paper 317.

Bank for International Settlements (BIS) (2014) Basel Committee on Banking Supervision reforms - Basel III, <Available from http://www.bis.org/bcbs/basel3/b3summarytable.pdf> Accessed 15 March 2014

Banking Reform and Macroprudential Regulation: Implications for Banks' Capital Structure and Credit Conditions', A Speech Given by Paul Tucker, Deputy Governor Financial Stability, at the SUERF/Bank of Finland Conference 2013, 'Banking after Regulatory Reform – Business as Usual', Helsinki Regulation Authority Board

Bannier, C., Behr, P. and Güttler, A. (2010) Rating Opaque Borrowers: Why Are Unsolicited Ratings Lower? *Review of Finance.* 14, pp. 263-294.

Bannier C. E. and Hirsch C. (2010), The Economic Function of Credit Rating Agencies: What does the Watchlist Tell Us*? Journal of Banking and Finance*, 34, 3037-3049.

Barth, J. R., Caprio, G. Jr., and Nolle, D. E. (2004) *Comparative International Characteristics of Banking. Office of the Comptroller of the Currency Economic and Policy Analysis.* Working Paper 2004-1 (January). Washington: US Office of the Comptroller of the Currency.

Barth, J. R., Caprio, G. and Levine, R. (2008) Bank Regulations are Changing: For Better or Worse? *Comparative Economic Studies.* 50, pp. 537-563.

Basel Committee on Banking Supervision (BCBS) (2005) *Studies on credit risk concentration: An overview of the issues and a synopsis of the results from the Research Task Force project*. Working Paper No. 15.

Basel Committee on Banking Supervision (BCBS) (2006) I*nternational Convergence of Capital Measurement and Capital Standards: A Revised Framework.* Bank for International Settlements, Basel, June, pp. 1–347.

Basel Committee on Banking Supervision (BCBS) (2009) *Revisions to the Basel II Market Risk Framework*. Bank for International Settlements, Basel, July.

Basel Committee on Banking Supervision (2010) *Principles for Enhancing Corporate Governance.* Bank for International Settlements, Basel, Consultation Document, pp. 1 – 40.

Basel Committee on Banking Supervision (2014) *Capital floors: The Design of Framework Based on Standardised Approaches.* Bank for International Settlements, Basel, Consultation Document, December, pp. 1–12.

Batta, G. (2011) The Direct Relevance of Accounting Information for CDS Pricing. *Journal of Business, Finance & Accounting.* 38(9&10), pp. 1096–1122.

Baysinger, B. D. and Butler, H. D. (1985) Corporate Governance and the Board of Directors: Performance Effects of Changes in Board Composition. J*ournal of Law, Economics and Organization*. 1, pp. 101–124.

Beatty, A. and Gron, A. (2001) Capital, Portfolio, and Growth: Bank Behavior under Risk-based Capital Requirements. *Journal of Financial Services Research.* 20, pp. 5–31.

Bedendo, M., Cathcart, L., El-Jahel, L. and Evans, L. (2013) The Credit Rating Crisis and the Informational Content of Corporate Credit Ratings. Available at: http://ssrn.com/abstract=1729231 [Accessed on 20 June 2014].

Beers, D. T. (2007) *The Future of Sovereign Credit Ratings.* RatingsDirect Report.

Bellotti, T., Matousek, R. and, Stewart, C. (2011) Are rating agencies' assignments opaque? Evidence from international banks. *Expert Systems with Applications* 38(4): 4206-4214

Beltratti, A. and Stulz, R. M. (2012) The Credit Crisis Around the Globe: Why Did Some Banks Perform Better? *Journal of Financial Economics.* 105, pp. 1–17

Benninga, S. (2014) *Financial Modelling*. 4th ed. Cambridge: MIT Press.

Bennell, J., Crabbe, D., Thomas, S. and Ap Gwilym. O. (2006) Modelling Sovereign Credit Ratings: Neural Networks Versus Ordered Probit. *Expert Systems with Applications.* 30, pp. 415–425.

Berger, A. N. and Bouwman, C. H. S. (2012) How Does Capital Affect Bank Performance During Financial Crises? *mimeo*, April 2012.

Berger, A. and DeYoung, R. (1997) Problem Loans and Cost Efficiency in Commercial Banks. *Journal of Banking and Finance.* 21, pp. 849–870.

Berger, A., DeYoung, R., Flannery, M., Lee, D. and Öztekin, Ö. (2008) How Do Large Banking Organisations Manage Their Capital Ratios? *Journal of Financial Services Research.* 34, pp. 123–149.

Berger, A. N., Imbierowicz, B. and Rauch, C. (2012) *The Roles of Corporate Governance in Bank Failures During the Recent Financial Crisis*. European Banking Centre. Discussion Paper No. 2012-023.

Besanko, D. and Kanatas, G. (1996) The Regulation of Bank Capital: Do Capital Standards Promote Bank Safety? *Journal of Financial Intermediation.* 5, pp. 160–183.

Bessis, J. (2010) *Risk Management in Banking.* 3rd ed. West Sussex: John Wiley and Sons Ltd.

Bhagat, S. and Black, B. (2002) The Non-Correlation Between Board Independence and Long Term Firm Performance. *Journal of Corporation Law.* 27, pp.231–274.

Bhojraj, S. and P. Sengupta (2003) Effect of Corporate Governance on Bond Ratings and Yields: The Role of Institutional Investors and Outside Directors. *The Journal of Business.* 76(3), pp. 455–475.

Binder, J. J. (1998) The Event Study Methodology Since 1969. *Review of Quantitative Finance and Accounting*. 11, pp. 111–137.

Bissoondoyal-Bheenick, E. and Treepongkaruna, S. (2011) An Analysis of the Determinants of Bank Ratings: Comparison Across Ratings Agencies. *Australian Journal of Management.* 36(3), 2011.

Blum, J. (1999) Do Capital Requirements Reduce Risks in Banking? *Journal of Banking and Finance.* 23, pp. 755–771.

Blume, M., Lim, F. and A. MacKinlay (1998) The Declining Credit Quality of US Corporate Debt: Myth or Reality? *Journal of Finance.* 53(4), pp. 1389–1413.

Bodie, Z., Kane, A. and Marcus, A. J. (2011) *Investments and Portfolio Management.* 9th ed. New York: McGraw-Hill/Irwin.

Boehmer, E., Musumeci, J. and Poulsen, A. (1991) Event Study Methodology Under Conditions of Event Induced Variance. *Journal of Financial Economics.* 30, pp. 253–272.

Bonti, G., Kalkbrener, M., Lotz, C. and Stahl, G. (2006). Credit Risk Concentrations Under Stress. *Journal of Credit Risk.* 2(3), pp. 115–136.

Boot, A. and Greenbaum, S. I. (1993) Bank-Regulation, Reputation and Rents: Theory and Policy Implications, in Mayer, C. and Vives, X.: *Capital Markets and Financial Intermediation*. Cambridge: Cambridge University Press.

Boot A., Milbourn T. and Schmeits, A. (2006) Credit Ratings as Coordination Mechanism. *Review of Financial Studies*. 19(1), pp. 81–118.

Borio, C. and Drehman, M. (2009) Assessing the risk of banking crises – revisited *BIS Quarterly Review, March 2009*

Bouzouita, R., and Young, A. (1998) A Probit Analysis of Best Ratings. *Journal of Insurance Issues.* 21(1), pp. 23–34 .

Brei M., Gambacorta, L. and Von Peter, G. (2013) Rescue Packages and Bank Lending. *Journal of Banking and Finance.* 37(2), pp. 490–505.

Bremer, R. and Zhang, Z. (2007) Extensions of The Standardized Cross-Sectional Approach to Short-Horizon Event Studies. *The Journal of Financial Research.* XXX(4), pp. 495–513.

Brockett, P. L., Chen, H. and Garven, J. R. (1999) A New Stochastically Flexible Event Methodology with Application to Proposition 103. *Insurance: Mathematics and Economics.* 25, pp. 197–217.

Brooks, C. (2009) *Introductory Econometrics for Finance.* Cambridge: Cambridge University Press.

Brown, S., and Warner, J. (1980) Measuring Security Price Performance. *Journal of Financial Economics*. 8, pp. 205–258.

Brown, S., and Warner, J. (1985) Using Daily Stock Returns: The Case of Event Studies. *Journal of Financial Economics*. 14, pp. 3–31.

Bruno, V. C., Cornaggia, J. and Cornaggia, K. J. (2011) The Information Content of Credit Ratings : Compensation Structure Does Matter, (812), 1–54. Available from: http://www.egan-jones.com/public/download/studies/2012_The_Information_Content_of_Credit_Ratings_Compensation_Structure_Does_Matter.pdf [Accessed 15 May 2014].

Brunnemeier, M. K. and Pedersen, L. H. (2007) *Market Liquidity and Funding Liquidity.* NBER Working Paper No. 12939

Bryant, J. (1980) A model of reserves, bank runs, and deposit insurance. *Journal of Banking and Finance.* 4(4), pp. 335–344.

Buch, C. and DeLong, G. (2008) Do Weak Supervisory Systems Encourage Bank Risk-taking? *Journal of Financial Stability.* 4, pp. 23–39.

Butler, J. S. and Moffatt, R. (1982) A Computationally Efficient Quadrature Procedure for the One-Factor Multinomial Probit Model. *Econometrica*. 50(3), pp. 761–764.

Cadman, E. (2014) "IMF's Lagarde attacks financial sector for blocking reform," *Financial Times*, May 27, 2014

Cai, J. and Thakor, A. N. (2008) *Liquidity Risk, Credit Risk, and Interbank Competition.* Working Paper, Center for Research in Economics and Strategy.

Calderoni, F., Colla, P. and Gatti, S. (2009) *Rating Changes: The European Evidence*. Carefin Università Bocconi, Research Paper.

Calmes, C. and Theoret, R. (2010) The Impact of Off-Balance Sheet Activities on Bank Returns: An Application of The ARCH-M to Canadian Data. *Journal of Banking and Finance.* 34, pp. 1719–1728.

Camanho, N., Deb P. and Liu, Z. (2011). Credit Rating and Competition, *Discussion paper 653, LSE Financial Markets Group Discussion Paper Series*.

Campbell, C. J., Cowan, A. R., Salotti, V. (2010) Multi-Country Event-Study Methods. *Journal of Banking and Finance*. 34, pp. 3078–3090.

Campbell, J. Y., Lo, A. W. and MacKinlay, A. C. (1996) *The Econometrics of Financial Markets.* Princeton: Princeton University Press, Chapter 4.

Campbell, C. J. and Wasley, C. E. (1993) Measuring Security Performance Using Daily NASDAQ Returns. *Journal of Financial Econometrics.* 33, pp. 73–92

Cannella, A. and Hambrick, D. (1993) Effects of Executive Departures on the Performance of Acquired Firms. *Strategic Management Journal* Vol. 14:137–52

Cantor, R. and Mann, C. (2003) *Measuring the performance of corporate bond ratings.* Special Comment, Moody's Investor Service, Global Credit Research.

Cantor, R. and Parker, F. (1995) Sovereign Credit Ratings. Current Issues in Economics and Finance. *Federal Reserve Bank of New York, Nova York*. 1(3), pp. 1–6.

Cantor, R. and Packer, F. (1997) Differences of opinion and selection bias in the credit rating industry. *Journal of Banking and Finance.* 21(10), pp. 1395–1417.

Cantor, R. (2001) Moody's Investors Service Response To The Consultative Paper Issued By The Basel Committee On Bank Supervision: A New Capital Adequacy Framework. *Journal of Banking Finance*. 25, pp. 171–185.

Cantwell, J. (2000) Rating Agency Evaluation: What Really Matters, in: AFP Exchange, 20. Jg., Heft 2, 2000, S. 6–10 .

Caporale G.M., Rault C., Sova R. and Sova A. (2009) *Financial Development and Economic Growth: Evidence from Ten New EU Members.* DIW working paper No. 940.

Caporale, G., Matousek, R. and Stewart, C. (2011) EU banks rating assignments: Is there heterogeneity between new and old member countries? *Review of International Economics* 19:189-206.

Cardone-Riportella, C., Samaniego-Medina, R. and Trujillo-Ponce, A. (2010) What Drives Bank Securitization? The Spanish Experience. *Journal of Banking and Finance.* 34(11), pp. 2639–2651.

Carey, M. and Hrycay, M. (2001) *Parameterizing Credit Risk Models with Rating Data.* FEDS Working Paper No. 2000-47.

Carey, M. and Stulz, R. M. (2006) *The Risk of Financial Institutions.* London: National Bureau of Economic Research.

Carpenter, J. N. and Lynch, A. W. (1999) Survivorship Bias and Attrition Effects in Measures of Performance Persistence *Journal of Financial Economics* 54 337-374

Carty, L. V. (1997) *Moody's Rating Migration and Credit Quality Correlation, 1920-1996.* Moody's Special Comment, Moody's Investor Service, New York.

Carty, L. and Fons, J. (1994) Measuring changes in credit quality. *Journal of Fixed Income.* 4, pp. 27–41.

Caton, G. L. and Goh, J. (2003) Are All Rivals Affected Equally By Bond-Rating Downgrades? *Review of Quantitative Finance and Accounting.* 20(1), pp 49–62.

Cebenoyan, A. S. Strahan, P. E. (2004) Risk Management, Capital Structure and Lending at Banks. *Journal of Banking and Finance*. 28, pp. 19-43.

CFA (2014) Global Market Sentiment Survey 2014 *CFA Institute*

Chakravartya, S. and John, J. and McConnella, J. J. (1999) Does Insider Trading Really Move Stock Prices? *Journal of Financial and Quantitative Analysis*. 34(2), pp. 191-209.

Chamberlain, G. (1982) Multivariate Regression Models for Panel Data. *Journal of Econometrics*. 1, pp. 5–46.

Chava, S. and Jarrow, R. A. (2004). Bankruptcy Prediction with Industry Effects. *Review of Finance*, 8(4), 537–569.

Chen, F., Gao, G. and Rui, O. M. (2006) Ownership Structure, Corporate Governance, and Fraud: Evidence from China. *Journal of Corporate Finance*. 12, pp. 424–448.

Cheung, S. (1996) *Provincial Credit Ratings in Canada: An Ordered Probit* Analysis Working Paper 96-6 / Document de travail 96-6, Bank of Canada.

Choy, E. Y. W., Gray, S. F., and Ragunathan, V. (2006) Effect of Credit Rating Changes on Australian Stock Returns. *Accounting and Finance*. 46(5), pp. 755–769.

Christensen, J. H. E., Hansen, E., Lando, D. (2004) Confidence Sets for Continuous-Time Rating Transition Probabilities. *Journal of Banking and Finance.* 28, pp. 2575–2602.

Ciancanelli, P. and Reyes-Gonzales. J. (2000) *Corporate Governance in Banking: A Conceptual Framework.* SSRN Working Paper. June 2000.

Ciro, T. (2013) *The Global Financial Crisis: Triggers, Responses and Aftermath.* Surrey: Ashgate Publishing.

Chu, S. H. and Freund, S. (1996) Volatility Estimation for Stock Index Options: A GARCH Approach. *Quarterly Review of Economics and Finance*. 36(4), pp. 431-450.

Cocheo, S. (2000) Performance Picture: Avoiding Efficiency as a Religion. *American Bankers Association, ABA Banking Journal.* 92(2), pp. 58–9.

Cole, R. A. and White, L. J. (2012). Deja vu All Over Again: The Causes of U.S. Commercial Bank Failures This Time Around. *Journal of Financial Services Research.* 42, pp. 5–29.

Commission of the European Communities (2006) Communication From The Commission on Credit Rating Agencies. *Journal of European Union*. 2006/c59/02, pp. 1–5.

Commission of the European Communities (2008) *CESR's Second Report to the European Commission on the compliance of credit rating agencies with the IOSCO Code and The role of credit rating agencies in structured finance.* CESR/08-277, pp. 1–68.

Commission of the European Communities (2010) *CESR's Guidance on common standards for assessment of compliance of credit rating methodologies with the requirements set out in Article 8.3.* Committee of European Securities Regulators, CESR/10–945.

Corbet, K. (2013) Financial Crisis,: Five Years After, 10 to Remember *TIME* Sept. 11 2013

Corhay, A. and Rad, T. (1994) Statistical Properties of Daily Returns: Evidence from European Stock Markets. *Journal of Business Finance and Accounting*. 21, pp. 271–282.

Cornett, M., Marcus, A., Saunders, A. and Tehranian, H. (2006) *Corporate Governance, Institutional Investors, and Financial Performance: The Impact of Earnings Management.* Working Paper, Boston: Boston College.

Cornett, M. M., McNutt, J. J., Strahan, P. and Tehranian, H. (2011) Liquidity Risk Management and Credit Supply in the Financial Crisis. *Journal of Financial Economics.* 10, pp. 297–312.

Corrado, C. J. (1989) A nonparametric test for abnormal security price performance in event studies. *Journal of Financial Econometrics*. 23, pp. 385–395.

Cosimano, T. F. and Hakura, D. S. (2011) *Bank Behavior in Response to Basel III: A Cross Country Analysis.* IMF Working Paper, IMF Institute.

Cousineau, D. and Chartier, S. (2010) Outliers Detection and Treatment: A Review. *International Journal of Psychological Research* 3 (1), 58–67.

Cowan, A. R. (1992) Nonparametric Event Study Tests. *Review of Quantitative Finance and Accounting.* 2, pp. 343–358.

Credit Risk Management Policy Group III (2008) Containing Systemic Risk: The Road to Reform The Report of the CRMPG III *CRMPOLICYGROUP* August 6 2008

Creighton A., Gower, L. and Richards, A. J. (2007) The Impact of Rating Changes in Australian Financial Markets. *Pacific-Basin Finance Journal*. 15, pp. 1–17.

Cremers, M., Nair, V. B. and Wei, C. (2004) The Congruence of Shareholder and Bondholder Governance. *Law and Economics Research Paper*. 04–007.

Cull, A. (2015) Financial Stability Board Unveils Global Rules to End 'Too Big to Fail', Available at: https://www.bba.org.uk/news/bba-voice/financial-stability-board-unveils-global-rules-to-end-too-big-to-fail/#.VsVxefmLSUk [Accessed 23 November 2015]

Cummins, J. D. and Phillips, R. D. (2009) Capital Adequacy and Insurance Risk-Based Capital Systems. *Journal of Insurance Regulation.* 28 (1), pp. 25–72.

Czarnitzki, D. and Kraft, K. (2004) Innovation Indicators and Corporate Credit Ratings: Evidence from German Firms. *Economic Letters.* 82(3), pp. 377-384.

Czarnitzki, D. and Kraft, K. (2006) R&D and Firm Performance in a Transition Economy. *KYKLOS*. 59(4), pp. 481–496.

Dalton, D. R., Hitt, M. A., Certo, S. T. and Dalton, C. M. (2007) The Fundamental Agency Problem and Its Mitigation: Independence, Equity and The Market for Corporate Control. *Academy of Management Annals.* 1, pp. 1–64.

Daniel, K. D., Hirshleifer, D. and Subrahmayam, A. (1998) Investor Psychology and Security Market Under- and Over-Reaction *Journal of Finance*, Vol. 53, 1839-1886

Darcy, D. (2009) Credit Rating Agencies and the Credit Crisis: How the 'Issuer Pays' Conflict Contributed and What Regulators Might Do About It. *Columbia Business Law Review.* pp. 605–611.

Daykin, A. R. and Moffatt, P. G. (2002) Analyzing Ordered Responses: A Review of the Ordered Probit Model. *Understanding Statistics.* l(3), pp. 157–66.

De Jong, F., Kemma, A. and Kloek, T. (1992) A Contribution to Event Study Methodology With an Application to the Dutch Stock Market. *Journal of Banking and Finance*. 16, pp. 11–36.

De Andrés, P. and Vallelado, E. (2008) Corporate Governance in Banking: The Role of the Board of Directors. *Journal of Banking and Finance.* 32(12), pp. 2570–2580.

Deakin, E. (1976) Distributions of Financial Accounting Ratios: Some Empirical Evidence. *Accounting Review* January 90-96

Deb, P., and G. Murphy, 2009, Rating Agencies - An Alternative Model, *Bank of England.*

Deb, P., Manning M., Murphy G., Penalver A. and Toth A. (2011) *Whither the Credit Ratings Industry?* Financial Stability Paper, Bank of England, No. 9.

DeMarzo, P. M. (2005) The Pooling and Tranching of Securities: A Model of Informed Intermediation. *Review of Financial Studies.*18(1), pp. 1–35.

Demirgüç-Kunt, A. and Detragiache, E. (2010) *Basel Core Principles and Bank Risk: Does Compliance Matter?* IMF Working Paper No. WP/10/81.

Demirovic, A. and Thomas D. (2007) The Relevance of Accounting Data in the Measurement of Credit Risk. *The European Journal of Finance.* 13(3), pp. 253–268.

Demsetz, R. S. and Strahan, P. E. (1997) Diversification, Size, and Risk at U.S. Bank Holding Companies. *Journal of Money, Credit, and Banking.* 29, pp. 300-313.

Demyanyk, Y. & Hasan, I. (2010) Financial crises and bank failures: A review of prediction methods. *Omega, Elsevier.* 38(5), pp. 315-324.

De Servigny, A. and Renault, O. (2004) *Measuring and Managing Credit Risk.* Standard & Poor's Press: Kindle Edition (The McGraw Hill Company).

