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Split credit ratings and the prediction of bank ratings in the Basel II environment

by

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ABSTRACT

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This thesis investigates two aspects of credit risk measurement in the context of Basel II: The International Convergence of Capital Measurement and Capital Standards. The first is the problem arising when two credit rating agencies disagree over the rating assigned to an issuer and a split rating arises. This has implications for the Standardised approach to assessing risk weighted assets under Basel II. The second area is the determination of internal credit rating models for use under the Internal ratings-based approach. A very small amount of the extensive literature in this area covers bank rating models. This thesis presents a variety of bank rating modes for individual and long term ratings across different agencies and regions.

Using an extensive database of credit rating agencies with a sample of over 52,000 split ratings covering a four year period from 1999 – 2004 the first study shows that there is a ranking of agencies from the most to least generous that is stable over time. In most cases, the differences between the mean ratings of the agencies are significantly different from each other at the 1% level. As reported in earlier studies, the greatest differences arise between the US and Japanese agencies. When the split ratings are compared in terms of Basel II risk weights the differences between the US and Japanese agencies are still highly significant and the conclusion is that supervisors should alter the mapping of the Japanese agencies to the risk assessments under the provisions of Annex 2 to Basel II.

Contrary to earlier research this study does not find that the highest level of split ratings arise for banks. The level of consensus between agencies appears to correspond to the average credit quality of the industry in question. Evidence is found that agencies are more generous to issuers from their own country (home country bias) and the level of agreement is higher between agencies from the same country.

Bank credit ratings are modelled from financial ratios and variables using ordinal logistic regression. Sample sizes exceeded 1,100 banks for the largest agencies. Fitch Individual ratings could be accurately modelled from the holdout sample 68% of the time but long term ratings are more difficult to model consistently because part of a rater's assessment of a bank takes into consideration whether financial assistance would be offered should the bank run into difficulties. This is called the support element and is predominantly driven by macroeconomic rather than financial inputs. Moody's BFSRs are modelled with 65% accuracy when Moody's long term ratings are included as one of the independent variables.

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Introduction

A brief glance at the results of Moody's and S&P will show that issuing credit ratings is a profitable business. With average margins of 48% the two big players in the credit rating market show that plenty of companies take their ratings seriously and pay substantial sums for the ratings of their debt. A good rating plays an important part in determining a company's cost of debt and can either send a positive or negative signal to financiers and investors alike.

The importance of credit ratings and the success of the agencies has been closely linked to the role that they play in regulation. Since the 1930s the distinction between investment grade and sub-investment grade debt has been very important and the rating decisions made by the agencies have a direct influence on the population of investments available to certain banks and insurance companies. With the introduction of the New Basel Accord (Basel Committee on Banking Supervision 2005) the role of credit ratings in legislation will be extended again. The Standardised approach to the assessment of credit risk requires the direct use of credit ratings from approved agencies to be input into the calculation of risk weighted assets. The first studies in this thesis consider the ratings of external agencies in detail. The frequency and extent of differences between the ratings assigned by different agencies are analysed along with the implication of these differences to the risk weights assigned to bank assets.

Many banks will opt for the internal ratings-based approach to calculate their risk weighted assets. Most large and internationally active banks already have models in place to determine internal ratings to the satisfaction of supervisors. The methodology behind models predicting credit ratings and the financial variables most often used are studied in this thesis and models are built to predict bank credit ratings. There is a substantial body of literature dating from the 1960s covering the prediction of corporate credit ratings but there are few studies focusing specifically on banks.

The two primary objectives of this thesis are as follows. Firstly to revisit earlier studies focusing on the split ratings between credit rating agencies. This study will add to prior research by using a larger and current data sample and more sophisticated software to allow a wider range of different analyses. The data used covers a 4 year period rather than one point in time. The second objective is to extend the area of bank credit rating models with a comparison of individual and long term rating models for Fitch and Moody's as well as long term rating models for eight other rating agencies. The importance of estimating individual models for each region is also considered.

The data used in this study was kindly provided by Financial Times Information Limited and Fitch Ratings Group. The quarterly publication Financial Times – Credit Ratings International for the periods May 1999 – March 2004 formed the database used for studies into split credit ratings and bank rating models. Fitch Ratings' detailed bank-specific financial accounting database was used for the selection of financial variables for the estimation of individual and long term rating models.