Diamond, D. W. and Dybvig, P. H. (1983) Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*. 91(3), pp. 401-419.

Diamond, D. W. and Rajan, R.G. (2005) Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking. *The Journal of Political Economy*. 109(2), pp. 287-327.

Diamond, D. W. and Rajan, R.G. (2001) Liquidity Shortages and Banking Crises. *Journal of Finance*. 60(2), pp. 615–647.

Dichev, I. (1998) Is the Risk of Bankruptcy a Systematic Risk? *The Journal of Finance.* 53(3), pp. 1131-1147.

Dichev, I. D. and Piotrovski, J. D. (2001) The Long-Run Stock Returns Following Bond Ratings Changes. *The Journal of Finance*. 56, pp. 173–203.

Dimson, E. (1979) Risk Measurement When Shares Are Subject to Infrequent Trading. *Journal of Financial Economics*. 5, pp. 263–278.

Distinguin, I., Hasan, I. and Tarazi, A. (2012) *Predicting Rating Changes for Banks: How Accurate are Accounting and Stock Market Indicators?* Bank of Finland Research Discussion Paper No. 15/2012, April.

Dodd-Franck Act (2010) *Impact on Credit Rating.* The Dodd-Frank Wall Stress Reform and Consumer Protection Act, September (2010).

Doherty, N. and Phillips, R. (2002) Keeping Up with the Joneses: Changing Rating Standards and the Buildup of Capital by US Property-liability Insurers. *Journal of Financial Services Research*. 21, pp. 55–78.

Doumpos, M. and Pasiouras, F. (2005) Developing and Testing Models for Replicating Credit Ratings: A Multicriteria Approach. *Computational Economics.* 25 (4), pp. 327–34.

Du, Y. and Suo, W. (2005) An Empirical Study on Credit Rating Change Behavior, *Unpublished Manuscript.*

Dudley, W. C. (2009) Financial Market Turmoil: The Federal Reserve and the Challenges Ahead *Remarks at the Council on Foreign Relations Corporate Conference 2009, New York City*

Duellmann, K. and Masschelein, N. (2006) *Sector Concentration in Loan Portfolios and Economic Capital.* Deutsche Bundesbank Discussion Paper.

Duff A., and Einig, S. (2009) Credit Ratings Quality: The Perceptions of Market Participants and Other Interested Parties. *The British Accounting Review*. pp. 1–16.

Duffee, G. R. and Zhou, C. (2001) Credit derivatives in banking: Useful tools for managing risk. *Journal of Monetary Economics*. 48, pp. 25–54.

Duffie, D., Saita, L., and Wang, K. (2007). Multi-Period Corporate Default Prediction with Stochastic Covariates. *Journal of Financial Economics*, 83(3), 635–665.

Dutta, S. and Shekhar, S. (1988) *Bond Rating: A Non-Conservative Application of Neural Networks.* IEEE International Conference on Neural Networks, II, pp. 443–450.

Dwyer, G. P. (2009) *Credit Ratings and Derivatives. Notes from the vault.* Centre for Financial Innovation and Stability, Federal Reserve Bank of Atlanta.

Ederington, L. (1985). Classification Models and Bond Ratings. *Financial Review.* 4 (20), pp. 237–62.

Ederington, L. and Goh, C. (1998) Bond Rating Agencies and Stock Analysts: Who Knows What When? *The Journal of Financial and Quantitative Analysis*. 33(4), pp. 569–585.

Egan, S. J. (2002) Statement of Egan-Jones on Credit Rating Agencies, Letter Submitted to the SEC, November 10, 1-90

Elkhoury, M. (2010) *Credit Rating Agencies and Their Impact on Developing Countries.* Saarbrücken: LAP Lambert Academic Publishing.

Elsinger, H., Lehar, A. and Summer, M. (2006) Using Market Information for Banking System Risk Assessment. *International Journal of Central Banking*, 1, pp. 137–66.

Ellul, A. and Yerramilli, V. (2013) Stronger Risk Controls, Lower Risk: Evidence From US Bank Holding Companies. *Journal of Finance*. 68(5), pp. 1757–1803.

Elton, E.J., Gruber, M.J. (1995) *Modern Portfolio Theory and Investment Analysis.* 5th ed. Wiley: New York.

Erkens, D., Hung, M., and Matos, P. P. (2010) *Corporate Governance in the 2007–2008 Financial Crisis: Evidence from Financial Institutions Worldwide*. ECGI—Finance Working Paper No. 249/200.

Erlenmaier, U. (2006) The Shadow Rating Approach – Experience From Bank Practice, The Basel II Risk Parameters. *Berlin Heidelberg*. pp. 39–77.

Ernst and Young (2014) Shifting Focus Risk Culture at the Forefront of Banking *EY 2014 Risk Management Survey of Major Financial Institutions*

Estrella, A., Park, S. and Peristiani, S. (2000) Capital Ratios as Predictors of Bank Failure. *FRBNY Economic Policy Review.* July 2000, 6(2), pp. 33–52.

European Banking Authority (EBA) (2014) *EBA announces details of 2016 EU-wide stress test*, European Banking Authority November 5 2015.

European Banking Authority (EBA) (2015) *Methodological note EU–wide Stress Test 2014*, European Banking Authority.

European Securities and Market Authority (ESMA) (2015) ESMA Sees Progress in Reform of EU Credit Rating Industry, *Press Release* ESMA/2015/1483

Fabozzi, F. (2012) *Bond Markets: Analysis and Strategies.* 8th ed., Prentice Hall

Fahlenbrach, R. and Stulz, R. M. (2011) Bank CEO Incentives and the Credit Crisis. *Journal of Financial Economics.* 99(1), pp. 11–26.

Falavigna, G. (2012) Financial Ratings with Scarce Information: A Neural Network Approach. *Expert System Application.* 39, pp. 1784–1792.

Faleye, O. and Krishnan, K. (2010) Risky Lending: Does Bank Corporate Governance Matter? Available at: http://ssrn.com/abstract=1661837 [Accessed 23 Mar 2012].

Fama, E. and French, K. (2014) A Five-Factor Asset Pricing Model *Fama-Miller Working Paper*

Fama, E. and Jensen, M. (1983) Separation of Ownership and Control. *Journal of Law and Economics.* 26, pp. 301–325.

Fama, E. F. (1991) Efficient Capital Markets II. *Journal of Finance*. 46, pp.1575–1617.

Farag, M., Harland, D. and Nixon, D. (2013) Bank Capital and Liquidity. *Bank of England Quarterly Bulletin 2013 Q3.*

FDIC (1997) Uniform Financial Institutions Rating System *Federal Deposit Insurance Corporation Federal Register*, Vol. 62, No. 3

Fernandes, N. and Ferreira, M. A. (2009) Insider Trading Laws and Stock Price Informativeness. *Review of Financial Studies*. 22, pp. 1845–1887.

Fei, F., Fuertes, A.M. and Kalotychou, E. (2012) Credit Rating Migration Risk and Business Cycles. *Journal of Business and Financial Accounting*. 39, pp. 229–263.

Fieberg, C., Varmaz , A., Prokop, J., Körner, F. N. (2013) *The News Content of Bank Rating Changes: Evidence from a Global Event Study.* ZenTra Working Paper in Transnational Studies No. 24 / 2013.

Figlewski, S., Frydman, H., and Liang, W. (2012). Modeling the Effect of Macroeconomic Factors on Corporate Default and Credit Rating Transitions. *International Review of Economics and Finance*, 21(1), 87–105.

Fight, A. (2000) *The Ratings Game.* John Wiley & Sons Ltd.

Financial Services Authority (FSA) (2009) *The Turner Review A Regulatory Response to the Global Banking Crisis*. FSA*,* March 2009.

Financial Conduct Authority (2015) FCA Fines Barclays £72 Million For Poor Handling of Financial Crime Risk *Financial Conduct Authority Press Release* November 26 2015

Financial Stability Board FSB (2010) Principles for Reducing Reliance on CRA Ratings *Financial Stability Board* October 27 2010

Financial Stability Board FSB (2013) 2013 Update of Group of Global Systemically Important Banks (G-SIBs) *Financial Stability Board* November 11 2013

Financial Stability Board FSB (2014) Guidance on Supervisory Interaction with Financial Institutions on Risk Culture A Framework for Assessing Risk Culture, *Financial Stability Board* April 7 2014

Financial Stability Forum (2008) Report of the Financial Stability Forum on Enhancing Market and Institutional Resilience *Financial Stability Forum* April 7 2008

Fiordelisi, F., Marques-Ibanez, D., Molyneux, P. (2011) Efficiency and Risk-Taking in European Banking. *Journal of Banking and Finance*. 35(5), pp. 1315-1326.

Fitch Ratings (2007) *Introduction to ratings: Fitch Rating Definitions.* Fitch Rating. 26, pp. 1-4.

Fitch Ratings (2007b) *Global Bank Individual Ratings Transition and Failure Study – 1990-2006*. Special Report. pp. 1–20.

Fitch Ratings (2014) Fitch Ratings – Definitions of Ratings and Other Forms of Opinion *FitchRatings* 1-59

Fitch Ratings (2015) Fitch Bank Rating Methodologies Available on *https://www.fitchratings.com/site/fitch-home/banks* [Accessed November 15 2015]

Foglia, A. (2009) Stress Testing Credit Risk: A Survey of Authorities' Approaches. *International Journal of Central Banking,* 5(3), pp. 9–45.

Followill, R. and Martell, T. (1997) Bond Review and Rating Change Announcements: An Examination of Informational Value and Market Efficiency. *Journal of Economics and Finance.* 21, pp. 75-82.

Fracassi, C., Petry, S. and Tate, G. (2014) *Do Credit Analysts Matter? The Effect of Analysts on Ratings, Prices, and Corporate Decisions.* USC FBE Finance Seminar.

Franke, G. and Krahnen, J. P. (2005) *Default Risk Sharing between Banks and Markets: The Contribution of Collateralized Debt Obligations.* NBER Working Paper. Available at: http://www.nber.org/chapters/c9620 [Accessed 15 June 2011].

Frecka, T. K. and Hopwood, W. S. (1983) The Effects of Outliers on the Cross-Sectional Distributional Properties of Financial Ratios *The Accounting Review* Vol. 58, No. 1 (Jan., 1983), pp. 115-128

Freixas, X. and Rochet, J. C. (2008) *Microeconomics of Banking*. 2nd ed. Cambridge: The MIT Press.

Frost, C. A. (2007) Credit Rating Agencies in Capital Markets: A Review of Research Evidence on Selected Criticisms of the Agencies. *Journal of Accounting, Auditing and Finance.* 22, pp. 469-480

Frydman, H. and Schuermann, T. (2008) Credit Rating Dynamics and Markov Mixture Models. *Journal of Banking and Finance.* 32(6), pp. 1062–1075.

Gadanecz, B., Kara, A. and Molyneux, P. (2012) Asymmetric information among lenders and the value of repeat lending. *Journal of International Financial Markets, Institutions and Money* 22, 913–935.

Galil, K. (2003) *The Quality of Corporate Credit Rating: An Empirical Investigation.* Working Paper, Beer-Sheva: Ben-Gurion University of the Negev.

Galindo, J. and Tamayo, P. (2000) Credit Risk Assessment Using Statistical and Machine Learning: Basic Methodology and Risk Modeling Applications. *Computational Economics.* 15(1-2), pp 107-143

Gallati, R (2003) *Risk Management and Capital Adequacy*. New York: McGraw-Hill

Gan, Y. (2004) *Why Do Firms Pay for Bond Ratings When They Can Get Them For Free?* Working Paper (University of Pennsylvania).

Gannon, J., Evans, K. P. and Goddard, J. (2006) The Stock Market Effects of the Sale of Live Broadcasting Rights for English Premiership Football. *Journal of Sports Economics.* 7(2), pp. 168-186

Gatev, E., Schuermann, T. and Strahan, P. E. (2009) Managing Bank Liquidity Risk: How Deposit-Loan Synergies Vary with Market Conditions. *Review of Financial Studies*. 22(3), pp. 995-1020.

Geithner, T.G. (2006) *Risk Management Challenges in the U.S. Financial System.* Remarks at the Global Association of Risk Professionals (GARP) 7th Annual Risk Management Convention & Exhibition in New York City.

Gentry, J., Whitford, D. and Newbold, P. (1988) Predicting Industrial Bond Ratings With a Probit Model and Funds Flow Components. *The Financial Review.* 23 (3), pp. 269-286.

Ghosh, D. and Vogt, A. (2012) Outliers: An Evaluation of Methodologies *Section on Survey Research Methods – JSM 2012*

Glascock, J. L., Davidson, W. N. and Henderson, G. V. (1987) Announcement Effects of Moody's Bond Rating Changes on Equity Returns. *Quarterly Journal of Business and Economics*. 26(3), pp. 67-78.

Goddard, J., Molyneux, P. and Wilson, J.O.S. (2004) The Profitability of European Banks: A Cross-Sectional and Dynamic Panel Analysis. *Manchester School.* 72 (3), pp. 363- 381.

Goderis, B., Marsh, I., Vall Castello, J., Wagner, W. (2007) *Bank Behaviour with Access to Credit Risk Transfer Markets.* Bank of Finland, Helsinki.

Goh, J. and Ederington, L. (1999) Cross–Sectional Variation in The Stock Market Reaction to Bond Rating Changes. *The Quarterly Review of Economics and Finance.* 39(1), pp. 101-112.

Golin, J. (2001) *The Bank Credit Analysis Handbook: A Guide for Analysts, Bankers and Investors*. John Wiley & Sons (Asia) Pre Ltd.

Golin, J. and Delhaise, P. (2013) *The Bank Credit Analysis Handbook: A Guide for Analysts, Bankers and Investors*. 2nd ed. John Wiley & Sons (Asia) Pre Ltd.

Gomez-Gonzalez, J. and Kiefer, N. M. (2009) Bank Failure: Evidence from the Colombian Financial Crisis. *The International Journal of Business and Finance Research.* 3(3), pp. 15–31

Gonis, E., Paul, S. and Tucker, J. (2012) Rating or no rating? That is the question: An empirical examination of UK companies European *Journal of Finance*

Gonzalez, F., Haas, F., Johannes, R., Persson, M., Toledo, L., Violi, R., Wieland, M. and Zins, C. (2004) Market dynamics associated with credit ratings. A literature review. *Banque de France Financial Stability Review.* 4, pp. 53-76

Gordy, M. (2003) A Risk-Factor Model Foundation for Ratings-Based Bank Capital Rules. *Journal of Financial Intermediation.* 12, pp. 199–232.

Gordy, M. and Lütkebohmert, E. (2013) Granularity Adjustment for Regulatory Capital Assessment. *International Journal of Central Banking*, September 2013.

Gorton, G. and Metrick, A. (2011) Securitized Banking and the Run on Repo. *Journal of Financial Economics.* 104(3), pp. 425–451.

Gopalan, R., Song, F. and Yerramilli, V. (2009) *Do credit rating agencies underestimate liquidity risk?* Working Paper.

Graham, J. and C. Harvey (2001) The Theory and Practice of Corporate Finance: Evidence from the Field. *Journal of Financial Economics.* 60 (2-3), pp.187–243.

Grandmont, R., Grant, G. and Silva, F. (2004) *Corporate Governance: Implications for Investors, Beyond the Numbers.* Deutsche Bank Equity Research, 1. April.

Gray, S., Mirkovic, A. and Ragunathan, V. (2006) The Determinants of Credit Ratings: Australian Evidence. *Australian Journal of Management*. 31(2), pp. 333–354.

Greene, W. (2003) *Econometric Analysis*. New Jersey: Prentice Hall.

Greene, W. (2004) Fixed and Random Effects in Stochastic Frontier Models. *Journal of Productivity Analysis*. 23, pp. 7-32.

Greene, W. H. and Hensher, D. A. (2009) *Modeling Ordered Choices: A Primer.* Cambridge: Cambridge University Press.

Greenspan, A. (2005) *Risk Transfer and Financial Stability*. Federal Reserve Bank of Chicago, Chicago IL.

Griffin, P. A. and Sanvicente, A. Z. (1982) Common Stock Returns and Rating Changes: A Methodological Comparison. *Journal of Finance.* 37(1), pp. 103–119.

Gropp, R., H. Hakenes, and I. Schnabel (2011). Competition, Risk-shifting, and Public Bail-out Policies. *Review of Financial Studies* 24(6). pp. 2084-2120.

Grothe, M. (2013) *Market Pricing Of Credit Rating Signals*. Working Paper Series 1623, European Central Bank.

Grove, H., Patelli, L., Victoravich, L. M. and Xu, P. (2011) Corporate Governance and Performance in the Wake Of The Financial Crisis: Evidence from US Commercial Banks. *Corporate Governance: An International Review*. 19 (5), pp. 418–436.

Gultekin-Karakaş, D., Hisarcikhlar, M. and Öztürk, H. (2011) Sovereign Risk Ratings: Biased Toward Developed Countries? *Emerging Markets Finance & Trade*, Vol 47, May-June.

Güttler, A. and Wahrenburg, M. (2007) The Adjustment of Credit Ratings in Advance of Defaults *Journal of Banking and Finance* 31, 751-767

Güttler, A. and Raupach, P. (2007) The Impact of Downward Rating Momentum. *Journal of Financial Services Research*. 37, pp. 1–23.

Gup, B.E. (2004) *Too Big to Fail: Policies and Practices in Governments Bailouts.* Praeger: Westport, Conn.

Haensel, D. and Krahnen, J.P. (2007) *Does Credit Securitisation Reduce Bank Risk? Evidence from the European CDO Market.* Goethe University, Frankfurt am Main.

Hand, J., Holthausen R. and Leftwich, R. (1992) The Effect of Bond Rating Agency Announcements on Bond and Stock Prices. *Journal of Finance*. 47, pp 733–52.

Haldane, A. and Madouros, V. (2012) The Dog and the Frisbee, *Paper presented at the Federal Reserve Bank of Kansas City's 36th Economic Policy Symposium ―The changing policy landscape,* August 31.

Hamilton, D. and Cantor, R. (2004) Rating Transitions and Defaults Conditional on Watchlist, Outlook, and Rating History, *Moody's Investors Service Special Comment*, February 2004

Hardle, W., Moro, R. and Schafer, D. (2005) *Predicting Bankruptcy With Support Vector Machines*. SFB 649 Discussion Paper 2005-009, Humbolt-Universiat zu Berlin.

Hau, H., Langfield, S., Marques-Ibanez, D. (2012) *Bank Ratings: What Determines Their Quality?* European Central Bank, Working paper series, No. 1484, October 2012.

Hau, H. and Thum, M.P. (2009) *Subprime Crisis and Board (In-)Competence: Private vs. Public Banks in Germany.* CESifo Working Paper Series No. 2640, ECGI - Finance Working Paper No. 247/2009.

He, Z. and Xiong, W. (2012a) Dynamic Debt Runs. *Review of Financial Studies*. 25(6), pp.1799-1843.

He, Z. and Xiong, W. (2012b) Rollover Risk and Credit Risk. *Journal of Finance*. 67(2), pp. 391-429.

Healy, P. M., & Wahlen, J. M. (1999). A review of the earnings management literature and its implications for standard setting. *Accounting horizons*,13 (4), 365-383

Heffernan, S. (2005) *Modern Banking.* Chichester, West Sussex: John Wiley and Sons.

Hermalin, B. E. and Weisbach, M. S. (2009) *Information Disclosure and Corporate Governance.* Ohio State University Fisher College of Business Working Paper 2008–03–016.

Hess, K. and Francis, G. (2004), Cost Income Ratio Benchmarking in Banking. *Benchmarking: An International Journal*. 11(3), pp. 303-319.

Higgins, E. J., Mason, J. R. and Mordel, A. (2010) The Information Content of Asset Backed Securities Downgrades and the Motivation Behind Them. *mimeo.*

Hill, R. C., Griffiths, W. E. and Lim, G. C. (2008) *Principles of Econometrics.* New York: John Wiley and Sons.

Hilliard, J. and Savickas, R. (2000) *On Stochastic volatility and more powerful parametric tests of event effects on unsystematic returns.* Working Paper, University of Georgia.

Hillman, A. J., Shropshire, C. and Cannella, A. A. Jr. (2007) Organizational predictors of women of corporate boards. *Academy of Management Journal.* 50 (4), pp. 941-952.

Hilscher, J. and Wilson, M. I. (2013 *Credit Ratings and Credit Risk: Is One Measure Enough?* AFA 2013 San Diego Meetings Paper.

Hirtle, B. (2009) Credit Derivatives and Bank Credit Supply. *Journal of Financial Intermediation.* 18, pp. 125-150.

Hite, G., Warga, A. (1997) The Effect of Bond-Rating Changes on Bond Price Performance. *Financial Analysts Journal.* 53(3), pp. 35-51

Holthausen, R.W. and Leftwich, R.W. (1986) The effect of bond rating changes on common stock prices. *Journal of Financial Economics.* 17, pp. 57-89.

Hong Kong Institute of Bankers (HBIK) (2012) *Credit Risk Management*. Singapore: Wiley Finance Series.

Horrigan, J. (1966) The Determination of Long-Term Credit Standing With Financial Ratios. *Journal of Accounting Research*. 4(3), pp. 44-62.

Hossari, G., Rahman, S. F. and Ratnatunga, J. (2007) An empirical evaluation of sampling controversies in ratio-based modelling of corporate collapse. *Journal of Applied Research in Accounting and Finance.* 2(2), pp. 15-26.

House of Commons Treasury Committee (2009) Banking Crisis: Dealing With the Failure of the UK Banks *HC* 416

Houston, J.F., Lin, L., Lin, P. and Ma, Y. (2010) Creditor Rights, Information Sharing, and Bank Risk Taking. *Journal of Financial Economics*. 96, pp. 485-512.

Howells, P. G. A. and Bains, K. (2008) *The Economics of Money, Banking and Finance: A European Text*. 4th ed. Essex: Financial Times/Prentice Hall.

Hsueh, L.P., and Liu, Y.A. (1992) Market Anticipation and the Effect of Bond Rating Changes on Common Stock Prices. *Journal of Business Research*. 24, pp. 225–239.

Hu, Y.-T., Kiesel, R., and Perraudin, W. (2002). The Estimation of Transition Matrices for Sovereign Credit Ratings. *Journal of Banking and Finance*, 26(7), 1383–1406.

Huang, Z., Chen, H., Hsu, C., Chen, W. and Wu, S. (2004) Credit Rating Analysis with Support Vector Machines and Neural Networks: A Market Comparative Study. *Decision Support Systems.* 37, pp. 543–558.

Hull, J. (2009) *Options, Futures and Other Derivatives.* 6th ed. New Jersey: Pearson Prentice Hall.

Hull, J., Predescu, M. and White, A. (2004) The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements. *Journal of Banking and Finance*. 28, pp. 2789-811.

Iannotta, G. and Pennacchi, G. (2012) Bank Regulation, Credit Ratings, and Systematic Risk. Available at: http://ssrn.com/abstract=2021355 [Accessed 12 January 2013].

Imad, M. (2010) Stock Market Contagion in The Early Stages Of The Global Financial Crisis: The Experience of The GCC Countries. *International Journal of Banking and Finance.* 7(1&2), pp. 19-34.

Imbierowicz, B. and Rauch, C. (2014) The Relationship Between Liquidity Risk and Credit Risk in Banks. *Journal of Banking and Finance.* 40(1), pp. 242-256.

Ince, O. S. and Porter, B. (2006) Individual Equity Return Data from Thomson Datastream: Handle with Care *Journal of Financial Research* Vol. 29, Issue 4, pages 463–479, Winter 2006

Instefjord, N. (2005) Risk and Hedging: Do Credit Derivatives Increase Bank Risk? *Journal of Banking and Finance*. 29, pp. 333–345.

Institute of Internal Finance (2008) Final Report of the IIF Committee on Market Best Practices: Principles of Conduct and Best Practice Recommendations: Financial

Services Industry Response to the Market Turmoil of 2007-2008 *Institute of International Finance Report* July 2008

International Monetary Funds (2002) Financial Soundness Indicators; Policy Paper. Available from: https://www.imf.org/external/np/sta/fsi/eng/fsi.htm [Accesses on 06 April 2012].

International Monetary Fund (2009) *Global Financial Stability Report*, Chapter 3 —What constitutes "systemic risk"? April (Washington: International Monetary Fund).

International Organisation of Securities Commissions (2003) Statement of Principles regarding the Activities of Credit Rating Agencies, Code of Conduct Fundamentals for Credit Rating. Available from: *http://www.iosco.org/library/pubdocs/pdf/IOSCOPD151.pdf.* [Accessed 3 December 2013].

International Organisation of Securities Commissions (2012 Credit Rating Agencies: Internal Controls Designed to Ensure the Integrity of the Credit Rating Process and Procedures to Manage Conflicts of Interest Available from: *http://www.iosco.org/library/pubdocs/pdf/IOSCOPD380.pdf* [Accessed 3 November 2015].

International Organisation of Securities Commissions (2015) Code of Conduct Fundamentals for Credit Rating Agencies Available from: *http://www.iosco.org/library/pubdocs/pdf/IOSCOPD482.pdf* [Accessed 3 November 2015].

Ioannidis, C., Pasiouras, F., and Zopounidis, C. (2010) Assessing bank soundness with classification techniques. *Omega.* 38(5), pp. 345-357.

Jackson, P. (2014) *Risk Culture and Effective Risk Governance* Risk Books London

Jafry, Y. and Schuermann, T. (2004) Measurement, Estimation and Comparison of Credit Migration Matrices. *Journal of Banking & Finance.* 28 (11), pp. 2603–2639.

Jarrow R.A., Lando D, Turnbull S.M. (1997) A Markov model for the term structure of credit risk spreads. *Review of Financial Studies.* 10, pp. 481-523.

Jensen, M (1993) The Modern Industrial Revolution, Exit, and the Failure of Internal Control Systems. *Journal of Finance*. 48 (3), pp. 831-880.

Jiangli, W., Pritsker, M. and Raupach, P. (2007) *Banking and Securitization*. Working Paper.

Jiangli, W. and Pritsker, M. .G (2008) *The Impacts of Securitization on US Bank Holding Companies.* Working Paper.

Johnson, R. (2003) *An Examination Of Rating Agencies Around the Investment-Grade Boundary.* Federal Reserve Bank of Kansas City, RWP 03-01.

Johnson, R. (2004) *Rating Agency Actions Around the Investment-Grade Boundary. Journal of Fixed Income.* 13, 25-38.

Johnson, C. and Kriz, K. (2002) Impact of Three Credit Ratings on Interest Cost of State GO Bonds. *Municipal Finance Journal*. 23(1), pp. 1-16.

Johnson, J. L., Daily, C. M. and Ellstrand, A. E. (1996) Boards of Directors: A Review and Research Agenda. *Journal of Management*. 22(3), pp. 409–438.

Jokipii, T. and Milne, A. (2006) *The Cyclical Behaviour of European Bank Capital Buffers*. Bank of Finland Research Discussion Papers, 17/2006.

Jones, M. T. (2005) *Estimating Markov Transition Matrices Using Proportions Data: An Application to Credit Risk*. IMF Working Paper WP/05/219.

Jones, E. and Mulet-Marquis, Q. (2014). *The Impact Of Credit Rating Changes on Stock Returns: Evidence from US-Listed Banks*. Paper presented at Midwest Finance Association, Orlando, United States.

Jorion, P., Shi, C. and Zhang, S. (2009) Tightening Credit Standards: The Role of Accounting Quality. *Review of Accounting Studies*. 14(1), pp. 123–160.

Kapan, T. and Minoiu, C. (2013) Balance Sheet Strength and Bank Lending During the Global Financial Crisis *IMF Working Paper* WP/13/102

Kaplan, R. and Urwitz, G. (1979) Statistical Models of Bond Ratings: A Methodological Inquiry. *Journal of Business.* 52(2), pp. 231–261.

Karafiath, I. (2009) Detecting Cumulative Abnormal Volume: A Comparison of Event Study Methods. *Applied Economics Letters.* (Impact Factor: 0.23). 16(8), pp. 797–802.

Katz, S. (1974) The price adjustment process of bonds to rating reclassifications: a test of bond market efficiency. *Journal of Finance.* 29 (2), pp. 551–9.

Katz, J., Munoz, E.S., Stephanou, C. (2009) *Credit Rating Agencies: No Easy Regulatory Solutions.* The World Bank Group, Financial and Private Sector Development Vice Presidency, Crisis Response Policy Brief 8.

Kavvathas, D. (2001) *Estimating Credit Rating Transition Probabilities for Corporate Bonds*. Working Paper, University of Chicago.

Keenan, S. C. and Sobehart, J. R. (2000) Credit Risk Catwalk. *Risk.* (July), 84–88.

Kendall, S. B. (1991) Bank Regulation under Nonbinding Capital Guidelines. *Journal of Financial Services Research.* 5, pp. 275-286.

Kenny, G. and Morgan, J. (2011) Some Lessons From the Financial Crisis for the Economic Analysis *ECB Occasional Paper Series* No 130/ October 2011

Kiefer, N. M. and Larson, C. E. (2004) Evaluating Design Choices in Economic Capital Modeling: A Loss Function Approach, in *Economic Capital: A Practitioner Guide*, ed. by A. Dev, Chap. 15. London: Risk Books.

Kim, C. J. (1993) Unobserved-Components Time Series Models with Markov Switching Heteroskedasticity: Changes In Regime And The Link Between Inflation Rates And Inflation Uncertainty. *Journal of Business and Economic Statistics*. 11, pp. 341–349.

Kisgen, D. (2006) Credit Ratings and Capital Structure. *Journal of Finance.* 61(3), pp. 1035-1072.

Klaar, A. and Riley, D. (2005). Fitch Sovereign Rating Outlook and Watch Study. *Fitch Ratings* November.

Klein, A. (1998) Firm Performance and Board Committee Structure. *The Journal of Law and Economics.* 41, pp. 275-303

Kliger, D. and Sarig, O. (2000) The Information Value of Bond Ratings. *Journal of Finance.* LV(6), pp. 2879-2902.

Koehn, M. and Santomero, A. M. (1980) Regulation Of Bank Capital and Portfolio Risk. *Journal of Finance.* 35, pp. 1235-1244.

Koh, H. C., and Low, C. K. (2004). Going Concern Prediction Using Data Mining Techniques. *Managerial Auditing Journal.* 19(3), pp. 462-476.

Kolari, J. W. and Pynnonen, S. (2011) *Nonparametric Rank Tests for Event Studies.* 21st Australasian Finance and Banking Conference 2008.

Konchitchki, Y. and O'Leary, D. (2011) Event Study Methodologies in Information Systems Research *International Journal of Accounting Information Systems* 12 (2011) 99–115

Kondo, K. (2011) *Have Credit Rating Agencies Become More Stringent Towards Japanese Regional Banks*? MPRA Paper 30500, University Library of Munich, Germany.

Konijn, S. J. J. and Rijken, H. A. (2010) *What Do Rating Agency Announcements Signal?: Confirmation or New Information.* Working Paper, 2010.

Kothari, S. P. and Warner, J. B. (2006) Econometrics of Event studies, in B. Espen Eckbo, Ed., *Handbook of Empirical Corporate Finance*, Elsevier-North-Holland.

Krahnen, J. P. and Wilde, C. (2006) *Risk Transfer with CDOs.* Goethe University, Frankfurt am Main.

Kramer, L. A. (2001) Alternative methods for robust analysis in event study applications, in Cheng-Few Lee, ed.: *Advances in Investment Analysis and Portfolio Management*, 8, pp. 109-132. Elsevier: NorthHolland.

Kryzanowski, L. and Zhang, H. (1993) Market Behaviour around Canadian stock-split ex-dates. *Journal of Empirical Finance.* 1, pp. 57-81.

Kumar, K. and Bhattacharya, S. (2006) Artificial neural network vs linear discriminant analysis in credit ratings forecast. *Review of Accounting and Finance.* 5(3), pp. 216 – 227.

Kwan, S. and Eisenbeis, R. (1997) Bank Risk, Capitalization and Operating Efficiency. *Journal of Financial Services Research.* 12, pp. 117-131.

Labonte, M. (2015) Systemically Important or "Too Big to Fail" Financial Institutions *Congressional Research Service* June 30 2015

Laere, E. V. and Baesens, B. (2011) *Analyzing Bank Ratings: Key Determinants and Procyclicality.* 24th Australasian Finance and Banking Conference 2011 Paper.

Laere, E.V., Vantieghem, J. and Baesens, B. (2012) *The difference between Moody's and S&P bank ratings: Is discretion in the rating process causing a split?* RMI Working Paper No. 12/05.

Laeven, L. and Levine, R. (2009) Bank governance, Regulation, and Risk Taking. *Journal of Financial Economics.* 93, pp. 259–275

Lando, D. and Skodeberg, T. (2002) Analyzing Rating Transitions and Rating Drift with Continuous Observations. *Journal of Banking and Finance.* 26 (2&3), pp. 423–444.

Langohr, H. and Langohr, P. (2008) *The Rating Agencies and Their Credit Ratings: What They Are, How They Work and Why They are Relevant.* West Sussex: John Wiley and Sons.

Larson, J. (2011) The Basel Capital Accords. [Online] Available at: http://ebook.law.uiowa.edu/ebook/sites/default/files/Basel%20Accords%20FAQ.pdf [Accessed 13 May 2012].

Lechner, M. (1995) Some Specification Tests for Probit Models Estimated on Panel Data. *Journal of Business & Economic Statistics*. 13, pp. 475-488.

Leung, W. S., Taylor, N. and Evans, K. P. (2015) The Determinants of Bank Risks: Evidence from the Recent Financial Crisis. *Journal of International Financial Markets, Institutions and Money.* 34, pp. 277-293.

Levich, R., Majnoni, G., Rinhart, C. (2002) *Ratings, Rating and Agencies and the Global Financial System*. New York: Kluwer Academic Press.

Levine, R. (2004) *The Corporate Governance of Banks: A Concise Discussion of Concepts and Evidence.* World Bank Policy Research Working Paper No. 3404.

Li, J., Shin, Y. and Moore, W. (2006) Reactions Of Japanese Markets to Changes in Credit Ratings by Global and Local Agencies. *Journal of Banking and Finance*. 30, pp. 1007–1021.

Liikanen Report (2012) High-Level Expert Group on Reforming the Structure of the EU Banking Sector: Final Report

Lindquist, K-G. (2004) Banks' Buffer Capital: How Important is Risk? *Journal of International Money and Finance*. 23, pp. 493–513.

Liu, P. and Thakor, A. (1984) Interest Yields, Credit Ratings, and Economic Characteristics of State Bonds: An Empirical Analysis. *Journal of Money Credit and Banking*. 16, pp. 344-351.

Loeffler, G. (2005) Avoiding The Rating Bounce: Why Rating Agencies are Slow to React to New Information. *Journal of Economic Behavior and Organization*. 56, pp. 365–381.

Löffler, G (2003) The Effects Of Estimation Error on Measures of Portfolio Credit Risk. *Journal of Banking and Finance*. 27, pp. 1427–1453.

Löeffler, G. and Posch, P. N. (2011) *Credit Risk Modeling using Excel and VBA.* 2nd ed. Chichester: John Wiley & Sons Ltd.

Long, J. S. and Freese, J. (2005) *Regression Models for Categorical Dependent Variables Using Stata.* Rev. ed. College Station, TX: Stata Press.

Lown, C. S., Morgan, D. P. and Rohatgi, S. (2000), Listening to Loan Officers: The Impact of Commercial Credit Standards on Lending and Output. *Federal Reserve Bank of New York Economic Policy Review.* 6(2), pp. 1–16.

Shen, C. and Lu, C. (2008) Is There a Silver Lining in the Cloudy Performance of Chinese Banks? An Empirical Investigation into the Determinants of Profitability and Risk *Emerging Topics in Banking and Finance* pp. 9-26

Lucas, D. and Lonski, J. (1992) Changes in Corporate Credit Quality: 1970-1990. *Journal of Fixed Income.* March, pp. 7–14.

Macey, J. and O'Hara, M. (2003) *The Corporate Governance of Banks.* Federal Reserve Bank of New York. Economic Policy Review. April 2003.

MacKinlay, A. C. (1997) Event Studies in Economics and Finance. *Journal of Economic Literature.* 35(1), pp. 13-39.

Maddala, G. S. (1987) Limited Dependent Variable Models Using Panel Data. *Journal of Human Resources*. XX11(3), pp. 307-337.

Mählmann, T. (2006) Estimation of Rating Class Transition Probabilities With Incomplete Data. *Journal of Banking and Finance.* 30, pp. 3235-3256.

Martin, R. and Wilde, T. (2002) Unsystematic Credit Risk. *Risk*. 15, pp. 123-128

Matthies, A. B. (2013) *Empirical Research on Corporate Credit Ratings: A Literature Review.* Economic Risk Discussion Paper. SFB 649 2013-003.

Mauboussin, M. J. (2006) *More Than You Know: Finding Financial Wisdom in Unconventional Places.* New York: Columbia University Press.

Mayes, D. G., and Wood, G. E. (2009) *The Northern Rock Crisis in the UK*, in T. Congdon, C. A. E. Goodhart, R. A. Eisenbeis, G. G. Kaufman, P. Hamalainen, R. M. Lastra, D. T. Llewellyn, D. G. Mayes, G. Wood, A. Milne & M. Onado (Eds.), The Failure of Northern Rock—A Multidimensional Case Study: SUERF—The European Money and Finance Forum.

McKinsey Global Institute (2012) *Debt and Deleveraging: Uneven progress on the path to growth.* McKinsey & Company.

McKinsey and Company (2013) Transforming a Global Bank's Approach to Market Risk *McKinsey and Company Risk*

Mehran, H. and Rosenberg, J. (2008) *The Effect of CEO Stock Options on Bank Investment Choice, Borrowing, and Capital.* Working Paper, Federal Reserve Bank of New York.

Melaschenko, P. and Reynolds, N. (2013) A Template for Recapitalising Too-Big-To-Fail Banks. *BIS Quarterly Review, June 2013.*

Merton, R. C. (1995) Financial Innovation and the Management and Regulation of Financial Institutions. *Journal of Banking and Finance.* 19, pp. 461–481.

Metrick, A. and Gorton, G. B. (2010) *Haircuts*. Yale ICF Working Paper No. 09-15.

Mikkelson, W. H. and Partch, M. M. (1998) Withdrawn Security Offerings. *Journal of Financial and Quantitative Analysis*. 23, 119–134.

Micu, M, Remolona, E. and Wooldridge, P. (2006) *The Price Impact Of Rating on Announcements: Which Announcements Matter?* BIS Working Papers, no 207.

Minow, N. and Bingham, K. (1995) *The Ideal Board in Corporate Governance.* Cambridge: Blackwell Publishers.

Minton, B. A., Taillard, J. and Williamson, R. G. (2010) *Do Independence and Financial Expertise of the Board Matter for Risk Taking and Performance?* Charles A. Dice Center Working Paper No. 2010–14.

Morck, R. and Yeung, B. (1992) Internalization: An Event Study Test. *Journal of International Econ* Vol. 33(1–2):41–56

Moody's Investors Service (2007) *Moody's Rating Symbols and Definitions.* Moody's Investors Service. pp. 1 – 52

Moody's Investors Service (2007b) *Bank Financial Strength Ratings.* Global Rating Methodology. pp. 1 – 40.

Moody, J. and Utans, J. (1994) Architecture selection strategies for neural networks: Application to corporate bond rating prediction, in Refenes, A. N., ed., '*Neural Networks in the Captial Markets'*. John Wiley & Sons.

Moon, C. and Stotsky J. (1993) Testing The Differences Between the Determinants of Moody's and Standard and Poor's Ratings. An Application of Smooth Simulated Maximum Likelihood Estimation. *Journal of Applied Econometrics.* 8 (1), pp. 51-69.

Mongiardino, A. and Plath, C. (2010) Risk Governance at Banks: Have Any Lessons Been Learnt? *Journal of Risk Management in Financial Institutions.* 3, pp. 116-123.

Morris, S. and Shin. H. S. (2009) *Illiquidity Component of Credit Risk.* Manuscript, Princeton University.

Mukhopadhyay, B. (2004) Moral Hazard with Rating Agency: An Incentive Contracting Approach, *Annals of Economics and Finance* 5, 313–333

Mundlak, Y. (1978) On the Pooling of Time Series and Cross Section Data. E*conometrica*. 46, pp. 69-85

Mnyanda, L. and Meakin, L. (2012) Sovereign Ratings a Lagging Indicator, Stheeman Says *Bloomberg Business News* March 22 2012

Nayar, N. and Rozeff, M. S. (1994) Ratings, Commercial Paper, and Equity Returns. *The Journal of Finance.* 49 (4), pp. 1431-1449.

Nayar, N. (1993) Asymmetric Information, Voluntary Ratings and the Rating Agency of Malaysia. *Pacific-Basin Finance Journal*. 1(4), pp. 369-380.

Nazari, M. (2013) Measuring Credit Risk of Bank Customers Using Artificial Neural Network *Journal of Management Research,* Vol. 5, No. 2

Nicholls, C.C. (2005) *Public and Private Uses of Credit Ratings.* A Capital Market Institute Policy Series

Nickell, P., Perraudin, W. and Varotto, S. (2000) Stability of Ratings Transitions. *Journal of Banking and Finance.* 24 (1), pp. 203–227.

Nijskens, R. and Wagner W. (2011) Credit Risk Transfer Activities and Systemic Risk: How Banks Became Less Risky Individually But Posed Greater Risks to the Financial System at the Same Time. *Journal of Banking and Finance.* 35(6), pp. 1391-1398.

Nikolaou, K. (2009) *Liquidity (risk) concepts: definitions and interactions*. ECB Working Paper Series 1008.

Norden, L. and Weber, M. (2004) Informational efficiency of credit default swap and stock markets: the impact of credit rating announcements. *Journal of Banking and Finance.* 28, pp 2813-43

Odder-White, E. R. and Ready, M. J. (2006) Credit Ratings and Stock Liquidity. *Review of Financial Studies.* 19(1), pp. 119-157.

Office of the Comptroller of the Currency (2011) *Supervisory Guidance on Model Risk Management.* Board of Governors of the Federal Reserve System Office of the Comptroller of the Currency, OCC 2011-12.

Öğüt, H., Doğanay, M. M., Ceylan, N.B. and Aktaş, R. (2012) Prediction Of Bank Financial Strength Ratings: The case of Turkey. *Economic Modelling.* 29, pp. 632–640.

Opler, T. C. and Sokobin, J. (1997) *Does Co-ordinated Institutional Activism Work? An Analysis of the Activities of the Council of Institutional Investors*. Working Paper, Ohio State University, Columbia.