The structure of this thesis is as follows:
Chapter two looks in detail at many aspects of the credit rating industry. This includes the purpose of credit ratings and how they are assigned, the history of the rating agencies and how regulation came to play such and important part in the demand for ratings. Observers have criticised a number of potential conflicts of interest within the industry such as the reliance on issuers fees and unsolicited ratings. Finally this chapter reviews studies into the information content of credit ratings and problems arising from procyclicality and the assignment of ratings.

Chapter three reviews the New Basel Capital Accord in detail (Basel II). It outlines the way in which Basel II differs from the existing Accord and analyses the Standardised approach in detail. In later chapters the rules setting out the allocation of risk weights to corporate, bank and sovereign claims according to external credit ratings are used to assess the importance of split ratings in the context of Basel II. Chapter three also summarises some of the major themes and criticisms that arose in the responses to the Consultative Papers issued while Basel II was being finalised. Finally this chapter looks in detail at Annex 2 of Basel II which sets out guidelines as to how individual country supervisors are to map agency ratings to the risk assessments of the Accord and works through examples with current cumulative default rates.

Chapter four reviews the literature directly relating to the studies in this thesis. These cover two separate areas; split credit ratings and bond rating prediction models. There is a limited amount of research in the area of split credit ratings with several studies being extremely relevant. These are Beattie and Searle (1992a and 1992b) and Cantor and Packer (1995). These studies also used data from the Financial Times Credit Rating International database but the data sample for this thesis uses more data, for a wider number of countries and industries and over a considerably longer time period.

The second part of the literature review gives a chronological review of the empirical studies on the modelling and prediction of credit ratings. The methodology used is discussed in detail highlighting the continual efforts of researchers to refine the prediction models. The selection of independent variables is also extremely important to the quality of the rating model. The variables used in previous studies are reviewed and the chapter concludes with a discussion of the most suitable variables for use in this thesis.

Chapter five discusses the data used for the split rating and rating prediction studies. Two large databases were used for the studies in this thesis; the FT-CRI database of worldwide credit rating data for ten major agencies and the bank financial accounting data from Fitch Ratings Group. Different agencies use different rating definitions and scales. In order to compare split ratings these must be mapped to a comparable scale. The problems with this mapping process and the maps chosen for this study are discussed in chapter five. The way in which split ratings are compared is also shown and a brief description is given of the software used to analyse such a large volume of split ratings. The chapter goes on to describe the bank financial accounting database used and how this was mapped to the credit rating data to give independent and dependent variables in order to build bank rating prediction models.

Chapters six to nine give the results of the studies comparing split credit ratings of different rating agencies. Chapter six focuses on the level of inter-rater agreement and compares overall rater agreement as well as the consensus between particular pairs of agencies. The study asks why some agencies agree much more frequently than others and reviews the quality distribution of the issuers to see if consensus is determined by credit quality.

Chapter seven establishes a ranking between the rating agencies where some appear to be consistently more generous than others. Changes in ranking which arise due to changes in credit quality are reviewed. The final part of this chapter re-examines findings from previous studies that show agency consensus to be greater when they are rating issuers from the same country and when agencies from the same country are compared with one another.

Chapter eight reviews the level of split ratings by country and industry. Previous research has found that the highest level of disagreement is over the ratings of banks. This study does not support that finding and shows that the ratings of manufacturing-type companies have a higher level of split ratings than finance-type companies.

Chapter nine is the final chapter presenting results of the studies of split ratings. This analyses split ratings in terms of Basel II risk weights and asks the question as to whether the split ratings identified in early chapters are likely to have a significant impact on the risk weighting allocated under the Standardised approach of the Accord.

Chapter ten applies ordinal logistic regression techniques to the matched bank credit rating and financial accounting data described in chapter five. A wide range of models are built and dealt with in a number of different sections within the chapter. The first set of models look at the different results of modelling individual vs. long term bank ratings for Fitch and Moody's. Models are then built for each of the ten agencies included in the FT-CRI database and a range of different prediction accuracies are shown. Results are also reported for models which breakdown the data sample by region, bank size and type to identify circumstances in which bank rating models based on financial accounting information have a high prediction accuracy.

The Credit Rating Industry

This chapter provides an introduction and background to the credit rating industry. The first part of the chapter looks at the nature of credit ratings and considers the process by which they are determined by the rating agencies. It goes on to look at the history of the credit rating industry and how this has grown from small roots in the US to about 130 worldwide agencies.