Ong, M. (2002) *Credit Ratings: Methodologies, Rationale and Default Risk.* London: Risk Books.

Ötker-Robe, I. and Podpiera, J. (2010) *The Fundamental Determinants of Credit Default Risk for European Large Complex Financial Institutions*. IMF Working Paper WP/10/153.

Packer, F. and Tarashev, N. (2011) *Rating Methodologies for Banks.* BIS Quarterly Review, June 2011.

Pagano M. and Volpin P. (2010) Credit Ratings Failures and Policy Options, *Economic Policy*, April, pp. 403–431.

Park, C. H. and Irwin, S.H. (2007) What Do We Know About The Profitability of Technical Analysis? *Journal of Economic Surveys.* 21 (4), pp. 786-826

Partnoy, F. (2009) *Rethinking Regulation of Credit Rating Agencies: An Institutional Investor Perspective.* White Paper for the Council of Institutional Investors. Washington.

Pasiouras F., Tanna S. and Zopounidis C. (2007) *Regulations, supervision and banks'cost and profit efficiency around the world: a stochastic frontier approach.* University of Bath, School of Management Working Paper Series 2007.05.

Pastor, J. M. and Serrano, L. (2005) Efficiency, Endogenous and Exogenous Credit Risk in the Banking Systems of the Euro Area. *Applied Financial Economics.* 15, pp. 631-649.

Patell, J. (1976) Corporate Forecast of Earnings Per Share and Stock Price Behavior: Empirical Tests. *Journal of Accounting Research.* Autumn, 246–276.

Pathan, S. (2009) Strong Boards, CEO Power and Bank Risk-Taking. *Journal of Banking and Finance.* 33(7), pp. 1340-1350

Petitjean, M. (2013) Bank Failures and Regulation: A Critical Review, *Journal of Financial Regulation and Compliance*, Vol. 21 Iss: 1, pp.16 – 38

Pender, K. (1992) *Demystifying the Ratings Game.* San Francisco Chronicle*,* February 17.

Pettit, J., Fitt, C., Orlov, S. and Kalsekar, A. (2004) *The New World of Credit Ratings.* UBS Investment Research (UBS Investment Bank).

Pinches, G. and K. Mingo (1973) A Multivariate Analysis of Industrial Bond Ratings. *Journal of Finance*. 28 (1), pp. 1–18.

Pinches, G. E. and Singleton, J. C. (1978) The adjustment of stock prices to bond rating changes. *The Journal of Finance*. 33(1), pp. 29–44

Poghosyan, T. and Cihák, M. (2011) Distress in European Banks: An Analysis Based on a New Dataset. *Journal of Financial Services Research.* 40 (3), pp. 163–184.

Pogue, T. F. and Soldofsky, R. M. (1969) What's in a Bond Rating? *Journal of Financial and Quantitative Analysis*. 4(2), pp. 201–228.

Poon, W. (2003) Are Unsolicited Credit Ratings Biased Downward? *Journal of Banking and Finance.* 27 (4), pp. 593-614.

Poon, W. and Firth, M. (2005) Are Unsolicited Credit Ratings Lower? International Evidence from Bank Ratings. *Journal of Business Finance and Accounting*. 32 (9&10), pp. 1741-1771.

Poon, W., Lee, J. and Gup, B.E. (2009) Do Solicitations Matter in Bank Credit Ratings? Results from a Study Of 72 Countries. *Journal of Money, Credit and Banking.* 41, pp. 285–314.

Poon, W. and Chan, K. (2010) *Solicited and Unsolicited Credit Ratings: A Global Perspective. ADBI* Working Paper Series.

Pottier, S. and Sommer, D. (1999) Property-Liability Insurer Financial Strength Ratings: Differences across Rating Agencies. *The Journal of Risk and Insurance*. 66 (4), pp. 621-642.

Purda, L. (2008) Risk Perception and the Financial System. *Journal of International Business Studies.* 39, pp. 1178-1196

PwC (2014) *Risk & Capital Management under Basel III.* PwC, Financial Services Risk and Regulation.

PwC (2014) *Passing The Stress Test PWC Survey on Regulatory Stress Testing in Banks.* PwC, Financial Services Risk and Regulation.

Purda, L. (2003) *Consistency of Global Credit Ratings: An Analysis of Firm Versus Country-Specific Factors.* Working Paper, Ontario: Queen's University.

Rajan, R. G. (2005) Has Financial Development Made the World Riskier? *NBER Working Paper* No. 11728

Ratha, D., De, P., and Mohapatra, S. (2007). Shadow sovereign ratings for unrated developing countries. *World Bank Policy Research Working Paper* 4269

Rawcliffe, G., Peach, J., Haas, S., Moss, J. E., Marshall, D. and Shaw, P. V. (2008) *Bank Rating Methodology.* Criteria Report (Fitch Ratings: Banks)

Rosengren, E. S. (2013) *Bank Capital: Lessons from the U.S. Financial Crisis.* Bank for International Settlements Forum on Key Regulatory and Supervisory Issues in a Basel III World Keynote Address, Seoul, Korea.

Resti, A. (1995) *Linear Programming and Econometric Methods for Bank Efficiency Evaluation: An Empirical Comparison Based on a Panel of Italian Banks.* Working paper.

Reyes, M. G. (1999) Size, Time-Varying Beta and Conditional Heteroscedasticity in UK Stock Returns. *Review of Financial Economics.* 8, pp. 1 – 10.

Reynold, D. (2009) Analysing Concentration Risk. *Algorithmic. pp.* 1 – 21

Richards, R. J. and Deddouche, D. (1999) *Bank Rating and Bank Stock Returns: Puzzling Evidence from the Emerging Markets*. IMF Working Paper No. WP/99/151

Riddiough, T. J. (1997) Optimal Design and Governance of Asset-Backed Securities. *Journal of Financial Intermediation.* 6, pp. 121-152.

Rime, B. (2005) *Do Too Big To Fail Expectations Boost Large Banks Issuer Ratings?* Working Paper, Systemic Stability Section, Swiss National Bank.

Roberts, M. and Whited, T. (2012) Endogeneity in Corporate Finance, forthcoming in George Constantinides, Milton Harris, and Rene Stulz, eds. *Handbook of the Economics of Finance* Volume 2, Elsevier.

Roberts, G. and Yuan, L. (2010) Does institutional ownership affect the cost of bank borrowing? *Journal of Economics and Business.* 62(6), pp. 604-626.

Rochet, J. C., Mathis, J. and Mc Andrews. J. (2008) Rating the Raters. *Banque de France–Toulouse School of Economics Conference on "Macroeconomicsand Liquidity",* 2008.

Rösch, D. (2005) An Empirical Comparison of Default Risk Forecasts From Alternative Credit Rating Philosophies. *International Journal of Forecasting.* 21(1), pp. 37-51.

Roy, A. D. (1952) Safety First and the Holding of Assets. *Econometrica*. 20(3), pp. 431-449.

Rule, D. (2001) *The Credit Derivative Market: Its Development and Possible Implementations for Financial Stability.* Bank of England, Financial Stability Review, London, June.

Ryan, H. E. Jr. and Wiggins, R. A. III. (2004) Who is in Whose Pocket? Director Compensation, Board Independence, and Barriers to Effective Monitoring. *Journal of Financial Economics*. 73, pp. 497-524.

Salas, V. and Saurina, J. (2003) Deregulation, Market Power and Risk Behavior in Spanish Banks. *European Economic Review*. 47, pp. 1061-1075.

Salinger, M. (1992) Standard Errors in Event Studies. *Journal of Financial and Quantitative Analysis.* 27, pp. 39–53.

Salvador, C., De Guevara, J. F. and Pastor, J.M. (2014) *The Adjustment of Bank Ratings in the Financial Crisis: International Evidence.* Documento De Trabajo No. 750/2014.

Sandri, D. and Mody, A. (2011) *The Eurozone Crisis: How Banks and Sovereigns Came to Be Joined At the Hip.* IMF Working Paper No. 11/269.

Sanger, G. C. and Peterson, J. D. (1990) An Empirical Analysis of Common Stock Delistings. *Journal of Financial and Quantitative Analysis.* 25(2), pp. 261-272

Savona, P. and Kirton, J.J. (2013) *Global Financial Crisis* (*Global Finance*)*.* Surrey: Ashgate Publishing Company.

Schuermann, T. (2004) *What Do We Know About Loss Given Default?* Wharton Financial Institutions Center Working Paper No. 04-01.

Schuermann, T. (2013) *Stress testing banks*. Financial Institutions Center, The Wharton School, University of Pennsylvania Working Paper 12-08.

Schweitzer, R., Szewczyk, S. and Varma, R. (1992) Bond Rating Agencies and their Role in Bank Market Discipline. *Journal of Financial Services Research*. 6, pp. 249-263.

Schwert, G. W. (2002) *Anomalies and Market Efficiency*. National Bureau of Economic Research (NBER) October 2002; Simon School of Business Working Paper No. FR 02-13.

Securities and Exchange Board of India (2010) *Guideline for Credit Rating Agencies.* Available from: http://www.sebi.gov.in/cms/sebi_data/attachdocs/1288154943197.pdf [Accessed 20 May 2011]

Sefcik, S. and Thompson, R. (1986) An Approach to Statistical Inference in Cross-sectional Models with Security Abnormal Returns as Dependent Variable. *Journal of Accounting Research.* 24, pp. 316-334.

Sengupta, P. (1998) Corporate Disclosure Quality and the Cost of Debt. *Accounting Review, October 1998.*

Senior Supervisor Group (2009) Risk Management Lessons from the Global Banking Crisis of 2008, October 29 2009

Seyhun, H. N. (1998) Inside Information. *Financial Planning*. 28, pp. 114-122.

Shen, C., Huang, Y. and Hasan, I. (2012) Asymmetric benchmarking in bank credit rating. *Journal of International Financial Markets, Institutions and Money*. 22, pp. 171-193.

Shin, Y. and Moore, W. (2003) Explaining Credit Rating Differences Between Japanese and U.S. Agencies. *Review of Financial Economic*. 12 (4), pp. 327-344.

Shleifer, A. and Vishny, R. (1986) Large Shareholders and Corporate Control. *Journal of Political Economy.* 94 (3), pp. 461-488.

Simpson, W. G. and Gleason, A. E. (1999) Board Structure, Ownership, and Financial Distress in Banking Firms. *International Review of Economics and Finance.*8(3), pp. 281-292.

Standard and Poor's (2005) *Corporate Ratings Criteria*. New York: Standard and Poor's. pp. 1-119.

Standard and Poor's (2007) *Recovery Analytic Update: Enhanced recovery scale and issue ratings framework.* Commentary Report. 30 (1–4)

Steeman, M. (2002) *Corporates and Credit Ratings: How to Respond to the Commodization of Credit Risk.* Bluebook Series 3 (NIB Capital).

Steiner, M. and Heinke, V. (2001) Event Study Concerning International Bond Price Effects Of Credit Rating Actions. *International Journal of Finance and Economics.* 6, pp. 139-157.

Studenmund, A. H. (2006). *Using Econometrics: A Practical Guide* (5th ed.). Pearson International.

Stulz, R. M. (2014) Governance, Risk Managemen, and Risk-Taking in Banks *European Corporate Governance Institute (ECGI) - Finance Working Paper No. 427/2014*

Sundararajan V., Enoch C., San José A., Hilbers, P., Krueger R., Moretti M. and Slack G. (2002): *Financial Soundness Indicators: Analytical Aspects and Country Practices.* IMF Occasional Paper No. 212.

Sufi, A. (2009) The Real Effects of Debt Certification: Evidence from the Introduction of Bank Loan Ratings. *Review of Financial Studies*. 22(4), pp. 1659-1691.

Switzer, L.N. and Wang, J. (2013) Default Risk Estimation, Bank Credit Risk, and Corporate Governance. *Financial Markets, Institutions & Instruments.* 22 (2), pp. 91–112

Tait, N. (2010) Rethink on Rating Agencies Urged *Financial Times Europe* April 29 2010

Taylor, P. (2013) The Role of Credit Rating Agencies in the International Financial System *United Nations General Assembly Thematic Debate* Sept. 10 2013

Thompson, G. and Vaz, P. (1990) Dual Bond Ratings: A Test of the Certification Function of Rating Agencies. *The Financial Review.* 25(3), pp. 457-471.

Treacy, W. F. and Carey, S. M. (2000) Credit Risk Rating System at Large U.S. Banks. *Journal of Banking and Finance.* 24, pp. 167-201.

Trigueiros, D. and Tamer, R. (1996) Neural Networks and Empirical Research in Accounting, *Accounting and Business Research* Vol. 26: 4 pp. 347-355.

Trueck, S. and Rachev, S.T. (2009) *Rating Based Modeling of Credit Risk: Theory and Application of Migration Matrices*. Amsterdam: Elsevier Inc.

Tucker, J., Guermat, C. and Prasert, S. (2012) *Short-Run Reaction to News Announcements: UK Evidence.* Centre for Global Finance Working Paper Series (ISSN 2041-1596) Paper Number: 05/12

Turullo, D.K. (2008) *Basel The Future of International Financial Regulation*. Washington: Peterson Institute for International Economics.

Uhde, A. and Michalak, T. C. (2010) Securitization and systematic risk in European banking: Empirical evidence. *Journal of Banking and Finance*. 34(12), pp. 3061-3077.

UBS (2004) Shareholder report on UBS's write-downs. Available at www. ubs.com. [Accessed on 15 June 2013].

U.S. Securities and Exchange Commission (2003) *Report on the Role and Function of Credit Rating Agencies in the Operation of the Securities Markets*. Washington DC: U.S. Securities and Exchange Commission. pp.1-47.

U.S. Securities and Exchange Commission (2009) *Amendments to Rules for Nationally Recognized Statistical Rating Organizations.* Securities and Exchange Commission Release No. 34-59342; File No. S7-13-08.

U.S. Securities and Exchange Commission (2011) *Report on Review of Reliance on Credit Ratings.* A Report by the Staff of the U.S. Securities and Exchange Commission, As Required by Section 939A(c) of the Dodd-Frank Wall Street Reform and Consumer Protection Act.

Ustig, S. (2010) *The Financial Crisis and the Regulation of Credit Rating Agencies: A European Banking Perspective*. ADBI Working Paper Series, No. 188.

Valdez, S. and Molyneux, P. (2013) *An Introduction to Global Financial Markets.* 7th ed. Houndmills, UK: Palgrave Macmillan

Van Laere, E. (2010) Capital regulation of financial institutions, the role of ratings and the tension field between regulation and economic reality. Available from: http://www.vlerick.com/en/research-and-faculty/knowledge-items/knowledge/bank-ratings-key-determinants-and-cyclicality [Accessed 22 December 2013]

Van Roy, P. (2006) *Is there a Difference in Treatment Between Solicited and Unsolicited Bank Ratings and, if so, Why?* Working Paper, University of Brussels.

Vazza, D., Leung, E., Alsati, M., and Katz, M. (2005). Credit Watch and Ratings Outlooks: Valuable Predictors of Ratings Behaviour. *Standard and Poor's* May

Vickers Report (2012) The Independent Commission on Banking: The Vickers Report *House of Commons Library SNBT 6171*

Wagner, W. (2005a) *The Liquidity Of Bank Assets and Banking Stability.* Working paper Cambridge Endowment for Research in Finance, University of Cambridge.

Wagner, W. (2005b) *Interbank Diversification, Liquidity Shortages and Banking Crises*. Working Paper, Cambridge Endowment for Research in Finance, University of Cambridge.

Wagner, W. (2007) The Liquidity of Bank Assets and Bank Liquidity. *Journal of Banking and Finance*. 31(1), pp. 121-139.

Wagner, W. and Marsh, I. W. (2006) Credit Risk Transfer and Financial Sector Performance. *Journal of Financial Stability.* 2, pp. 173‐193.

Wakeman, L. M. (1984). The Real Function of Bond Rating Agencies. In M. C. Jensen and C. W. Smith (Eds.), *The Modern Theory of Corporate Finance*. New York, N.Y.: North-Holland Publishing Company.

Walker Report (2009) A Review of Corporate Governance in UK Banks and Other Financial Industry Entities: Final Recommendations

Wappenschmidt, C. (2009) *Ratinganalyse durch internatinale Ratingagenturen.* Frankfurt am Main usw.

Wang, W., Lu, W. and Lin, Y. (2012) Does Corporate Governance Play an Important Role in BHC Performance? Evidence from the U.S. *Economic Modelling.* Vol. 29, pp. 751–760.

Wansley, J. W. and Clauretie, T. M. (1985) The impact of Creditwatch placements on equity re-turns and bond prices. *Journal of Financial Research.* 8(1), 31–42.

Weinstein, M. (1977) The Effect of a Rating Change Announcement on Bond Price. *Journal of Financial Economics.* 5, pp 329–50.

West, R. (1970) An Alternative Approach to Predicting Corporate Bond Ratings. *Journal of Accounting Research.* 7 (Spring), pp. 118-127.

White, L. J. (2002) The Credit Rating Industry: An Industrial Organization Analysis, in ed. R. Levich, *Ratings, Rating Agencies, and the Global Financial System,* Amsterdam: Kluwer.

Wilson, J.O.S. and Williams J.M. (2000) The Size and Growth of Banks: Evidence From Four European Countries. *Applied Economics.* 32(9), pp. 1101-1109.

Wooldridge J. (2002) *Simple Solutions to The Initial Conditions Problem In Dynamic Non Linear Panel Data Models With Unobserved Heterogeneity.* WP CEMMAP, London, 18/02.

Wooldridge, J. M. (2010) *Econometric analysis of cross section and panel data.* 2^{nd} ed. MIT Press

World Economic and Financial Surveys (2014) *Global Financial Stability Report Risk Taking, Liquidity, and Shadow Banking Curbing Excess while Promoting Growth.* The Global Financial Stability Report (GFSR), October 2014.

Zahra S. A. and Pearce II J. A. (1989) Boards of Directors and Corporate Performance: A Review and Integrative Model. *Journal of Management.* 15(2), pp. 291-334.

Zhuang, J. (1999). Some conceptual issues of corporate governance. EDRC Briefing Notes Number 13 [Online] Available: www.adb.org/Documents/Books/Corporate_Governance/Vol1/chapter2.pdf.

APPENDIX A: LIST OF BANKS AND ISIN NUMBERS

S/n	Bank Name	Country Name	Specialisation	ISIN Number
1	Banco Macro SA	ARGENTINA	Commercial Banks	ARBANS010010
2	Raiffeisen Bank International AG	AUSTRIA	Commercial Banks	AT0000606306
3	Erste Group Bank AG	AUSTRIA	Bank Holding & Holding Companies	AT0000652011
4	Commonwealth Bank of Australia	AUSTRALIA	Commercial Banks	AU000000CBA7
5	Bank of Queensland Limited	AUSTRALIA	Commercial Banks	AU000000BOQ8
6	Australia and New Zealand Banking Group	AUSTRALIA	Commercial Banks	AU000000ANZ3
7	Bendigo and Adelaide Bank Limited	AUSTRALIA	Commercial Banks	AU000000BEN6
8	National Australia Bank Limited	AUSTRALIA	Commercial Banks	AU000000NAB4
9	Westpac Banking Corporation	AUSTRALIA	Commercial Banks	AU000000WBC1
10	Suncorp Group Limited	AUSTRALIA	Bank Holding & Holding Companies	AU000000SUN6
11	Macquarie Group Ltd	AUSTRALIA	Bank Holding & Holding Companies	AU000000MQG1
12	Demirbank Open Joint Stock Company	AZERBAIJAN	Commercial Banks	DE0005140008
13	Ahli United Bank BSC	BAHRAIN	Commercial Banks	BH0005508765
14	Arab Banking Corporation BSC	BAHRAIN	Commercial Banks	BH0008794115
15	National Bank of Bahrain	BAHRAIN	Commercial Banks	BH0005508773
16	BBK B.S.C.	BAHRAIN	Commercial Banks	BH0004659916
17	KBC Groep NV/ KBC Groupe SA-KBC Group	BELGIUM	Bank Holding & Holding Companies	BE0003565737
18	Dexia	BELGIUM	Bank Holding & Holding Companies	BE0003796134
19	Bank of Africa - Benin	BENIN	Commercial Banks	BJ0000000048
20	Bank of N.T. Butterfield & Son Ltd. (The)	BERMUDA	Commercial Banks	BMG0772R1097
21	Itau Unibanco Holdings	BRAZIL	Bank Holding & Holding Companies	BRITUBACNPR1
22	Banco do Brasil S.A.	BRAZIL	Commercial Banks	BRBBASACNOR3
23	Banco PanAmericano S.A.	BRAZIL	Commercial Banks	BRBPNMACNPR6
24	Banco BTG Pactual SA	BRAZIL	Commercial Banks	BRBPACACNOR7
25	Banco Daycoval SA	BRAZIL	Commercial Banks	BRDAYCACNPR2
26	Banco da Amazonia SA	BRAZIL	Commercial Banks	BRBAZAACNOR0
27	Banco Santander (Brasil) S.A.	BRAZIL	Commercial Banks	BRSANBACNOR8
28	Banco Bradesco SA	BRAZIL	Commercial Banks	BRBBDCACNPR8
29	Banco do Estado do Rio Grande do Sul S.A. BANRISUL	BRAZIL	Commercial Banks	BRBRSRACNOR3
30	Banco ABC - Brasil SA	BRAZIL	Commercial Banks	BRABCBACNPR4
31	Banco Pine SA	BRAZIL	Commercial Banks	BRPINEACNPR8
32	First Investment Bank AD	BULGARIA	Commercial Banks	BG1100106050
33	Royal Bank of Canada RBC	CANADA	Commercial Banks	CA7800871021
34	Toronto Dominion Bank	CANADA	Commercial Banks	CA8911605092
35	Canadian Imperial Bank of Commerce CIBC	CANADA	Commercial Banks	CA1360691010
36	Bank of Montreal-Banque de Montreal	CANADA	Commercial Banks	CA0636711016
37	National Bank of Canada-Banque Nationale du Canada	CANADA	Commercial Banks	CA6330671034
38	Bank of Nova Scotia (The) - SCOTIABANK	CANADA	Commercial Banks	CA0641491075
39	Home Capital Group Inc	CANADA	Bank Holding & Holding Companies	CA4369131079
40	Banco de Credito e Inversiones - BCI	CHILE	Commercial Banks	CLP321331116
41	Banco de Chile	CHILE	Commercial Banks	CLP0939W1081
42	Banco Santander Chile	CHILE	Commercial Banks	CLP1506A1070
43	Shanghai Pudong Development Bank	CHINA	Commercial Banks	CNE0000011B7
44	China Merchants Bank Co Ltd	CHINA	Commercial Banks	CNE1000002M1
45	China Everbright Bank Co Ltd	CHINA	Commercial Banks	CNE100000SL4
46	Ping An Bank Co Ltd	CHINA	Commercial Banks	CNE000000040
47	Hua Xia Bank co., Limited	CHINA	Commercial Banks	CNE000001FW7
48	Bank of China Limited	CHINA	Commercial Banks	CNE1000001Z5
49	China CITIC Bank Corporation Limited	CHINA	Commercial Banks	CNE1000001Q4
50	Agricultural Bank of China Limited	CHINA	Commercial Banks	CNE100000Q43
51	Industrial Bank Co Ltd	CHINA	Commercial Banks	CNE000001QZ7
52	China Minsheng Banking Corporation	CHINA	Commercial Banks	CNE0000015Y0
53	Bank of Beijing Co Ltd	CHINA	Commercial Banks	CNE100000734
54	China Construction Bank Corporation	CHINA	Commercial Banks	CNE1000002H1
55	BBVA Colombia SA	COLOMBIA	Commercial Banks	COB13PA00019
56	Banco de Bogota	COLOMBIA	Commercial Banks	COB01PA00030
57	Grupo Aval Acciones y Valores S.A.	COLOMBIA	Bank Holding & Holding Companies	COT29PA00025
58	Banco Davivienda	COLOMBIA	Commercial Banks	COB51PA00076
59	Bancolombia S.A.	COLOMBIA	Commercial Banks	COB07PA00078
60	Zagrebacka Banka dd	CROATIA	Commercial Banks	HRZABARA0009