The second part of the chapter considers some current topics in the industry. Four key issues are discussed:

- The role of regulation in the growth of wealth and importance of the credit rating agencies.
- Payment of fees by issuers to the agencies and the potential conflict of interests this presents.
- The timeliness of ratings and their information content.
- The impact of credit ratings on procyclicality in capital markets.

2.1 What is a credit rating?

"Credit ratings are the very structure of the marketplace. They are the risk language that we all speak and rely on." (Strauss 2002)

Credit rating agencies argue that they provide superior information about the ability of corporations or governments to make timely repayment of principal and interest on borrowings.

But not everyone agrees:

> "'Senseless'. 'Nonsense'. 'Irrelevant'. Capital-markets folk with a kind word for credit-ratings agencies are almost as rare as modest bond-traders." (Economist 1999)

In Standard and Poor's word's "a credit rating is Standard and Poor's opinion of the general credit worthiness of an obligor, or the creditworthiness of an obligor with respect to a particular debt security or other financial obligation, based on relevant risk factors" (Standard and Poor's 2002a). In the words of Moody's it is "..an opinion on the future ability and legal obligation of an issuer to make timely payments of principal and interest on a specific fixed income security" (Moody's 2006).

One of the original purposes of credit ratings was to distinguish investment grade ratings from non-investment grade. There is still a clear cut-off between the two categories but there are also a wide variety of ratings within each section. Full details of the rating scales used by the main agencies is included in Appendix 1.