61	**Komercni Banka**	CZECH REPUBLIC	Commercial Banks	CZ0008019106
62	**Danske Bank A/S**	DENMARK	Commercial Banks	DK0010274414
63	**Deutsche Postbank AG**	GERMANY	Commercial Banks	DE0008001009
64	**Commerzbank AG**	GERMANY	Commercial Banks	DE000CBK1001
65	**Deutsche Bank AG**	GERMANY	Commercial Banks	DE0005140008
66	**Banco de la Produccion SA - PRODUBANCO-Grupo Financiero Produccion**	ECUADOR	Commercial Banks	ECP7914V1044
67	**Banco Pichincha C.A.**	ECUADOR	Commercial Banks	ECP1322M1036
68	**Commercial International Bank (Egypt) S.A.E.**	EGYPT	Commercial Banks	EGS60121C018
69	**Pohjola Bank plc-Pohjola Pankki Oyj**	FINLAND	Commercial Banks	FI0009003222
70	**Société Générale**	FRANCE	Commercial Banks	FR0000130809
71	**Crédit Industriel et Commercial - CIC**	FRANCE	Commercial Banks	FR0005025004
72	**BNP Paribas**	FRANCE	Commercial Banks	FR0000131104
73	**Natixis**	FRANCE	Commercial Banks	FR0000120685
74	**Liberty Bank**	GEORGIA	Commercial Banks	GE1100000300
75	**Bank of Georgia**	GEORGIA	Commercial Banks	GE1100000276
76	**Alpha Bank AE**	GREECE	Commercial Banks	GRS015013006
77	**National Bank of Greece SA**	GREECE	Commercial Banks	GRS003003019
78	**Piraeus Bank SA**	GREECE	Commercial Banks	GRS014003008
79	**Eurobank Ergasias SA**	GREECE	Commercial Banks	GRS323003004
80	**Chong Hing Bank Limited**	HONG KONG	Commercial Banks	HK1111036765
81	**Allied Irish Banks plc**	IRELAND	Commercial Banks	IE0000197834
82	**Bank of Ireland-Governor and Company of the Bank of Ireland**	IRELAND	Commercial Banks	IE0030606259
83	**Bank Negara Indonesia (Persero) - Bank BNI**	INDONESIA	Commercial Banks	ID1000096605
84	**Bank Rakyat Indonesia (Persero) Tbk**	INDONESIA	Commercial Banks	ID1000118201
85	**Bank Pan Indonesia Tbk PT-Panin Bank**	INDONESIA	Commercial Banks	ID1000092703
86	**PT Bank CIMB Niaga Tbk**	INDONESIA	Commercial Banks	ID1000098007
87	**Bank Mandiri (Persero) Tbk**	INDONESIA	Commercial Banks	ID1000095003
88	**Bank Internasional Indonesia Tbk**	INDONESIA	Commercial Banks	ID1000099302
89	**Bank OCBC NISP Tbk**	INDONESIA	Commercial Banks	ID1000094402
90	**Bank Danamon Indonesia Tbk**	INDONESIA	Commercial Banks	ID1000094204
91	**Bank Central Asia**	INDONESIA	Commercial Banks	ID1000109507
92	**Union Bank of India**	INDIA	Commercial Banks	INE692A01016
93	**Canara Bank**	INDIA	Commercial Banks	INE476A01014
94	**Bank of Baroda**	INDIA	Commercial Banks	INE028A01013
95	**State Bank of India**	INDIA	Commercial Banks	INE062A01012
96	**Indian Bank**	INDIA	Commercial Banks	INE562A01011
97	**Punjab National Bank**	INDIA	Commercial Banks	INE160A01014
98	**AXIS Bank Limited**	INDIA	Commercial Banks	INE238A01026
99	**ICICI Bank Limited**	INDIA	Commercial Banks	INE090A01013
100	**Bank Hapoalim BM**	ISRAEL	Commercial Banks	IL0006625771
101	**Bank Leumi Le Israel BM**	ISRAEL	Commercial Banks	IL0006046119
102	**Banco di Desio e della Brianza SpA-Banco Desio**	ITALY	Commercial Banks	IT0001041000
103	**Intesa Sanpaolo**	ITALY	Commercial Banks	IT0000072618
104	**Credito Emiliano SpA-CREDEM**	ITALY	Commercial Banks	IT0003121677
105	**Credito Bergamasco**	ITALY	Commercial Banks	IT0000064359
106	**Banca Monte dei Paschi di Siena SpA-Gruppo Monte dei Paschi di Siena**	ITALY	Commercial Banks	IT0001334587
107	**Banca Carige SpA**	ITALY	Commercial Banks	IT0003211601
108	**UniCredit SpA**	ITALY	Commercial Banks	IT0004781412
109	**National Commercial Bank Jamaica Limited**	JAMAICA	Commercial Banks	JMP710541039
110	**Arab Bank Plc**	JORDAN	Commercial Banks	JO1302311013
111	**Bank of Jordan Plc**	JORDAN	Commercial Banks	JO1102211017
112	**Sumitomo Mitsui Financial Group, I**	JAPAN	Bank Holding & Holding Companies	JP3890350006
113	**Mizuho Financial Group**	JAPAN	Bank Holding & Holding Companies	JP3885780001
114	**Suruga Bank, Ltd. (The)**	JAPAN	Commercial Banks	JP3411000007
115	**Shizuoka Bank**	JAPAN	Commercial Banks	JP3351200005
116	**Daiwa Securities Group Inc**	JAPAN	Bank Holding & Holding Companies	JP3502200003
117	**Nomura Holdings Inc**	JAPAN	Bank Holding & Holding Companies	JP3762600009
118	**BTA Bank JSC**	KAZAKHSTAN	Commercial Banks	KZ1C34920013
119	**Bank CenterCredit**	KAZAKHSTAN	Commercial Banks	KZ1C36280010
120	**Kazkommertsbank Joint-Stock Company**	KAZAKHSTAN	Commercial Banks	KZ000A0JC858

121	**Ahli United Bank KSC**	KUWAIT	Commercial Banks	KW0EQ0100051
122	**Gulf Bank KSC (The)**	KUWAIT	Commercial Banks	KW0EQ0100028
123	**Al Ahli Bank of Kuwait (KSC)**	KUWAIT	Commercial Banks	KW0EQ0100044
124	**Commercial Bank of Kuwait SAK (The)**	KUWAIT	Commercial Banks	KW0EQ0100036
125	**National Bank of Kuwait S.A.K.**	KUWAIT	Commercial Banks	KW0EQ0100010
126	**Bank Audi SAL**	LEBANON	Commercial Banks	LB0000010415
127	**Byblos Bank S.A.L.**	LEBANON	Commercial Banks	LB0000010613
128	**Hong Leong Bank Berhad**	MALAYSIA	Commercial Banks	MYL5819OO007
129	**Malayan Banking Berhad - Maybank**	MALAYSIA	Commercial Banks	MYL1155OO000
130	**Grupo Financiero BANORTE**	MEXICO	Bank Holding & Holding Companies	MXP370711014
131	**Banco Nacional de Mexico, SA - BANAMEX**	MEXICO	Commercial Banks	MXCFDA020005
132	**Attijariwafa Bank**	MOROCCO	Commercial Banks	MA0000011926
133	**ING Groep NV**	NETHERLANDS	Bank Holding & Holding Companies	NL0000303600
134	**Bank of Africa - Niger**	NIGER	Commercial Banks	NE0000000015
135	**Fidelity Bank Plc**	NIGERIA	Commercial Banks	NGFIDELITYB5
136	**United Bank for Africa Plc**	NIGERIA	Commercial Banks	NGUBA0000001
137	**Access Bank Plc**	NIGERIA	Commercial Banks	NGACCESS0005
138	**Union Bank of Nigeria Plc**	NIGERIA	Commercial Banks	NGUBN0000004
139	**Diamond Bank Plc**	NIGERIA	Commercial Banks	NGDIAMONDBK6
140	**Zenith Bank Plc**	NIGERIA	Commercial Banks	NGZENITHBNK9
141	**Guaranty Trust Bank Plc**	NIGERIA	Commercial Banks	NGGUARANTY06
142	**Bank Sohar SAOG**	OMAN	Commercial Banks	OM0000003398
143	**Bank Dhofar SAOG**	OMAN	Commercial Banks	OM0000002549
144	**Bank Muscat SAOG**	OMAN	Commercial Banks	OM0000002796
145	**National Bank of Oman (SAOG)**	OMAN	Commercial Banks	OM0000001483
146	**Banco Internacional del Peru - Interbank**	PERU	Commercial Banks	PEP148001006
147	**Scotiabank Peru SAA**	PERU	Commercial Banks	PEP140001004
148	**Banco Interamericano de Finanzas S.A. - BIF**	PERU	Commercial Banks	PEP121001007
149	**Banco de Credito del Peru**	PERU	Commercial Banks	PEP120001008
150	**BDO Unibank Inc**	PHILIPPINES	Commercial Banks	PHY077751022
151	**Security Bank Corporation**	PHILIPPINES	Commercial Banks	PHY7571C1000
152	**Bank of The Philippine Islands**	PHILIPPINES	Commercial Banks	PHY0967S1694
153	**Union Bank of the Philippines**	PHILIPPINES	Commercial Banks	PHY9091H1069
154	**Rizal Commercial Banking Corp.**	PHILIPPINES	Commercial Banks	PHY7311H1463
155	**Metropolitan Bank & Trust Company**	PHILIPPINES	Commercial Banks	PHY6028G1361
156	**China Banking Corporation - Chinabank**	PHILIPPINES	Commercial Banks	PHY138161229
157	**mBank SA**	POLAND	Commercial Banks	PLBRE0000012
158	**Bank Zachodni WBK S.A.**	POLAND	Commercial Banks	PLBZ00000044
159	**Bank Polska Kasa Opieki SA-Bank Pekao SA**	POLAND	Commercial Banks	PLPEKAO00016
160	**Bank Ochrony Srodowiska SA - BOS SA-Bank Ochrony Srodowiska Capital Group**	POLAND	Commercial Banks	PLBOS0000019
161	**Bank Millennium**	POLAND	Commercial Banks	PLBIG0000016
162	**Bank Handlowy w Warszawie S.A.**	POLAND	Commercial Banks	PLBH00000012
163	**ING Bank Slaski S.A. - Capital Group**	POLAND	Commercial Banks	PLBSK0000017
164	**BANIF - Banco Internacional do Funchal, SA**	PORTUGAL	Commercial Banks	PTBAF0AM0002
165	**Banco Comercial Português, SA-Millennium bcp**	PORTUGAL	Commercial Banks	PTBCP0AM0007
166	**Banco BPI SA**	PORTUGAL	Bank Holding & Holding Companies	PTBPI0AM0004
167	**Al Khalij Commercial Bank**	QATAR	Commercial Banks	QA000A0M6MD5
168	**Qatar National Bank**	QATAR	Commercial Banks	QA0006929895
169	**Doha Bank**	QATAR	Commercial Banks	QA0006929770
170	**Commercial Bank of Qatar (The)**	QATAR	Commercial Banks	QA0007227752
171	**Ahli Bank QSC**	QATAR	Commercial Banks	QA0001200748
172	**Transilvania Bank-Banca Transilvania SA**	ROMANIA	Commercial Banks	ROTLVAACNOR1
173	**BRD-Groupe Societe Generale SA**	ROMANIA	Commercial Banks	ROBRDBACNOR2
174	**OJSC Promsvyazbank**	RUSSIAN FEDERATION	Commercial Banks	RU000A0JNX47
175	**Urals Transport Joint-Stock Bank - UralTransBank**	RUSSIAN FEDERATION	Commercial Banks	RU000A0JRWL0
176	**JSC Rosbank**	RUSSIAN FEDERATION	Commercial Banks	RU000A0HHK26
177	**SDM Bank JSC**	RUSSIAN FEDERATION	Commercial Banks	RU000A0JQ8X5
178	**Bank UralSib**	RUSSIAN FEDERATION	Commercial Banks	RU0006929536
179	**AK Bars Bank**	RUSSIAN FEDERATION	Commercial Banks	RU000A0JQMF5
180	**Joint-Stock Investment Commercial Bank Novaya Moskva-NOMOS-Bank**	RUSSIAN FEDERATION	Commercial Banks	RU000A0JRAF8

181	**Bank Zenit**	RUSSIAN FEDERATION	Commercial Banks	RU000A0JPCR3
182	**Probusiness Bank**	RUSSIAN FEDERATION	Commercial Banks	RU0006454527
183	**Open Joint-Stock Social Commercial Bank of Primorye 'Primsotsbank'**	RUSSIAN FEDERATION	Commercial Banks	RU0009100945
184	**Open Joint-Stock Company "MTS Bank**	RUSSIAN FEDERATION	Commercial Banks	RU000A0JPBL8
185	**Saudi Investment Bank (The)**	SAUDI ARABIA	Commercial Banks	SA0007879063
186	**Samba Financial Group**	SAUDI ARABIA	Commercial Banks	SA0007879097
187	**Saudi British Bank (The)**	SAUDI ARABIA	Commercial Banks	SA0007879089
188	**Banque Saudi Fransi**	SAUDI ARABIA	Commercial Banks	SA0007879782
189	**Arab National Bank**	SAUDI ARABIA	Commercial Banks	SA0007879105
190	**Bank Al-Jazira**	SAUDI ARABIA	Commercial Banks	SA0007879055
191	**Riyad Bank**	SAUDI ARABIA	Commercial Banks	SA0007879048
192	**Saudi Hollandi Bank**	SAUDI ARABIA	Commercial Banks	SA0007879071
193	**Investec Limited**	SOUTH AFRICA	Bank Holding & Holding Companies	ZAE000081949
194	**Nedbank Group Limited**	SOUTH AFRICA	Bank Holding & Holding Companies	ZAE000004875
195	**Nordea Bank AB (publ)**	SWEDEN	Bank Holding & Holding Companies	SE0000427361
196	**Svenska Handelsbanken**	SWEDEN	Commercial Banks	SE0000193120
197	**Skandinaviska Enskilda Banken AB**	SWEDEN	Commercial Banks	SE0000148884
198	**United Overseas Bank Limited UOB**	SINGAPORE	Commercial Banks	SG1M31001969
199	**Oversea-Chinese Banking Corporation Limited OCBC**	SINGAPORE	Commercial Banks	SG1S04926220
200	**Nova Kreditna Banka Maribor d.d.**	SLOVENIA	Commercial Banks	SI0021104052
201	**Banco Agricola**	EL SALVADOR	Commercial Banks	SV0011300317
202	**Banco Davivienda Salvadoreno, SA**	EL SALVADOR	Commercial Banks	SV0011100311
203	**Banco Bilbao Vizcaya Argentaria SA**	SPAIN	Commercial Banks	ES0113211835
204	**Bankia, SA**	SPAIN	Commercial Banks	ES0113307021
205	**Banco Santander SA**	SPAIN	Commercial Banks	ES0113900J37
206	**UBS AG**	SWITZERLAND	Commercial Banks	CH0024899483
207	**EFG International**	SWITZERLAND	Commercial Banks	CH0022268228
208	**Credit Suisse Group AG**	SWITZERLAND	Bank Holding & Holding Companies	CH0012138530
209	**Sinopac Financial Holdings**	TAIWAN	Bank Holding & Holding Companies	TW0002890001
210	**CTBC Financial Holding Co Ltd**	TAIWAN	Bank Holding & Holding Companies	TW0002891009
211	**Waterland Financial Holdings Co., Ltd**	TAIWAN	Bank Holding & Holding Companies	TW0002889003
212	**Taichung Commercial Bank**	TAIWAN	Commercial Banks	TW0002812005
213	**King's Town Bank**	TAIWAN	Commercial Banks	TW0002809001
214	**Chang Hwa Commercial Bank Ltd.**	TAIWAN	Commercial Banks	TW0002801008
215	**Far Eastern International Bank**	TAIWAN	Commercial Banks	TW0002845005
216	**Taishin Financial Holding Co., Ltd**	TAIWAN	Bank Holding & Holding Companies	TW0002887007
217	**Jih Sun Financial Holding Co., Ltd**	TAIWAN	Bank Holding & Holding Companies	TW0005820005
218	**Siam Commercial Bank Public Company Limited**	THAILAND	Commercial Banks	TH0015010000
219	**TMB Bank Public Company Limited**	THAILAND	Commercial Banks	TH0068010Z07
220	**Krung Thai Bank Public Company Limited**	THAILAND	Commercial Banks	TH0150010Z03
221	**Bank of Ayudhya Public Company Ltd.**	THAILAND	Commercial Banks	TH0023010000
222	**SCB (Thai) Public Company Limited**	THAILAND	Commercial Banks	TH0067010007
223	**CIMB Thai Bank Public Company Limited**	THAILAND	Commercial Banks	TH0041010Y05
224	**Bangkok Bank Public Company Limited**	THAILAND	Commercial Banks	TH0001010006
225	**Arab Tunisian Bank**	TUNISIA	Commercial Banks	TN0003600350
226	**Denizbank A.S.**	TURKEY	Commercial Banks	TREDZBK00015
227	**Turkiye Vakiflar Bankasi TAO**	TURKEY	Commercial Banks	TREVKFB00019
228	**Alternatifbank A.S.**	TURKEY	Commercial Banks	TRAALNTF91N6
229	**Sekerbank T.A.S.**	TURKEY	Commercial Banks	TRASKBNK91N8
230	**Finansbank A.S.**	TURKEY	Commercial Banks	TRAFINBN91N3
231	**Akbank T.A.S.**	TURKEY	Commercial Banks	TRAAKBNK91N6
232	**Tekstilbank-Tekstil Bankasi A.S.**	TURKEY	Commercial Banks	TRATEKST91N0
233	**Turk Ekonomi Bankasi A.S.**	TURKEY	Commercial Banks	TRATEBNK91N9
234	**Turkiye Garanti Bankasi A.S.**	TURKEY	Commercial Banks	TRAGARAN91N1
235	**Yapi Ve Kredi Bankasi A.S.**	TURKEY	Commercial Banks	TRAYKBNK91N6
236	**Turkiye Halk Bankasi A.S.**	TURKEY	Commercial Banks	TRETHAL00019
237	**Turkiye is Bankasi A.S. - ISBANK**	TURKEY	Commercial Banks	TRAISCTR91N2
238	**Emirates NBD PJSC**	UNITED ARAB EMIRATES	Commercial Banks	AEE000801010
239	**Union National Bank**	UNITED ARAB EMIRATES	Commercial Banks	AEU000401015
240	**National Bank of Ras Al-Khaimah (P.S.C.) (The)-RAKBANK**	UNITED ARAB EMIRATES	Commercial Banks	AEN000601015