2.1.1 Measuring relative and absolute credit risks

A credit rating is a grade or score intended to distinguish relatively risky organisations or issues from ones that are relatively safe. For credit ratings to be meaningful they need to be able to indicate the relative level of credit risk of one issuer in comparison with others as well as providing an estimate of the absolute risk, i.e. the probability of default. Credit ratings perform better as ordinal rankings of default risk rather than absolute measures of default probability that are constant through time.

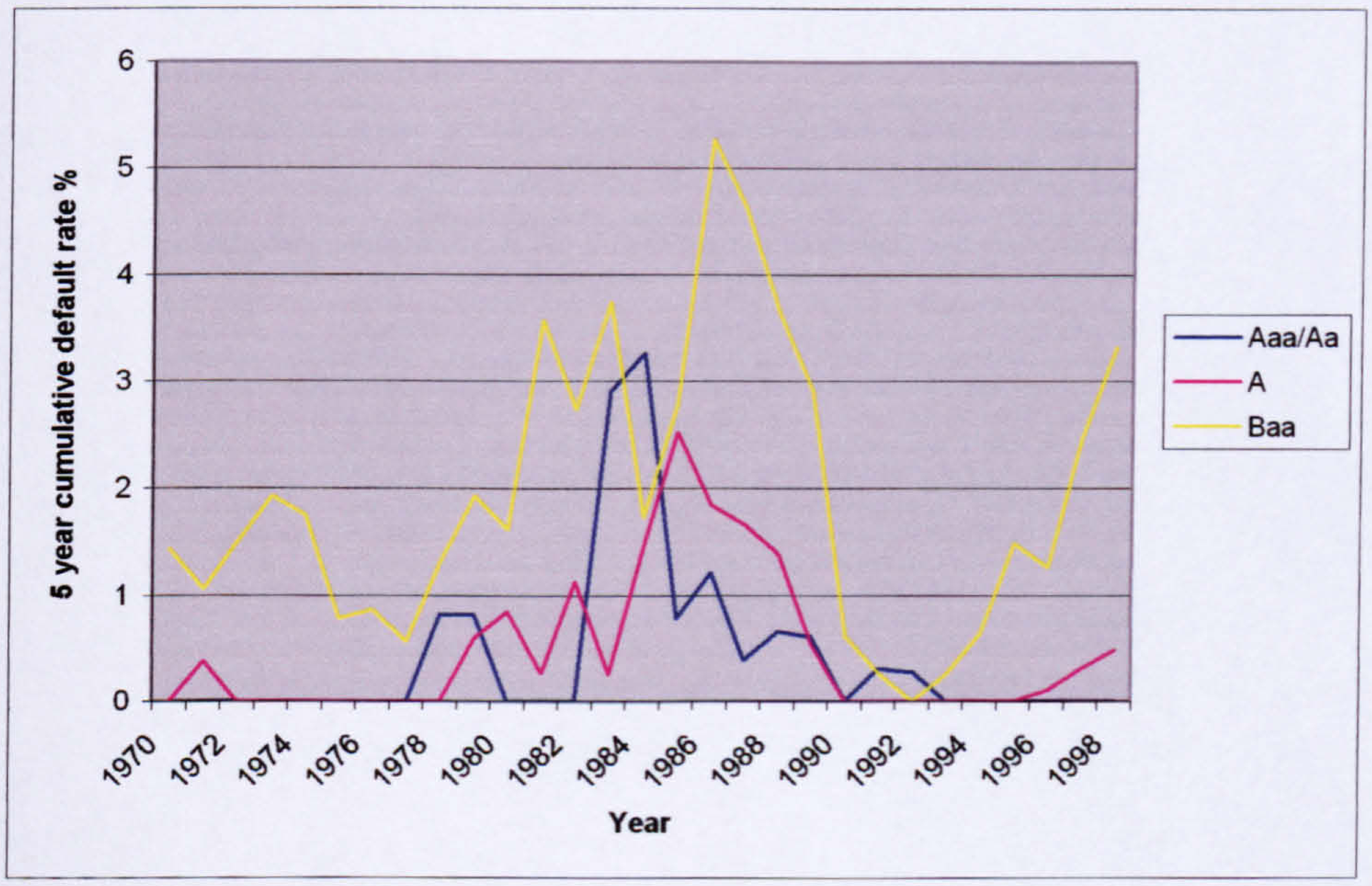
Cantor and Packer (1995) argue that the rating industry measures relative credit risks with reasonable accuracy. This is demonstrated by the relationship between bond ratings and average bond yield spreads and also the correlation between average short term and long term default rates and credit ratings. Shin and Moore (2003) compare US and Japanese credit ratings and find that the relative default risk is quite similar although Japanese agencies are considerably more lenient in their ratings than US agencies. Altman (1989) shows that each letter grade decline in ratings corresponds with an increase in yield spread. He finds this result to be robust for S&P ratings. Moody's and S&P publish corporate bond default studies[1] that show lower corporate bond ratings to be associated with a higher probability of default. The default probability increases as the time horizon is lengthened but the relationship between ratings and default probability remains the same. The relationship between ratings and bond yield spreads as well as default studies suggests that ratings are an effective way to rank relative credit risk.

A review of trends in five year cumulative default rates[2] (CDRs) over time illustrates large fluctuations in the percentage of defaulting companies over the business cycle.

[1] e.g. Moody's Investors Service (2006)
[2] The definition and calculation of annual and cumulative default rates are covered in detail in chapter three.

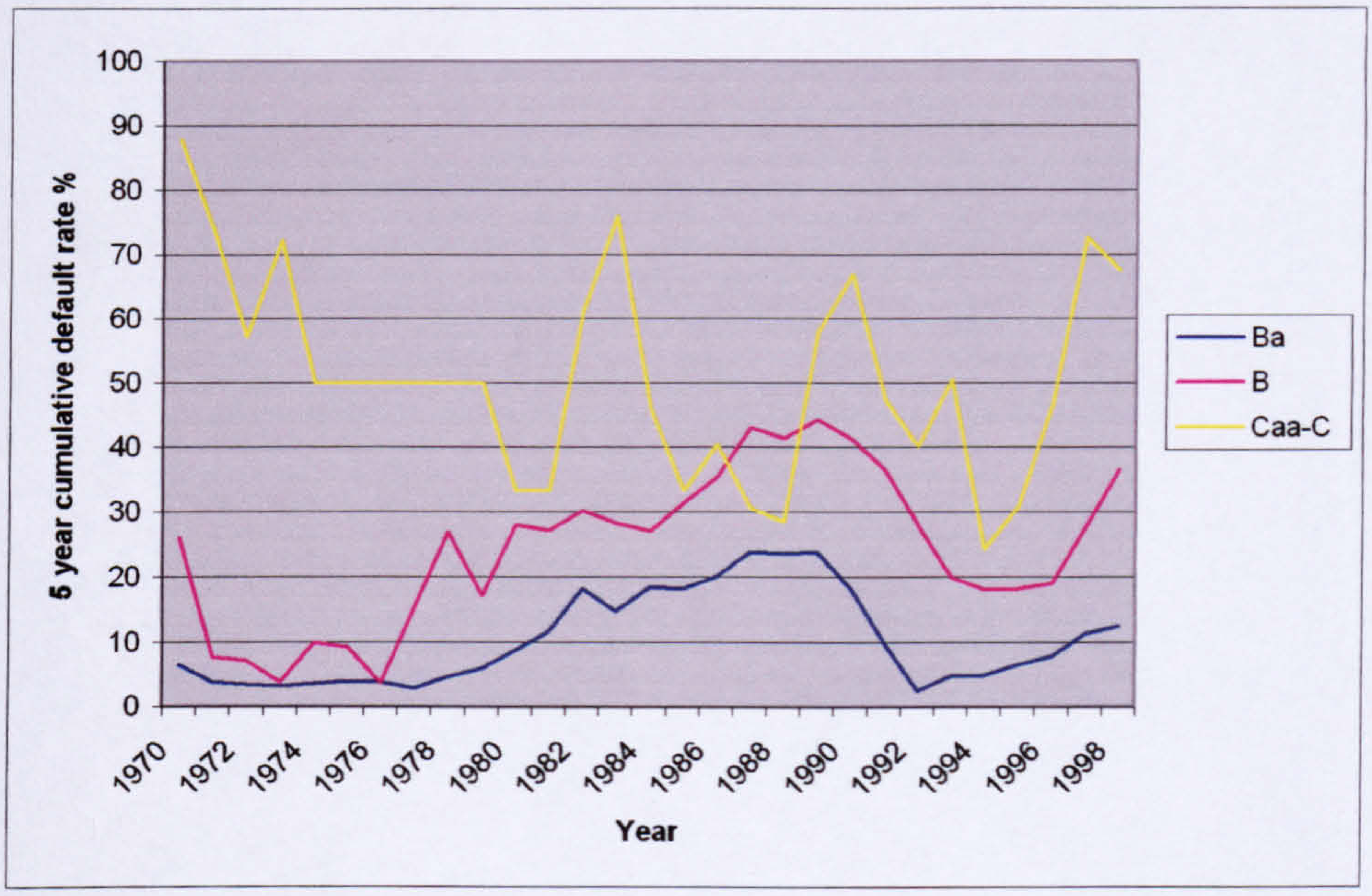
Figures 2.1 and 2.2 show that ratings do not correspond to the same probability of default at every point in time. Agencies state that they do not make rating changes based on short-term business cycles even though default probabilities will go up during recession. They argue that long-term default probabilities at the different ratings levels should exhibit relative stability over long periods of time (Cantor and Packer 1995). Figures 2.1 and 2.2 show 5 year CDRs over a twenty eight year period, the default rates show little stability over this time period.

Figure 2.1: Trends in five year cumulative default rates by credit rating – Investment grades



Data extracted form Moody's 2002

Figure 2.2: Trends in 5 year cumulative default rates by credit rating: sub-investment grades



Data extracted form Moody's 2002

When legislators embed specific credit rating grades into law and regulation they are relying on long term stability but accept that in the short term the probability of default associated with a particular rating will fluctuate.

2.1.2 Organisation and issue credit ratings

Ratings may be provided on a specific organisation (issuer) or a particular bond issue. The instrument-specific credit ratings are a current opinion of the creditworthiness of an obligor with respect to a specific financial obligation or class of obligations. It will take into account the credit worthiness of the issuer but also factors specific to that issue. Often instrument ratings are the same as organisation ratings but they may be lower, depending on the nature of the obligation.

For example S&P show the following ratings for IBM Corporation:

Organisation ratings

Long term rating	A+
Watch grade	Stable
Short term rating	A-1

Instrument ratings

Commercial paper	A-1
Euro 8bn Senior unsecured medium term notes issued 3/9/1999	A+
$20bn Senior unsecured/ subordinated issued 1/2/2003	A

An organisation credit rating gives an opinion as to the obligor's overall capacity to meet its financial obligations. This is not specific to any particular bond or debt issue.

Since the first credit rating agency was set up in the US in 1909, rating credit has become big business. Rating changes are found in the financial press each day, regulation around the world uses ratings to determine which investments can legally be held by certain organisations and agencies are powerful and wealthy organisations.

2.1.3 Bank Individual and support ratings

Banks differ substantially from other entities in that they have access to outside support if they run into serious financial difficulties. Because of the repercussions of bank failure on other parts of the economy most Governments would step in to assist a bank at risk of default. A crucial part of the raters' assessment of a bank consists in considering whether, and in what circumstances, a bank in trouble would be rescued and by whom. A support rating is a judgement of the likelihood of support for a bank and is independent to the financial stability of the bank itself.