241	**First Gulf Bank**	UNITED ARAB EMIRATES	Commercial Banks	AEF000201010
242	**Commercial Bank of Dubai P.S.C.**	UNITED ARAB EMIRATES	Commercial Banks	AEC000201017
243	**National Bank of Abu Dhabi**	UNITED ARAB EMIRATES	Commercial Banks	AEN000101016
244	**Mashreqbank PSC**	UNITED ARAB EMIRATES	Commercial Banks	AEM000101018
245	**Bank of Sharjah**	UNITED ARAB EMIRATES	Commercial Banks	AEB000101011
246	**Abu Dhabi Commercial Bank**	UNITED ARAB EMIRATES	Commercial Banks	AEA000201011
247	**Joint-Stock Commercial Bank for Social Development - Ukrsotsbank**	UKRAINE	Commercial Banks	UA1002231009
248	**Pivdennyi Joint-Stock Bank**	UKRAINE	Commercial Banks	UA1500091103
249	**Pravex Bank**	UKRAINE	Commercial Banks	UA4000068159
250	**VTB Bank (Ukraine) JSC**	UKRAINE	Commercial Banks	UA4000012702
251	**Bank Forum**	UKRAINE	Commercial Banks	UA1006051007
252	**HSBC Holdings Plc**	UNITED KINGDOM	Bank Holding & Holding Companies	GB0005405286
253	**Barclays Plc**	UNITED KINGDOM	Bank Holding & Holding Companies	GB0031348658
254	**Royal Bank of Scotland Group Plc (The)**	UNITED KINGDOM	Bank Holding & Holding Companies	GB00B7T77214
255	**Schroders Plc**	UNITED KINGDOM	Bank Holding & Holding Companies	GB0002405495
256	**Standard Chartered Plc**	UNITED KINGDOM	Bank Holding & Holding Companies	GB0004082847
257	**Lloyds Banking Group Plc**	UNITED KINGDOM	Bank Holding & Holding Companies	GB0008706128
258	**Independent Bank Corp.**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US4538361084
259	**Metlife, Inc.**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US59156R1086
260	**Bank of New York Mellon Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US0640581007
261	**New York Community Bancorp, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US6494451031
262	**People's United Financial, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US7127041058
263	**East West Bancorp, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US27579R1041
264	**Astoria Financial Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US0462651045
265	**Prudential Financial Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US7443201022
266	**Fulton Financial Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US3602711000
267	**First Commonwealth Financial Corp.**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US3198291078
268	**Hancock Holding Company**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US4101201097
269	**AmeriServ Financial, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US03074A1025
270	**First Interstate Bancsystem, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US32055Y2019
271	**Community Bank System, Inc.**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US2036071064
272	**Ocwen Financial Corp**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US6757463095
273	**Trustmark Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US8984021027
274	**First National of Nebraska, Inc.**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US3357201082
275	**Associated Banc-Corp.**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US0454871056
276	**First Midwest Bancorp, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US3208671046
277	**Ally Financial Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US02005N1000
278	**Wells Fargo & Company**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US9497461015
279	**SunTrust Banks, Inc.**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US8679141031
280	**PNC Financial Services Group Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US6934751057
281	**Comerica Incorporated**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US2003401070
282	**Northern Trust Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US6658591044
283	**KeyCorp**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US4932671088
284	**State Street Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US8574771031
285	**Huntington Bancshares Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US4461501045
286	**First Horizon National Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US3205171057
287	**UMB Financial Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US9027881088
288	**Regions Financial Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US7591EP1005
289	**Cullen/Frost Bankers, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US2298991090
290	**Zions Bancorporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US9897011071
291	**Fifth Third Bancorp**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US3167731005
292	**City National Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US1785661059
293	**FirstMerit Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US3379151026
294	**Popular, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	PR7331747001
295	**M&T Bank Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US55261F1049
296	**Synovus Financial Corp**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US87161C1053
297	**JPMorgan Chase & Co**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US46625H1005
298	**Dime Community Bancshares, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US2539221083
299	**First BanCorp**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	PR3186727065
300	**American Express Company**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US0258161092

301	**US Bancorp**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US9029733048
302	**Capital One Financial Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US14040H1059
303	**KKR Financial Holdings, LLC**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US48248A3068
304	**First Niagara Financial Group, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US33582V1089
305	**CVB Financial Corp**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US1266001056
306	**Webster Financial Corp**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US9478901096
307	**Cathay General Bancorp Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US1491501045
308	**Citigroup Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US1729674242
309	**Doral Financial Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	PR25811P8521
310	**BB&T Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US0549371070
311	**TCF Financial Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US8722751026
312	**Central Pacific Financial Corp.**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US1547604090
313	**Bank of America Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US0605051046
314	**Morgan Stanley**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US6174464486
315	**Goldman Sachs Group, Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US38141G1040
316	**BOK Financial Corporation**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US05561Q2012
317	**GFI Group Inc**	UNITED STATES OF AMERICA	Bank Holding & Holding Companies	US3616522096
318	**Open Joint Stock Commercial Bank Agrobank**	UZBEKISTAN	Commercial Banks	CZ0000000203.
319	**Banco Provincial**	VENEZUELA	Commercial Banks	VEV001271007
320	**Banco del Caribe CA**	VENEZUELA	Commercial Banks	VEV0021410A5
321	**Banco Occidental de Descuento, Banco Universal CA**	VENEZUELA	Commercial Banks	VEV002241009
322	**Banco Exterior, C.A. - Banco Universal**	VENEZUELA	Commercial Banks	VEV000771007

APPENDIX B: LIST OF BANK RATINGS

S/N	Country	Bank	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
1	ARGENTINA	BANCO MACRO SA				B	B	B	B+	B+	B	B	B	B	B-
2	AUSTRIA	RAIFFEISEN BANK INTERNATIONAL			A-	A-	A	A	A	A-	A-	A-	A-	A	A
3		ERSTE GROUP BANK	A	A	A	A	A	A-	A	A	A	A	A-	A	A
4	AUSTRALIA	AUSTRALIA AND NEW ZEALAND BANKING GROUP	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
5		BANK OF QUEENSLAND		BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB+	BBB+	BBB+	BBB+
6		COMMONWEALTH BANK OF AUSTRALIA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA-
7		BENDIGO AND ADELAIDE BANK	BBB	BBB	BBB	BBB	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-
8		WESTPAC BANKING CORP	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA	AA	AA
9		NATIONAL AUSTRALIA BANK		AA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA-
10		MACQUARIE GROUP				A	A	A	A	A	A	A	A	A	A-
11		SUNCORP	A	A	A	A	A	A	A	A+	A+	A+	A+	A	A+
12	AZERBAIJAN	DEMIRBANK OPEN JOINT STOCK COMPANY					CCC+	CCC+	CCC+	B-	B-	B-	B-	B-	B
13	BAHRAIN	AHLI UNITED BANK				BBB+	BBB+	BBB+	A-	A-	A-	A-	A-	BBB+	BBB+
14		BBK B.S.C.				BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	BBB+	BBB+
15		ARAB BANKING CORP	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB	BBB+	BBB+	BBB+	BBB	BBB-	BB+
16		NATIONAL BANK OF BAHRAIN		BBB	A-	A-	A-	A-	A-	A	A	A	A	BBB	BBB
17	BELGIUM	KBC GROEP NV	A+	A+	A+	A+	A+	A+	AA-	AA-	A+	A	A	A	A-
18		DEXIA				AA+	AA+	AA+	AA+	AA+	AA-	A+	A+	A+	A+
19	BENIN	BANK OF AFRICA						B+	B+	B+	B	B	B	B	B
20	BERMUDA	BANK OF N.T. BUTTERFIELD		A	A	A	A	A	A	A	A	A-	A-	A-	A-
21	BRAZIL	BANCO DO BRASIL S.A.			B	B+	BB-	BB-	BB+	BBB-	BBB-	BBB-	BBB-	BBB	BBB
22		BANCO ABC						BB-	BB	BB+	BB+	BB+	BB+	BB+	BB+
23		BANCO DAYCOVAL								BB-	BB-	BB	BB	BB	BB+
24		BANCO DA AMAZONIA						BB-	BB	BB+	BBB-	BBB-	BBB-	BBB	BBB
25		BANCO BTG PACTUAL					BB-	BB-	BB+	BBB-	BBB	BB+	BBB-	BBB-	BBB-
26		BANCO PANAMERICANO				BB	BB	BB	BB+	BB+	BB+	BB+	BB+	BB+	BB+
27		BANCO BRADESCO	BB-	BB-	B	B+	BB-	BB-	BB+	BBB-	BBB	BBB	BBB	BBB+	BBB+
28		BANCO SAN (BRASIL) S.A.				BB+	BB+	BB+	BB+	BBB-	BBB	BBB	BBB	BBB+	BBB
29		BANCO PINE				B+	B+	B+	B+	B+	B+	B+	BB-	BB-	BB
30		BANCO DO ESTADO DO RIO GRANDE DO SUL			BB	BB	BB-	BB-	BB	BB	BB+	BB+	BB+	BB+	BB+
31		ITAU UNIBANCO HOLDING				B	BB-	BB-	BB+	BBB-	BBB	BBB	BBB	BBB+	BBB+
32	BULGARIA	FIRST INVESTMENT BANK						BB-	BB-	BB-	BB-	BB-	BB-	BB-	BB-
33	CANADA	CANADIAN IMPERIAL BANK OF COMMERCE	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
34		BANK OF MONTREAL-BANQUE DE MONTREAL	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
35		NATIONAL BANK OF CANADA	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+
36		BANK OF NOVA SCOTIA	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
37		ROYAL BANK OF CANADA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA
38		TORONTO DOMINION BANK	AA	AA	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
39		HOME CAPITAL BANK					BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB	BBB
40	CHILE	BANCO SAN CHILE	A-	A-	A-	A-	A-	A	A+	A+	A+	A+	AA-	A+	A+

41		BANCO DE CREDITO E INVERSIONES	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-
42		BANCO DE CHILE			A-	A-	A-	A	A	A	A	A	A	A	A
43	CHINA	BANK OF BEIJING				BB	BB	BB+	BB+	BB+	BB+	BB+	BB+	BB+	BB+
44		BANK OF CHINA	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A	A	A	A	A	A
45		SHANGHAI PIUDONG DEVELOPMENT BANK				BB+	BB+	BB+	BB+	BB+	BB+	BB+	BB+	BB+	BB+
46		CHINA MERCHANT BANK				BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB+
47		CHINA EVERBRIGHT BANK CO				BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB
48		AGRICULTURAL BANK OF CHINA				A	A	A	A	A	A	A	A	A	A
49		INDUSTRIAL AND COMM BANK OF CHINA	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A	A	A	A	A	A
50		HUA XIA BANK CO			BB+	BB	BB-	BB-	BB-	BB	BB	BB+	BB+	BB+	BB+
51		PING AN BANK CO			BB	BB	BB	BB	BB	BB	BB+	BB+	BB+	BB+	BB+
52		CHINA CONSTRUCTION BANK CORP						A-	A-	A	A	A	A	A	A
53		CHINA MINSHENG BANKING COPR			BB-	BB-	BB-	BB+	BB+	BB+	BB+	BB+	BB+	BB+	BB+
54		CHINA CITIC BANK			BBB-	BBB-	BBB-	BBB	BBB+	BBB+	BBB	BBB	BBB	BBB	BBB
55	COLOMBIA	BBVA	BB+	BB+	BB	BB	BB	BB	BB+	BB+	BB+	BB+	BB+	BBB	BBB
56		BANCO DE BOGOTA			BBB	BBB	BBB	BBB	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB
57		BANCOCOLOMBIA					BB	BB	BB+	BB+	BB+	BB+	BBB-	BBB-	BBB
58		BANCO DAVIVIENDA				BBB-	BBB	BBB	BBB	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
59		GRUPO AVAL ACCIONES Y VALORES			BBB+	BBB+	BBB	BBB	BBB	BBB	BBB	BBB-	BBB-	BBB-	BBB-
60	CROATIA	ZAGREBACKA BANKA	BB+	BB+	BB+	BBB-	BBB-	BBB-	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+
61	CZECH REPUBLIC	KOMERCNI BANKA	BBB	BBB+	BBB+	A-	A+	A+	AA-	AA-	A+	A	A	A	A
62	DENMARK	DANSKE BANK	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A+	A+	A+	A
63	GERMANY	DEUTSCHE POSTBANK	A+	A+	A+	A+	A	A	A	A	A	A+	A+	A+	A+
64		COMMERZBANK AG	A+	A+	A-	A-	A-	A-	A	A	A	A+	A+	A+	A+
65		DEUTSCHE BANK	AA	AA	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A+	A+
66	ECUADOR	BANCO DE LA PRODUCCION		CCC+	CCC+	CCC+	B-	B-	B-	B-	B-	B-	B-	B-	B-
67		BANCO PICHINCHA		CCC+	CCC+	CCC+	B-	B-	B-	B-	B-	B-	B-	B-	B-
68	EGYPT	COMMERCIAL INTERNATIONAL BANK	BBB-	BBB-	BB+	BB+	BB+	BB+	BB+	BB+	BB+	BB+	BB+	BB	B+
69	FINLAND	POHJOLA BANK PLC	A+	A+	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A+	A+
70	FRANCE	SOCIETE GENERALE	AA	AA	AA	AA-	AA-	AA-	AA	AA-	AA-	A+	A+	A+	A+
71		CREDIT INDUSTRIAL ET COMMERCIAL	A	A	A	A+	A+	AA-	AA-	AA-	AA-	AA-	AA-	A+	A+
72		BNP PARIBAS	AA-	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA-	AA-	A+
73		NATIXIS		AA-	AA-	AA	AA+	AA+	AA	AA-	A+	A+	A+	A+	A+
74	GEORGIA	LIBERTY BANK			B-	B-	B-	B	B	B	B	B	B	B	B
75		BANK OF GEORGIA							B-	B+	B	B	B+	BB-	BB-
76	GREECE	ALPHA BANK AE	A-	A-	A-	A-	A-	A-	A-	A-	A-	BBB+	BBB-	B-	CCC
77		EUROBANK ERGASIAS	A-	A-	A-	A-	A-	A-	A	A	A	BBB+	BBB-	C-	CCC
78		NATIONAL BANK OF GREECE	A-	A-	A-	A-	A-	A-	A-	A-	A-	BBB+	BBB-	B-	B-
79		PIRAEUS BANK	BBB	BBB	BBB	BBB+	BBB+	BBB+	BBB+	BBB+	A-	BBB+	BBB-	B-	CCC
80	HONG KONG	CHONG HING BANK							BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+

81	IRELAND	BANK OF IRELAND-GOV		AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A-	BBB	BBB	BBB
82		ALLIED IRISH BANK		AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A-	BBB	BBB	BBB
83	INDONESIA	BANK DANAMON			B	B+	B+	BB-	BB-	BB-	BB	BB	BB+	BB+	BB+
84		BANK CENTRAL ASIA			B	B+	B+	BB-	BB-	BB-	BB	BB	BB+	BBB-	BBB-
85		BANK RAKYAT			B	B+	B+	BB-	BB-	BB-	BB	BB	BB+	BBB-	BBB-
86		BANK NEGARA			B	B+	B+	BB-	BB-	BB-	BB	BB	BB+	BBB-	BBB-
87		BANK MANDIRI		B-	B	B+	B+	BB-	BB-	BB-	BB	BB	BB+	BB+	BBB-
88		BANK INTERNASIONAL	B-	B-	B-	B	B+	BB-	BB-	BB-	BB	BB	BB+	BB+	BBB
89		BANK OCBC		B-	B	B+	B+	BB-	BB-	BB-	BB	BB	BB+	BB+	BBB
90		BAN PAN INDONESIA			BB-	BB-	BB-	BB-	BB-	BB-	BB-	BB	BB	BB	BB
91		PT BANK CIMB NIAGA			BB-	BB-	BB-	BB-	BB-	BB-	BB	BB	BB+	BB+	BBB
92	INDIA	UNION BANK OF INDIA				BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB
93		CANARA BANK			BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
94		BANK OF BARODA			BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
95		STATE BANK OF INDIA					BB+	BB+	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
96		INDIAN BANK			BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
97		PUNJAB NATIONAL BANK			BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
98		AXIS BANK				BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
99		ICICI BANK						BB+	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
100	ISRAEL	BANK HAPOALIM	A-	A-	A-	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	A-	A-
101		BANK LEUMI LE ISRAEL	A-	A-	A-	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	A-	A-
102	ITALY	BANCO DI DESIO	BBB+	BBB+	BBB+	A-	A-	A-	A-	A	A	A	A	A-	BBB+
103		INTESA SANPAOLO	A+	A+	A+	A+	A+	A+	AA-	AA-	AA-	AA-	AA-	A	A-
104		UNICREDIT		AA-	AA-	AA-	AA-	A+	A+	A+	A+	A	A	A-	A-
105		BANK CARIGE	A	A	AA	AA-	A	A	A	A	A	A	A	BBB	BB+
106		CREDITO EMILIANO	A	A	A	A	A	A	A	A	A	A	A	BBB+	BBB+
107		BREDITO BERGAMASCO					A	A	A	A	A	A-	A-	BBB+	BBB
108		BANCA MONTE DEI PASHI DE SIENA	A+	A+	A+	A+	A+	A+	A+	A+	A	A	A-	BBB+	BBB
109	JAMAICA	NATIONAL COMMERCIAL BANK				B+	B+	B+	B+	B+	B	CCC	B-	B-	B-
110	JAPAN	SHIZUOKA			A-	A-	A-	A	A	A+	A+	A+	A+	A	A
111		SURUGA BANK				BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	A-	A-
112		MIZUHO FIN GROUP		A	A	A	A	A	A	A+	A+	A	A	A	A-
113		SUMITOMO MITSUI FIN GROUP				A	A	A	A	A+	A+	A	A	A	A-
114		NOMURA HOLDING INC			BBB	BBB	BBB	BBB	BBB+	BBB+	BBB+	BBB	BBB	BBB	BBB
115		DAIWA GROUP	BBB+	BBB+	BBB	BBB	BBB	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+
116	JORDAN	ARAB BANK			BBB+	BBB+	BBB+	BBB+	A-	A-	A-	A-	A-	A-	A-
117		BANK OF JORDAN						BB-	BB-	BB-	BB-	BB-	BB-	BB-	BB-
118	KAZAKHSTAN	KAZKOMMERTSBANK	B+	B+	BB-	BB	BB	BB+	BB+	BB+	BB	B-	B-	B-	B
119		BANK CENTERCREDIT	B	B	B-	B+	B+	BB-	BB-	BB-	BB-	B+	B	B	B
120		BTA BANK	B+	B+	B+	B+	B+	BB	BB+	BB+	BB+	CCC	B-	C	C

121	KUWAIT	GULF BANK KSC	BBB+	BBB+	A-	A-	A-	A-	A	A	A+	A+	A+	A+	A+
122		NATIONAL BANK OF KUWAIT	A-	A	A+	A+	A+	A+	A+	A+	AA-	AA-	AA-	AA-	AA-
123		AHLI UNITED BANK					BBB+	BBB+	A-	A-	A-	A-	A-	A-	A-
124		AL AHLI BANK OF KUWAIT					BBB+	BBB+	A-	A-	A-	A-	A-	A-	A-
125		COMMERCIAL BANK OF KUWAIT	BBB+	BBB+	A-	A-	A-	A-	A	A	A+	A+	A+	A+	A+
126	LEBANON	BYBLOS BANK	BB-	B+	B-	B-	B-		B-	B-	B-	B-	B	B	B
127		BANK AUDI SAL	BB-	B+	B-	B-	B-	B-	B-	B-	B-	B-	B	B	B
128	MALAYSIA	HONG LEONG BANK						BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+
129		MALAYAN BANKING BERHAN	BBB-	BBB-	BBB+	BBB+	A-	A-	A-	A-	A-	A-	A-	A-	A-
130	MEXICO	GRUPO FINANCIERO BANORTE					BBB-	BBB-	BBB	BBB	BBB	BBB	BBB	BBB	BBB
131		BANNCO NACIONAL DE MEXICO	BB+	BB+	BBB-	BBB-	BBB-	BBB+	A-	A	A	A-	A-	A-	A-
132	MOROCCO	ATTIJARIWAFA BANK			BB	BB	BB	BB	BB	BB	BB+	BB+	BB+	BB+	BB+
133	NETHERLANDS	ING GROEP NV			AA-	AA-	AA-	AA-	AA-	AA-	AA-	A	A	A	A
134	NIGER	BANK OF AFRICA				B-	B-	B-	B-	B-	B	B	B	B	B
135	NIGERIA	GUARANTY TRUST BANK				B+	B+	B+	B+	B+	B+	B+	B+	B+	B+
136		ACCESS BANK			B-	B-	B-	B-	B-	B-	B-	B	B	B-	B
137		UNITED BANK FOR AFRICA			B+	B+	B+	B+	B+	B+	B+	B+	B+	B+	B+
138		UNION BANK OF NIGERIA				B+	B+	B+	B+	B+	B+	B+	B-	B-	B+
139		DIAMOND BANK				B	B	B	B	B	B	B	B	B	B
140		ZENITH BANK			BB-	BB-	BB	B+	B+	B+	B+	B	B+	B	B+
141		FIDELITY BANK				B+	B+	B+	B+	B+	B+	B	B+	B	B+
142	OMAN	BANK SOHAR				BBB	BBB	BBB	BBB	BBB	BBB-	BBB	BBB+	BBB+	BBB+
143		BANK MUSCAT SAOG	BBB-	BBB	BBB	BBB	BBB	BBB	A-	A-	A-	A-	A-	A-	A
144		BANK DHOFAR	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+
145		NATIONAL BANK OF OMAN			BBB-	BBB-	BBB	BBB	BBB	BBB	BBB+	BBB+	BBB+	BBB+	BBB
146	PERU	BANCO INTERNATIONAL DEL PERU				BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB-
147		SCOTIABANK	B+	BB-	BB-	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB+	BBB+
148		BANCO CONTINENTAL			BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB	BBB	BBB+	BBB+
149		BANCO DE CREDITO DEL PERU			BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB	BBB	BBB-
150	PHILIPPINES	CHINA BANKING CORP			BB	BB	BB	BB	BB	BB	BB	BB	BB	BB	BB
151		RIZAL COMM BANK				BB-	BB-	BB-	BB-	BB-	BB-	BB-	BB-	BB-	BB-
152		BANK OF THE PHILIPPINE ISLAND		BB-	BB-	BB	BB	BB	BB+	BB+	BB+	BB+	BB	BB+	BB+
153		UNION BANK OF PHILIPPINES		BB-	BB-	BB-	BB	BB	BB+	BB+	BB+	BB-	BB	BB-	BB-
154		SECURITY BANK CORP				BB	BB	BB	BB	BB	BB	BB	BB	BB	BB
155		BDO UNIBANK		BB-	BB-	BB-	BB	BB	BB+	BB+	BB+	BB+	BB+	BB+	BB
156		METROPLITAN BANK & TRUST			BB	BB	BB	BB-	BB-	BB	BB	BB	BB	BB	BB
157	POLAND	BANK HANDLOWY	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	A	A	A	A
158		BANK ZACHODNI WBK	BBB+	BBB+	BBB+	BBB+	A	A	A+	A+	A+	BBB+	BBB+	A+	BBB
159		BANK POLSKA KASA OPIEKI	BBB+	BBB+	BBB+	BBB+	A	A	A	A	A	A-	A-	A-	A-
160		ING BANK SLASKI	BBB+	BBB+	BBB+	BBB+	A	A	A+	AA-	AA-	A	A	A	A