Individual Ratings (called Bank Financial Strength Ratings by Moody's) are internationally comparable and express a judgment as to how a bank would be viewed if it were entirely independent and could not rely on external support. These ratings are designed to assess a bank's exposure to, appetite for, and management of risk, and thus represent the raters' view on the likelihood that it would run into significant difficulties such that it would require support. The traditional long term ratings issued for a bank combine the individual rating with the support element.

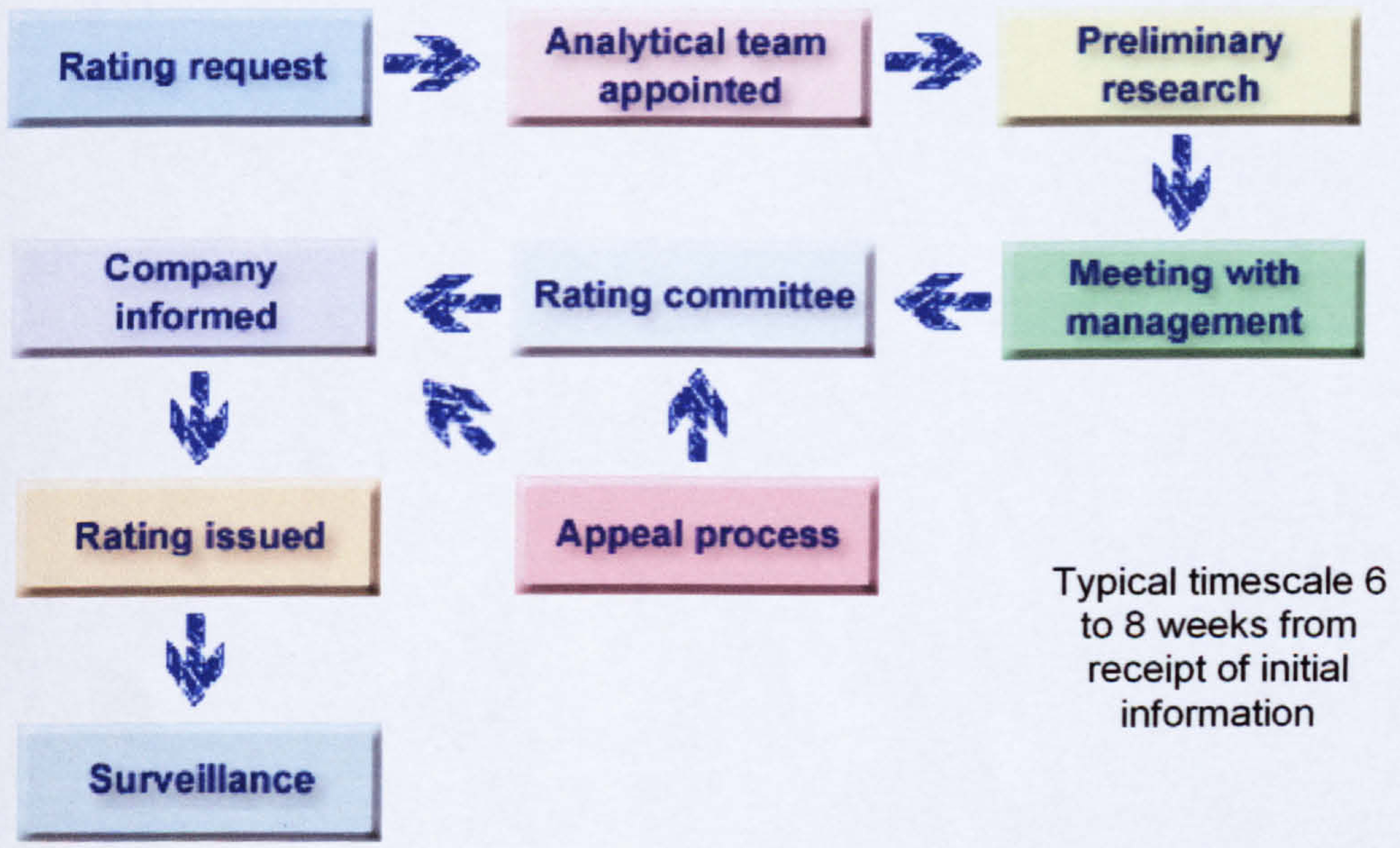
Individual bank ratings are published by Moody's and Fitch Ratings. These are called Bank Financial Strength Ratings (BFSR) and Individual ratings by Moody's and Fitch respectively. S&P have no publicly available equivalent to these individual ratings.