161		BANK MILLENNIUM								A	A	A	A-	BBB-	BBB-
162		BANK OCHRONY SCRODOWISKA	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB	BBB	BBB	BBB	BBB
163		MBANK	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	A	A	A	A
164	PORTUGAL	BANCO COMERCIAL	AA-	AA-	A+	A+	A+	A+	A+	A+	A+	A+	BBB+	BB+	BB+
165		BANIF				BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB-	BB	BB
166		BANCO BPI	A	A	A	A+	A+	A+	A+	A+	A+	A+	A-	BB+	BB+
167	QATAR	AL KHALIJ COMMERCIAL BANK				A	A	A-	A-	A-	A-	A-	A-	A-	A-
168		COMMERCIAL BANK OF QATAR				BBB+	BBB+	BBB+	A	A	A+	A	A+	A	A
169		AHLI BANK QSC								BBB+	A-	A	A-	A-	A-
170		QATAR NATIONAL BANK	BBB	BBB+	A-	A-	A-	A-	A	A+	AA-	A+	A+	A	A+
171		DOHA BANK			A	A	A	A	A	A	A	A	A+	A	A
172	ROMANIA	TRANSILVANIA BANK						BB-	BB-	BB-	BB-	BB-	BB-	BB-	BB-
173		BRD	B-	B	BB-	BB	BBB-	BBB-	A-	A-	BBB	BBB	BBB	BBB+	BBB+
174	RUSSIA	URALS TRANSP. JOINT-STOCK BANK				B-	B-	B-	B-	B-	B-	B	B-	B	B-
175		SDM BANK			B-	B-	B-	B-	B-	B-	B-	B-	B	B	B
176		JSC ROSBANK		B-	B-	B-	B	B	B+	BB-	A-	BBB+	BBB+	BBB+	BBB+
177		BANK URALSIB			B	B	B	B	B+	B+	B+	B+	B+	BB-	BB-
178		JOINT STOCK COMMERCIAL BANK					BB+	BBB-	BBB-	BBB	BBB	BBB-	BBB-	BBB-	BBB
179		BANK ZENIT			B-	B-	B-	B	B	B	B+	B+	B+	B+	B+
180		PROBUSINESS BANK	B-	B-	B-	B-	B-	B-	B-	B-	B-	B-	B-	B-	B-
181		JOINT-STOCK INVST COMM BANK	CCC+	B-	B	B	B	B	B+	B+	B+	B+	BB-	BB	BB
182		OPEN JOINT STOCK COMPANY			B-	B-	B-	B	B	B+	B+	B+	B+	B+	B+
183		OJSC PROMSVYAZBANK	CCC+	CCC+	B-	B-	B	B	B+	B+	B+	B+	BB-	BB-	BB-
184		AK BARS BANK			B-	B-	B-	B+	B+	BB-	BB	BB	BB	BB	BB-
185	EL SALVADOR	BANCO AGRICOLA	BB+	BB+	BB+	BB	BB	BB	BB+	BB+	BB+	BB+	BB+	BBB-	BBB-
186		BANCO DAVIVIENDA			BB+	BB	BB	BB	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BB+
187	SAUDI ARABIA	SAUDI HOLLANDI BANK	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	A-	A-	A-	A-
188		SAUDI INVESTMENT BANK			A	A	A+	A	A	A-	A-	A-	A-	A-	A-
189		SAMBA FINANCIAL GROUP	BBB+	BBB+	BBB+	A-	A-	A	A	A	A+	A+	A+	A+	A+
190		BANK AL-JAZIRA		BBB-	BBB-	BBB-	BBB-	BBB-	BBB+	BBB+	A-	A-	A-	A-	A-
191		BANQUE SAUDI FRANSI		BBB+	BBB+	A-	A-	A	A	A	A	A	A	A	A
192		RIYAB BANK		BBB+	BBB+	A-	A-	A	A	A	A+	A+	A+	A+	A+
193		ARAB NATIONAL BANK		BBB	BBB	BBB+	BBB+	A-	A-	A	A	A	A	A	A
194		SAUDI BRITISH BANK		BBB+	BBB+	A-	A-	A	A	A	A	A	A	A	A
195	SPAIN	BANKIA				BBB-	BBB-	BBB	BBB+	BBB	BBB	AA-	A-	A-	BBB
196		BANCO BILBAO VIZCAYA ARGENTARIA	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A+	BBB+
197		BANCO SANTANDER	AA-	AA-	AA-	A+	AA-	AA-	AA	AA	AA	AA	AA	AA-	BBB+
198	SINGAPORE	OVERSEA-CHINESE BANKING CORP	A+	A+	A+	A+	A+	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
199		UNITED OVERSEAS BANK	A+	A+	A+	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
200	SLOVENIA	NOVA KREDITNA BANKA			BBB	BBB+	A-	A-	A-	A-	A-	A-	A-	BBB+	BBB

201	SOUTH AFRICA	NEDBANK						BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB+
202		INVESTEC	BBB-	BBB-	BBB-	BBB	BBB	BBB	BBB	BBB+	BBB+	BBB	BBB	BBB	BBB
203	SWEDEN	SKANDINAVISKA ENSKILDA BANKEN	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+
204		SVENSKA HANDELSBANKEN	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
205		NORDEA BANK					AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
206	SWITZERLAND	EFG INTERNATIONAL				A-	A-	A-	A-	A	A	A	A	A	A
207		UBS AG	AA	AA	AA	AA+	AA+	AA+	AA	A+	A+	A+	A+	A	A
208		CREDIT SUISSE	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A	A
209	TAIWAN	KING'S TOWN BANK			BB	BB	BB-	BB-	BB	BB+	BB+	BB+	BB+	BBB-	BBB-
210		FAR EASTERN INTERNATIONAL BANK	BBB+	BBB-	BBB-	BBB-	BBB	BBB	BBB	BBB	BBB-	BBB-	BBB-	BBB-	BBB-
211		CHANG HWA COMMERCIAL BANK	A+	BBB+	BBB	BBB	BBB	BBB	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+
212		TAICHUNG COMMERCIAL BANK			BBB+	BBB+	BBB	BBB	BBB-	BBB-	BBB-	BBB-	BB+	BB+	BB+
213		SINOPAC FINANCIAL HOLDINGS					BBB	BBB	BBB	BBB	BBB	BBB	BBB-	BBB-	BBB
214		CTBC FINANCIAL			BBB+	BBB+	A-	A-	A-	A	A	A	A	A	A
215		WATERLAND FINANCIAL						BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB
216		JIH SUN FINANCIAL			BB-	BB-	BB	BB	BB+	BB+	BB	BB	BB	BB+	BB+
217		TAISHIN FINANCIAL				BBB-	BBB	BBB	BBB-	BBB-	BBB-	BBB-	BBB	BBB	BBB
218	THAILAND	TMB BANK			BB+	BB+	BB+	BB+	BB+	BB+	BBB-	BBB-	BBB-	BBB-	BBB-
219		BANK OF AYUDHYA		B+	B+	B+	BB-	BB	BB+	BBB-	BBB	BBB	BBB	BBB	BBB
220		SCB THAI BANK				BBB	BBB	A-	A-	A-	A-	BBB+	BBB+	BBB+	BBB+
221		KRUNG THAI BANK	BB+	BB+	BBB-	BBB-	BBB-	BBB+	BBB+	BBB+	BBB+	BBB	BBB	BBB	BBB
222		BANGKOK BANK	BB+	BB+	BBB-	BBB-	BBB-	BBB	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+
223		SIAM COMMERCIAL BANK	BB+	BB+	BBB-	BBB-	BBB	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+
224		CIMB THAI				BBB	BBB	BBB	BBB	BBB	BBB-	BBB-	BBB-	BBB	BBB
225	TUNISIA	ARAB TUNISIA					BBB-	BBB-	BBB	BBB+	BBB+	BBB+	BBB+	BBB	BBB-
226	TURKEY	DENIZBANK			B	B	B+	BB-	BB	BB	BB	BBB-	BBB-	BBB-	BBB-
227		TURKIYE VAKIFLAR BANKASI	BB-	B	B-	B	B+	BB-	BB-	BB-	BB-	BB+	BB+	BB+	BBB-
228		TEKSTILBANK TEKSTIL BANKASI				B-	B	B	B	B	B	B	B+	B+	B+
229		TURK EKONOMI BANKASI	BB-	B	B	B	B+	BB	BB	BB	BBB-	BBB-	BBB-	BBB-	BBB
230		FINANSBANK	BB-	B	B-	B	B+	BB-	BB	BB	BB	BBB-	BBB-	BBB-	BBB-
231		ALTERNATIFBANK	BB-	B	B-	B-	B-	B+	B+	BB-	BB-	BB	BB	BB	BB
232		TURKIYE GARANTI BANKASI	BB-	B	B	B	B+	BB-	BB	BB	BB	BBB-	BBB	BBB	BBB
233		AKBANK	BB-	BB-	B	B	B+	BB-	BB	BB	BB	BBB-	BBB-	BBB-	BBB
234		TURKIYE HALK BANKASI	BB-	B	B	B	B+	BB-	BB-	BB-	BB-	BB+	BB+	BB+	BBB-
235		SEKERBANK					B-	B-	B-	B	B	B	B+	BB-	BB-
236		TURKIYA IS BANKASI	BB-		B	B	B	B+	BB-	BB	BB	BB	BBB-	BBB-	BBB
237		YAPI VE KREDI BANKASI	BB-	B	B-	B	B+	BB-	BB	BB	BB	BBB-	BBB-	BBB-	BBB
238	UAE	EMIRATE NBD PJSC				A-	A	A	A+	A+	A+	A+	A+	A+	A+
239		UNION NATIONAL BANK	A	A-	A-	A-	A-	A-	A	A+	A+	A+	A+	A+	A+
240		MASHREQBANK		**A-**	**A-**	A-	A-	A-	A	A +	A+	A	A	A	A

241		FIRST GULF BANK						BBB+	BBB+	A	A+	A+	A+	A+	A+
242		NATIONAL BANK OF ABU DHABI	A+	A	A	A	A	A	A	A+	AA-	AA-	AA-	AA-	AA-
243		COMMERCIAL BANK OF DUBAI	A	A-	A-	A-	A-	A-	A	A	A	A-	A-	A-	A-
244		ABU DHABI COMMERCIAL BANK				A-	A	A	A	A+	A+	A+	A+	A+	A+
245		BANK OF SHARJAH		BBB+	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	BBB+	BBB+	BBB+	BBB+
246		NATIONAL BANL OF RAS AL-KHAIMOH						BBB+	A-	A-	A-	BBB+	BBB+	BBB+	BBB+
247	UKRAINE	JOINT-STOCK COMMERCIAL BANK						B-	B-	B	B+	B-	B	B	B
248		VTB BANK							BB-	BB-	B+	B-	B	B	B
249		PIVDENNYI JOINT STOCK						CCC+	B-	B-	B-	B-	B-	B-	B-
250		PRAVEX BANK								B-	B+	B-	B	B	B
251		BANK FORUM							B-	B-	B+	B-	B	B	CC
252	UNITED KINGDOM	HSBC HOLDING	AA-	AA-	AA-	AA-	AA	AA	AA	AA	AA	AA	AA	AA	AA-
253		ROYAL BANK OF SCOTLAND			AA+	AA+	AA	AA	AA+	AA+	AA-	AA-	AA-	A	A
254		BARCLAYS PLC					AA+	AA+	AA+	AA+	AA	AA-	AA-	A	A
255		SCROEDERS PLC	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+
256		STANDARD CHARTERED PLC				A+	A+	A+	A+	A+	A+	A+	AA-	AA-	AA-
257		LLOYDS BANK	AA	AA	AA	AA	AA	AA	AA	AA+	AA+	AA-	AA-	A	A
258	UNITED STATES	ALLY FINANCIAL INC	A	A-	A-	BBB+	BBB	BB	BB+	BB+	CCC	B	B	BB	BB-
259		AMERICAN EXPRESS COMPANY	AA-	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+
260		AMERISERV FIN INC	BB+	BB+	BBB	B	B+	B+	BB-	BB	BB	BB	BB	BB	BB
261		ASSOCIATED BANC-CORP	A-	A-	A-	A-	A-	A-	A-	A-	BBB+	BB+	BBB-	BBB-	BBB-
262		ASTORIA FIN CORP							BBB+	BBB+	BBB+	BBB-	BBB-	BBB-	BBB-
263		BANK OF AMERICA CORP	AA-	AA-	AA-	AA	AA-	AA-	AA-	AA	A+	A+	A+	A	A
264		BANK OF NEW YPRK MELLON CORP	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
265		BB&T CORP	A	A+	A+	A+	A+	AA-	AA-	AA-	AA-	A+	A+	A+	A+
266		BOK FIN CORP	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A
267		CAPITAL ONE FIN CORP							BBB+	A-	A-	A-	A-	A-	A-
268		CATHAY GENERAL BANCORP						BB+	BBB-	BBB-	BBB-	BB	BB	BB	BB
269		CENTRAL PACIFIC FIN CORP						BBB	BBB	BBB	BBB	CCC	CC	B+	BB-
270		CITIGROUP INC	AA	AA	AA+	AA+	AA+	AA+	AA+	AA	A+	A+	A+	A	A
271		CITY NATIONAL CORP	BBB+	BBB+	BBB+	BBB+	A-	A-	A-	A-	A-	A-	A-	A-	A-
272		COMERICA INCORP	A+	A+	A+	A+	A+	A+	A+	A+	A+	A	A	A	A
273		COMMUNITY BANK SYSTEM	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB
274		CULLEN/FROST BANKERS INC	BBB+	BBB+	A-	A-	A-	A-	A-	A-	A-	A-	A	A	A
275		CVB FIN CORP			BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB	BBB	BBB
276		DIME COMMUNITY BANCSHARES	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB
277		DORAL FIN CORP	BBB	BBB	BBB	BBB+	BBB	BB-	B+	CCC	CCC	CCC	CCC	CCC	CCC
278		EAST WEST BANCORP				BBB+	BBB+	BBB	BBB-	BBB-	BBB-	BBB	BBB	BBB	BBB
279		FIFTH THIRD BANCORP	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A	A-	A-	A	A-
280		FIRST BANCORP	BBB	BBB	BBB	BBB	BBB	BB	BB	BB	BB	B-	CC	CCC	B-

281		FIRST COMMONWEALTH FIN CORP	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB-
282		FIRST HORIZON NATIONAL CORP	A	A	A	A	A	A	A	A	BBB+	BBB+	BBB+	BBB+	BBB-
283		FIRST INTERSTATE BANCSYSTEM	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB	BBB	BBB	BBB	BBB	BBB-
284		FIRST MIDWEST BANCORP	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB+	BBB	BBB-	BBB-	BBB-
285		FIRST NATIONAL OF NEBRASKA							BBB	BBB	BBB	BB+	BB+	BB+	BB+
286		FIRST NIAGARA FIN CORP	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB-
287		FIRSTMERIT CORP	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	BBB+
288		FULTON FIN CORP	A-	A-	A	A	A	A	A	A-	A-	A-	A-	A-	A-
289		GFI			BBB+	BBB+	BBB	BBB	BBB-	BBB-	BBB	BBB	BBB	BBB	BBB-
290		GOLDMAN SACHS GROUP	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	A+	A+	A	A
291		HANCOCK HOLDING COMPANY				BBB	BBB+	BBB+	BBB	BBB	BBB+	BBB+	BBB+	BBB+	BBB+
292		HUNTINGTON BANCSHARES	A	A	A	A	A	A	A	A-	A-	BBB	BBB+	BBB+	BBB+
293		INDEPENDENT BANK CORP	BB+	BB+	BB+	BB+	BB+	BB+	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB
294		JPMORGAN CHASE & CO	AA-	AA-	A+	A+	A+	A+	A+	AA-	AA-	AA-	AA-	AA-	A+
295		KEYCORP	A+	A	A	A	A	A	A	A	A	A-	A-	A-	A-
296		KKR FIN HOLDING					BBB+	BBB	BBB	BBB-	BBB-	BBB	BBB	BBB	BBB
297		M&T BANK CORP	A	A	A	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-
298		METLIFE INC		AA-	AA	A	A	A	A+	A+	A+	A+	A	A	A
299		MORGAN STANLEY	AA	AA	AA-	AA-	AA-	AA-	AA-	AA-	A	A	A	A	A
300		NEW YORK COMMUNITY BANCORP		BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB+
301		NORTHERN TRUST CORP	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
302		OCWEN FIN CORP	B	B	B	B	B	B	B	B+	B+	B+	B+	B+	B
303		PEOPLE'S UNITED FINANCIAL			BBB+	BBB	BBB	BBB	BBB	BBB	BBB+	A-	A-	A-	A-
304		PNC FIN SERV GROUP	A+	A+	A	A	A	A	A	A+	A+	A+	A+	A+	A+
305		POPULAR INC	A	A	A	A	A	A	A	A-	A-	B	B	B+	B+
306		PRUDENTIAL FIN INC		A	A	A	A	A	A+	A+	A	BBB+	A-	A-	A-
307		REGIONS FIN CORP	A+	A+	A+	A+	A+	A+	A+	A+	A+	BBB+	BBB-	BBB-	BBB-
308		STATE STREET COPR	AA	AA	AA	AA	AA-	AA-	AA-	AA-	AA-	A+	A+	A+	A+
309		SUNTRUST BANK	AA-	AA-	AA-	AA-	A+	A+	A+	A+	A+	A-	BBB+	BBB+	BBB+
310		SYNOVUS FIN CORP	A	A	A	A	A	A	A	A	A-	BB-	BB-	BB-	BB-
311		TCF FIN CORP	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	BBB
312		TRUSTMARK CORP	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-	A-
313		UMB FIN CORP	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+
314		US BANCORP	A+	A+	A+	A+	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-	AA-
315		WEBSTER FIN CORP	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB
316		WELLS FARGO & CO	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA-	AA-	AA-	AA-
317		ZION BANCORP	A-	A-	A-	A-	A-	A-	A-	A-	A-	BBB	BBB-	BBB-	BBB-
318	UZBEKISTAN	OPEN JOINT STOCK COMMERCIAL BANK					B	B-	B-	B-	B-	B	B	B-	B-
319	VENEZUELA	BANCO EXTERIOR	B+	BB-	B	B-	B+	B+	B+	B+	B+	B+	B+	B+	B+
320		BANCO PROVINCIAL		BB-	B	B-	B+	B+	B+	B+	B+	B+	B+	B+	B+
321		BANCO DEL CARIBE		BB-	B	B-	B+	B+	B+	B	B	B	B	B	B
322		BANCO OCCIDENTAL DEL DESCUENTO	B+	B+	B	CCC+	B-	B-	B-	B-	B-	B-	B-	B-	B-

APPENDIX C: RATING GRADING SCHEDULE

Fine Grading		Coarse Grading	
AAA	9	AAA	3
AA+		AA+	
AA	8	AA	
AA-	7	AA-	
A+	6	A+	2
A	5	A	
A-	4	A-	
BBB+	3	BBB+	1
BBB	2	BBB	
BBB-	1	BBB-	
BB+	0	BB+	0
BB		BB	
BB-		BB-	
B+		B+	
B		B	
B-		B-	
CCC+		CCC+	
CCC		CCC	
CCC-		CCC-	
CC		CC	
C		C	
D		D	

Note: Fine and coarse grading of the numerical ratings. Rating structure is based on the Fitch's rating letters. The BBB- is the investment-grade threshold rating category