Fitch Ratings specifically state that their long term debt ratings are derived from the support and individual ratings. Moody's are less specific about the relationship between BFSRs and the support element but they do say that the ratings do not take into account the probability that the bank will receive external support. They go onto explain that BFSRs include bank-specific elements as well as other risk factors in the bank's operating environment such as the economy and quality of bank regulation.

2.2 The process of assigning a credit rating

Usually a company will approach Moody's or Standard and Poor's when it is going to sell or register a new debt issue. Issuers often like to find out the likely rating in advance so that they can asses the impact of the new debt on existing debt. The process is outlined in figure 2.3.

Figure 2.3: Standard and Poor's debt ratings process



Source: Dinwoodie (2002)

An analyst is allocated to the issuer who has specialism in that sector. There will be one key day-to-day contact but other analysts will also be involved who have general knowledge of the issuer.

A meeting with management will be arranged and a preliminary assessment will be made by the agency. Financial statements, descriptions of operations, products and corporate structure will all be reviewed.

At the management meeting the analyst will gather information to conduct a quantitative, qualitative and legal analysis. They will also find out about key strategic, operating and financial plans, management policy, other credit factors, quality of senior management, information about the industry and undertake a tour of the facility.

Figure 2.4: Moody's rating analysis of an industrial company

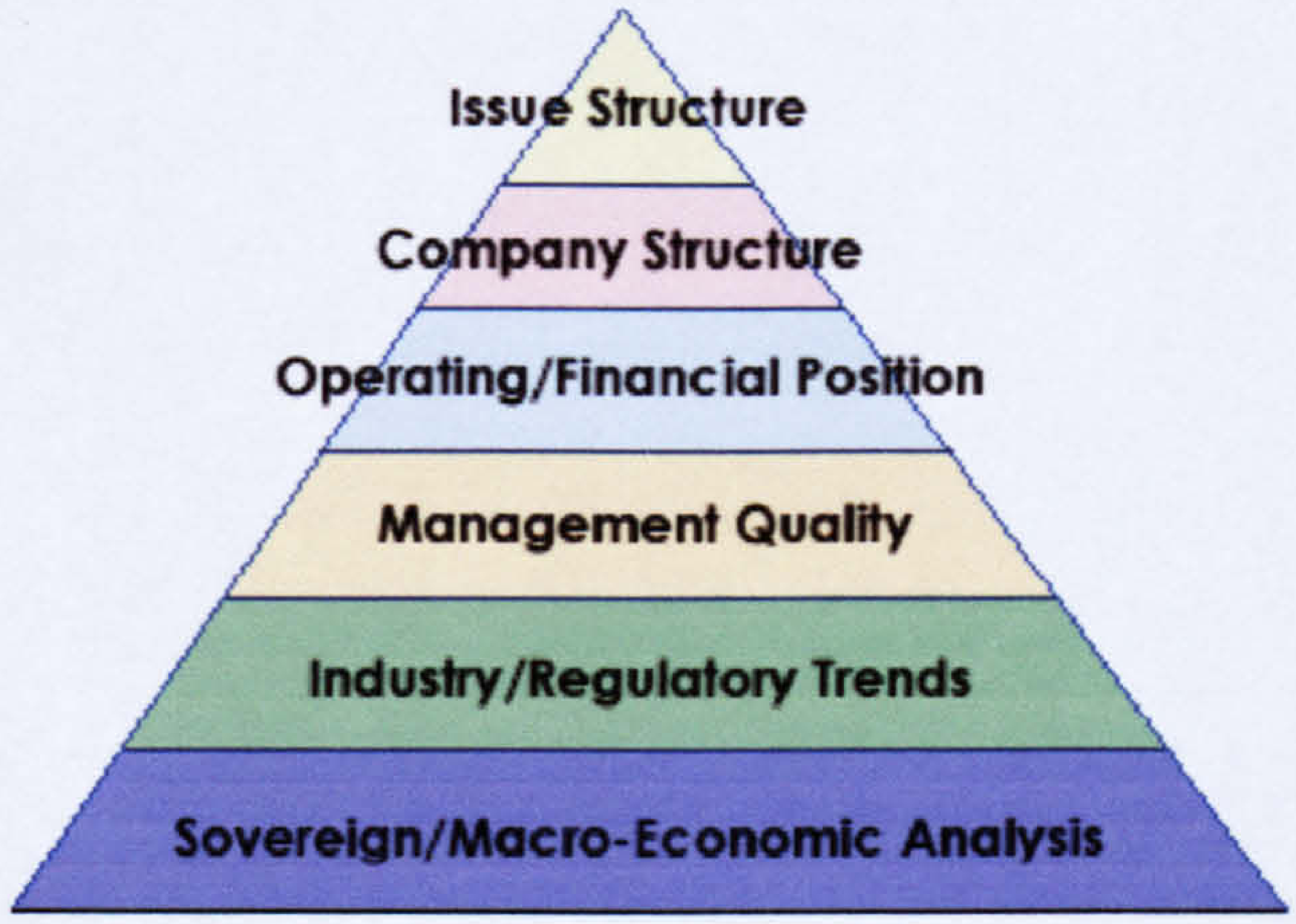


Figure 2.4 illustrates how Moody's describe their rating process. They start by reviewing sovereign and macro-economic issues, industry outlook and regulatory trends, then look at specific attributes of the organisation including the quality of management, operating and financial positions and company structure. Finally the issue-specific structure of the financial instrument is considered. Both major agencies stress that many qualitative, rather than purely quantitative aspects are considered.

After the management meeting, the rating committee within the agency will meet to determine the credit rating. There are usually 5 to 7 voting members at the meeting. The analyst will make a presentation which includes the nature of the company's business and its operating environment, evaluation of the company's strategic and financial management, financial analysis and a rating recommendation.

The company will be notified of the rating and has the opportunity to appeal and provide additional data. If there is an appeal it is conducted as quickly as possible and the company is informed again of the rating before it is released to the media. The ratings are monitored at least once a year.

2.3 History of the credit rating industry