APPENDIX D: RESULTS OF THE BANK CREDIT RATING DETRMINANTS MODELS EMPLOYING COARSE RATING

Table D.1. Contemporaneous rating determinants model results (coarse grading)

Panel A Parameter estimates

Independent variables	Hypothesised Sign	Model X Coefficient	Model X Z-stat	Model XI Coefficient	Model XI Z-stat	Model XII Coefficient	Model XII Z-stat
Intercept		-6.6547	-3.69***	1.3145	21.22***	-6.2514	-3.25***
TIER1	$+ (H_1)$	0.0654	5.24***	-	-	0.1021	5.84***
LLR/GL	$- (H_2)$	-0.0426	-2.24**	-	-	-0.0724	-3.55***
ROA	$+ (H_3)$	0.0988	2.98**	-	-	0.0996	2.65**
LTA	$- (H_4)$	-0.0251	-3.21***	-	-	-0.0102	-4.54***
INTER	$+ (H_4)$	0.0544	3.10***	-	-	0.0681	3.74***
BETA	$- (H_5)$	-0.0252	2.22**	-	-	-0.0106	1.78*
IDIO	$- (H_6)$	-0.0109	-1.62*	-	-	-0.0116	-1.79*
In(Z-Score)	$+ (H_7)$	0.0621	2.98***	-	-	0.0633	2.44**
LR	$- (H_8)$	-0.0658	-3.06***	-	-	-0.0269	-3.39***
CRK	$- (H_9)$	-0.0194	-7.51***	-	-	-0.0208	-6.31***
CI	$- (H_{10})$	-0.0051	-0.76	-	-	-0.0984	2.35***
InTA	$+ (H_{11})$	0.6847	10.25***			0.7392	11.62***
TBTF	$+ (H_{12})$	-	-	0.0401	3.25***	0.0425	4.69***
OWN	$+ (H_{13})$	-	-	0.0124	1.67*	0.0135	1.79*
INST	$+ (H_{14})$	-	-	0.0103	1.39*	0.0124	1.85*
INDD	$+ (H_{15})$	-	-	0.0014	0.89	0.0102	0.69
SOVAA	$+ (H_{16})$	-	-	0.0215	6.98***	0.0456	7.21***
SOVA	$+ (H_{16})$	-	-	0.0621	5.85***	0.0695	6.66***
SOVBBB	$+ (H_{16})$	-	-	0.0051	2.65***	0.0107	3.58***
YEARD	$- (H_{17})$	-	-	-0.0125	0.21	-0.0251	-0.68

Panel B: Selected model statistics

	Model X	Model XI	Model XII
Log-likelihood	-1,324.214	-1,565.695	-1,258.214
Restr.log-lik.	-1,954.115	-1,987.254	-1,725.369
No. of obs.	3,682	3,682	3,682
χ^2 statistic	672.687***	635.1251***	765.584***
Pseudo- $R^2\varsigma$	38.25%	37.18%	43.09%

Notes: The dependent variable of all ordered probit models is the categorical variable CR (fine ratings). The independent variables are defined in Appendix A. All significance levels are determined using the two-tailed Z-test. ***, **,* denote significance at the 1%, 5% and 10%, respectively. Ç This measure of goodness-of-fit is a simple computational statistic [$\text{pseudo} - R^2 = \frac{\chi 2}{\chi 2 + N}$] proposed by Aldrich and Nelson (1984). The upper boundary represents the threshold for each of the rating categories; in this model the categories represent the fine ratings. The SOV (dummies) captures any country related variables as this measure the sovereign ratings of the countries.

Table D.2. Marginal effects of Model XII (full specification)

	Rating Category			
Variables	Below BB+	BBB	A	AA, AAA
TIER1	-0.04*	-0.13*	0.06*	0.12*
LLR/GL	0.01**	0.05*	-0.06*	-0.04*
ROA	-0.02*	-0.01*	0.05*	0.03*
LTA	0.03*	0.01	-0.02*	-0.08**
INTER	-0.01	-0.02*	0.06*	0.05*
BETA	0.00	0.03*	-0.06*	-0.06*
IDIO	0.00	-0.01*	0.03*	0.01*
In(Z-Score)	-0.06**	-0.03*	0.08*	0.10**
LR	0.02*	-0.01*	-0.03*	-0.02*
CRK	0.08*	-0.04*	-0.02*	-0.08*
CI	0.07*	0.05	-0.02*	-0.10*
InTA	-0.12*	0.17*	0.10*	0.21*
TBTF	-0.06*	0.05	0.02**	0.07*
OWN	-0.02*	0.01*	0.01*	0.06*
INST	-0.04*	-0.01*	0.04	0.06*
INDD	-0.02	0.00	0.03	0.02
SOVAA	-0.08*	-0.03	0.12	0.15**
SOVA	-0.05*	-0.06*	0.11	0.10*
SOVBBB	-0.02*	-0.01*	0.06*	0.03
YEARD	0.00	-0.02*	0.00	0.00

Table D.3. Contemporaneous rating determinants specification (coarse rating): Prediction Evaluation (Model XII)

Estimated Equation (2000-2008):

Year: 2009

Panel A:

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	95	89	6	6	6.31	36
BBB	1	89	66	23	23	25.84	529
A	2	106	81	25	25	23.58	625
AA and above	3	32	22	10	10	31.25	196
Total		**322**	**258**				

Mean Absolute Percentage Error: 21.75%
Root-Mean-Squared-Error: 18.61
Total percentage predicted: 80.12%

Year: 2010

Panel B:

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	90	88	2	2	2.22	4
BBB	1	95	62	33	33	34.73	1,089
A	2	103	80	23	23	22.33	529
AA and above	3	34	18	16	16	47.06	256
Total		**322**	**248**				

Mean Absolute Percentage Error: 26.85%
Root-Mean-Squared-Error: 21.66
Total percentage predicted: 77.02%

Year: 2011

Panel C:

Dependent Variable	**Dependent Value**	**Actual Obs.**	**Predicted Obs.**	**Forecast Error**	**Absolute Deviation**	**Absolute (%) of Error**	**Squared Error**
BB+ and below	0	92	84	8	8	8.69	64
BBB	1	104	66	38	38	36.54	1,444
A	2	102	71	31	31	30.39	961
AA and above	3	24	16	8	8	33.33	64
Total		**322**	**237**				

Mean Absolute Percentage Error: 27.24%
Root-Mean-Squared-Error: 25.16
Total percentage predicted: 73.60%

Year: 2012

Panel D:

Dependent Variable	**Dependent Value**	**Actual Obs.**	**Predicted Obs.**	**Forecast Error**	**Absolute Deviation**	**Absolute (%) of Error**	**Squared Error**
BB+ and below	0	89	77	12	12	13.48	144
BBB	1	114	75	39	39	34.21	1,521
A	2	98	62	36	36	36.73	1,296
AA and above	3	21	11	10	10	47.61	100
Total		**322**	**225**				

Mean Absolute Percentage Error: 33.01%
Root-Mean-Square-Error: 27.66
Total percentage predicted: 69.88%

Panel E: Year	Mean Absolute Percentage Error	Root-Mean-Squared-Error	Total percentage predicted
2009	21.75%	18.61	80.12%
2010	26.85%	21.66	77.02%
2011	27.24%	25.16	73.60%
2012	33.01%	27.66	69.88%

Table D.4.Predictive rating determinants model results (coarse grading)

Panel A Parameter estimates							
	Hypothesised	**Model XIII**		**Model XIV**		**Model XV**	
Independent variables	Sign	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Intercept		-6.6547	-3.98***	1.5471	21.22***	-6.3254	-3.65***
TIER1	+ (H_1)	0.0547	6.21***	-	-	0.1257	6.01***
LLR/GL	− (H_2)	-0.0624	-2.87***	-	-	-0.0855	-3.28***
ROA	+ (H_3)	0.0885	3.02**	-	-	0.0752	3.54***
LTA	− (H_4)	-0.0128	-2.99***	-	-	-0.0166	-3.65***
INTER	+ (H_4)	0.0668	2.21**	-	-	0.0724	2.86***
BETA	− (H_5)	-0.0325	-2.20**	-	-	-0.0293	-2.77**
IDIO	− (H_6)	-0.0221	-2.78***	-	-	-0.0339	-2.88***
In(Z-Score)	+ (H_7)	0.0557	2.65***	-	-	0.0752	2.99***
LR	− (H_8)	-0.0854	-3.25***	-	-	-0.0656	-3.21***
CRK	− (H_9)	-0.0322	-6.33***	-	-	-0.0395	-4.22***
CI	− (H_{10})	-0.0412	-1.78*	-	-	-0.0458	-2.23**
InTA	+ (H_{11})	0.7845	9.74***			0.8835	10.33***
TBTF	+ (H_{12})	-	-	0.0528	3.29***	0.0657	4.12***
OWN	− (H_{13})	-	-	-0.0265	-1.08	-0.0354	-1.66*
INST	+ (H_{14})	-	-	0.0133	1.48*	0.0265	1.82*
INDD	+ (H_{15})	-	-	0.0106	1.83*	0.0222	0.89
SOVAA	+ (H_{16})	-	-	0.0365	6.59***	0.0426	6.65***
SOVA	+ (H_{16})	-	-	0.0695	6.01***	0.0894	6.22***
SOVBBB	+ (H_{16})	-	-	0.0111	4.21***	0.0131	4.36***
YEARD	− (H_{17})	-	-	-0.0195	0.88	-0.0308	-1.05
Panel B: Selected model statistics							
Log-likelihood		-1,402.226		-1,651.014		-1,330.517	
Restr.log-lik.		-1,822.165		-1,999.059		-1,524.630	
No. of obs.		3,402		3,402		3,402	
χ^2 statistic		695.221***		666.265***		758.667***	
Pseudo- $R^2\varsigma$		40.55%		42.69%		47.02%	

Notes: The dependent variable of all ordered probit models is the categorical variable CR (coarse ratings). The independent variables are defined in Appendix A. All significance levels are determined using the two-tailed Z-test. ***, **,* denote significance at the 1%, 5% and 10% respectively. ϹThis measure of goodness-of-fit is a simple computational statistic [$pseudo - R^2 = \frac{\chi 2}{\chi 2 + N}$] proposed by Aldrich and Nelson (1984). The upper boundary represents the threshold for each of the rating categories; in this model the categories represent the coarse ratings. The SOV (dummies) captures any country related variables as this measure the sovereign ratings of the countries.

Table D.5. Marginal effects of Model XV (full specification)

	Rating Category			
Variables	Below BB+	BBB	A	AA, AAA
TIER1	-0.06*	-0.10*	0.04*	0.18*
LLR/GL	0.10**	0.13*	-0.05*	-0.15*
ROA	-0.03*	-0.04*	0.02*	0.07*
LTA	0.08*	0.03	-0.06*	-0.10*
INTER	-0.03	-0.04*	0.07*	0.09*
BETA	0.01	0.03*	-0.02*	-0.05*
IDIO	0.01	0.02*	-0.02*	-0.05*
In(Z-Score)	-0.03**	-0.04*	0.01*	0.07*
LR	0.02*	0.02*	-0.01*	-0.03*
CRK	-0.02*	-0.04*	0.03*	0.07*
CI	0.06*	-0.03*	-0.03*	-0.10*
InTA	-0.09*	-0.03*	0.05*	0.07*
TBTF	-0.07*	-0.02*	0.03**	0.09*
OWN	0.01*	0.01*	-0.02*	-0.03*
INST	-0.04*	-0.01*	0.04	0.06*
INDD	-0.02	0.00	0.03	0.01
SOVAA	-0.06*	-0.01	0.02	0.05*
SOVA	-0.04*	-0.03*	0.03	0.06*
SOVBBB	-0.03*	-0.04*	0.02*	0.05*
YEARD	0.00	0.00	0.00	0.00

Table D.6. Predictive rating determinants model specification (coarse rating): Prediction Evaluation (Model XV)

Estimated Equation (2001-2009):

Year: 2009

Panel A:

Dependent Variable	**Dependent Value**	**Actual Obs.**	**Predicted Obs.**	**Forecast Error**	**Absolute Deviation**	**Absolute (%) of Error**	**Squared Error**
BB+ and below	0	95	83	12	12	12.63	144
BBB	1	89	78	11	11	12.36	121
A	2	106	80	26	26	24.53	676
AA and above	3	32	25	7	7	21.87	49
Total		**322**	**266**				

Mean Absolute Percentage Error: 17.85%
Root-Mean-Squared-Error: 15.73
Total percentage predicted: 82.61%

Year: 2010

Panel B:

Dependent Variable	**Dependent Value**	**Actual Obs.**	**Predicted Obs.**	**Forecast Error**	**Absolute Deviation**	**Absolute (%) of Error**	**Squared Error**
BB+ and below	0	90	82	12	12	13.33	144
BBB	1	95	70	25	25	26.31	625
A	2	103	85	18	18	17.48	324
AA and above	3	34	19	15	15	44.12	225
Total		**322**	**256**				

Mean Absolute Percentage Error: 25.31%
Root-Mean-Squared-Error: 18.15
Total percentage predicted: 79.50%

Year: 2011

Panel C:

Dependent Variable	**Dependent Value**	**Actual Obs.**	**Predicted Obs.**	**Forecast Error**	**Absolute Deviation**	**Absolute (%) of Error**	**Squared Error**
BB+ and below	0	92	80	12	12	13.04	144
BBB	1	104	61	43	43	41.35	1,849
A	2	102	70	32	32	31.37	1,024
AA and above	3	24	18	6	6	25.00	36
Total		**322**	**229**				

Mean Absolute Percentage Error: 27.69%

Root-Mean-Squared-Error: 27.63

Total percentage predicted: 71.12%

Year: 2012

Panel D:

Dependent Variable	**Dependent Value**	**Actual Obs.**	**Predicted Obs.**	**Forecast Error**	**Absolute Deviation**	**Absolute (%) of Error**	**Squared Error**
BB+ and below	0	89	70	19	19	21.35	361
BBB	1	114	73	41	41	35.96	1,681
A	2	98	60	38	38	38.76	1,444
AA and above	3	21	13	8	8	38.09	64
Total		**322**	**216**				

Mean Absolute Percentage Error: 33.54%

Root-Mean-Square-Error: 29.79

Total percentage predicted: 67.08%

Panel E:

Year	**Mean Absolute Percentage Error**	**Root-Mean-Squared-Error**	**Total percentage predicted**
2009	17.85%	15.73	82.61%
2010	25.31%	18.15	79.50%
2011	27.69%	27.63	71.12%
2012	33.54%	9.79	67.08%

Table D.7: Lagged rating determinants model specification results (coarse grading)

Panel A Parameter estimates							
	Hypothesised	**Model XVI**		**Model XVII**		**Model XVIII**	
Independent variables	Sign	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
Intercept		-10.1254	-6.29***	1.6251	10.51***	-12.5147	-9.54***
TIER1	$+ (H_1)$	0.0794	6.55***	-	-	0.1547	6.99***
LLR/GL	$- (H_2)$	-0.0435	-3.11**	-	-	-0.0821	-3.98***
ROA	$+ (H_3)$	0.1021	2.21**	-	-	0.0992	2.25**
LTA	$- (H_4)$	-0.0298	-2.32**	-	-	-0.0314	-5.02***
INTER	$+ (H_4)$	0.0166	2.14**	-	-	0.0782	3.21***
BETA	$- (H_5)$	-0.0264	-3.08***	-	-	-0.0287	-4.21**
IDIO	$- (H_6)$	-0.0214	-1.69*	-	-	-0.0325	-1.54*
ln(Z-Score)	$+ (H_7)$	0.0854	3.85***	-	-	0.0754	4.51***
LR	$- (H_8)$	-0.0785	-1.08*	-	-	-0.0984	-1.12*
CRK	$- (H_9)$	- 0.0325	-7.95***	-	-	-0.0384	-8.24***
CI	$- (H_{10})$	-0.0109	-1.74*	-	-	-0.0214	-3.54***
lnTA	$+ (H_{11})$	0.7951	11.34***			0.8412	12.14***
TBTF	$+ (H_{12})$	-	-	0.1005	4.35***	0.1251	4.62***
OWN	$+ (H_{13})$	-	-	0.0154	2.22**	-0.0254	2.12**
INST	$+ (H_{14})$	-	-	0.0063	1.42*	0.0107	2.22**
INDD	$+ (H_{15})$	-	-	0.0061	1.79*	0.0111	2.34**
SOVAA	$+ (H_{16})$	-	-	0.0841	7.02***	0.0865	8.45***
SOVA	$+ (H_{16})$	-	-	0.0621	5.69***	0.0745	7.21***
SOVBBB	$+ (H_{16})$	-	-	0.0103	2.99***	0.0225	4.68***
YEARD	$- (H_{17})$	-	-	-0.0149	1.69	-0.0285	-1.88*

Panel B: Selected model statistics			
Log-likelihood	-1,441.215	-1,651.168	-1,524.654
Restr.log-lik.	-2,514.515	-2641.226	-2,325.159
No. of obs.	3,682	3,682	3,682
χ^2 statistic	824.547***	785.214**	882.214**
Pseudo- $R^2\varsigma$	30.84%	31.22%	32.18%

Notes: The dependent variable of all ordered probit models is the categorical variable CR (fine ratings). All significance levels are determined using the two-tailed Z-test. ***, **,* denote significance at the 1%, 5% and 10%, respectively. Ϛ This measure of goodness-of-fit is a simple computational statistic [$\text{pseudo} - R^2 = \frac{\chi 2}{\chi 2 + N}$] proposed by Aldrich and Nelson (1984). The upper boundary represents the threshold for each of the rating categories; in this model the categories represent the fine ratings. The SOV (dummies) captures any country related variables as this measure the sovereign ratings of the countries.

Table D.8: Marginal effects of Model XVIII (full specification)

	Rating Category			
Variables	Below BB+	BBB	A	AA, AAA
TIER1	-0.02*	-0.10*	0.04*	0.10*
LLR/GL	0.03**	0.06*	-0.05*	-0.05*
ROA	-0.03*	-0.02*	0.03*	0.02*
LTA	0.02	0.02	-0.03*	0.01
INTER	-0.02	-0.01*	0.05*	0.04*
BETA	0.01	0.02*	-0.07	-0.08
IDIO	0.00	-0.00	0.00	0.00
ln(Z-Score)	-0.05**	-0.01*	0.07*	0.11**
LR	-0.03*	-0.03*	0.02*	0.03*
CRK	-0.07*	-0.03*	0.01*	0.06*
CI	0.02*	-0.01*	-0.02*	-0.05*
InTA	-0.06*	-0.12*	0.11*	0.13*
TBTF	-0.03*	-0.02*	0.03**	0.07*
OWN	0.04*	0.02*	-0.02*	-0.05*
INST	-0.03*	-0.06*	0.01	0.06*
INDD	-0.02	0.01	0.02	0.05
SOVAA	-0.06*	-0.02	0.13	0.13**
SOVA	-0.06*	-0.05*	0.10	0.12*
SOVBBB	-0.01*	-0.07*	0.07*	0.05*
YEARD	0.01	-0.01	0.01	0.01

Table D.9: Lagged rating determinants model specification (coarse rating): Prediction Evaluation (Model XVIII)

Estimated Equation (2000-2008):

Panel A **Year: 2009**

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	95	85	10	10	10.53	100
BBB	1	89	71	18	18	20.22	324
A	2	106	88	18	18	16.98	324
AA and above	3	32	29	3	3	9.37	9
	Total	**322**	**273**				

Mean Absolute Percentage Error: 15.02% **Root-Mean-Squared-Error Magnitude: 13.76** **Total percentages predicted: 84.78%**

Panel B **Year: 2010**

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	90	79	29	29	32.22	841
BBB	1	95	70	25	25	26.31	625
A	2	103	75	28	28	27.18	784
AA and above	3	34	25	9	9	26.47	81
	Total	**322**	**249**				

Mean Absolute Percentage Error: 28.04% **Root-Mean-Squared-Error Magnitude: 24.14** **Total percentage predicted: 77.33%**

Panel C **Year: 2011**

Dependent Variable	Dependent Value	Actual Obs.	Predicted Obs.	Forecast Error	Absolute Deviation	Absolute (%) of Error	Squared Error
BB+ and below	0	92	85	7	7	7.61	49
BBB	1	104	68	36	36	34.61	1296
A	2	102	65	37	37	36.27	1369
AA and above	3	24	15	9	9	37.50	81
	Total	**322**	**233**				

Mean Absolute Percentage Error: 28.99% **Root-Mean-Squared-Error Magnitude: 26.41** **Total percentages predicted: 72.36%**

Panel D	**Year: 2012**						
Dependent Variable	**Dependent Value**	**Actual Obs.**	**Predicted Obs.**	**Forecast Error**	**Absolute Deviation**	**Absolute (%) of Error**	**Squared Error**
BB+ and below	0	89	69	20	20	22.47	400
BBB	1	114	72	42	42	36.84	1,764
A	2	98	59	39	39	39.79	1,521
AA and above	3	21	14	7	7	33.33	49
Total		**322**	**214**				

Mean Absolute Percentage Error: 33.10% **Root-Mean-Square-Error Magnitude: 30.55** **Total percentages predicted: 66.46%**

Panel E:

Year	**Mean Absolute Percentage Error**	**Root-Mean-Squared-Error**	**Total percentage predicted**
2009	15.02%	13.76	84.78%
2010	28.04%	24.14	77.33%
2011	28.99%	26.41	72.36%
2012	33.10%	30.55	66.46%