Credit rating agencies as they exist today were not found anywhere in the world until the first was established in the US by John Moody in 1909 (Partnoy 1999). This seems surprising as the first government bonds had been created by the Dutch shortly before 1600. England's financial system became increasingly developed in the seventeenth century, with the founding of the Bank of England in 1694, and overtook the Dutch economy as the leading economy of the world in the eighteenth and nineteenth centuries. As Sylla points out (Sylla 2001),

> "By the time of John Moody's bond rating innovation in 1909, Dutch investors had been buying bonds for three centuries, English investors for two and American investors for one century, all the time without the benefit of agency ratings. Why?"

The answer is that most of the bond investment was in public, or sovereign debts of nations and governments that were trusted by their investors. Businesses were still operating on a small scale so their financing requirements could be met by bank loans and equity issues.

In the US growth started to occur during the nineteenth century on a scale that could no longer be funded on a local, or state, level. In the US there was less state and national debt, partly because there had not been the same need to finance wars as in Europe and also because the country was segmented into a number of different states. US states did issue sovereign bonded debt to build canals and other infrastructure projects but largely withdrew from this after nine states defaulted in the early 1840s. As the country grew local governments replaced states as bond issuers but they were dwarfed by the private sector, the corporate bond market.

Funding railroads became a key reason to raise money. At the outset these companies were locally based and could raise funds from local banks and stock issues but as the companies merged together and became larger it was not possible to raise local finance and bonds were required. A huge market in bonded debt of US railroad corporations grew from the 1850s. By 1909 the US corporate bond market (essentially US railroad bond market) was several times larger than that of any other country. It is interesting that the business survived for at least 50 years without a rating industry and this may be explained by the fact that the industry was relatively small and confined to one sector.

However investors were helped with their decisions by the financial press and specialist journals. A publication called *The American Railroad Journal* started publishing information for investors when Henry Poor became editor in 1849. The journal contained information on property, assets, liabilities and earnings of railroads corporations. Henry and his son John, specialised in their own publication Poor's *Manual of the Railroads of the United States* in 1868. Henry died in 1905 but the Poor company went on and entered the bond rating business itself in 1916. The company merged with Standard Statistics, another information and ratings company, in 1941 to form Standard and Poor's (S&P). This company was taken over by McGraw Hill in the 1960s and is still owned by this publishing company today. Standard and Poor's remains one of the largest credit rating agencies in the world.

A separate branch of the development of the credit rating industry was started by Lewis Tappan in 1841 when he founded the Mercantile Agency from his own extensive records of credit worthiness of his dry goods and silk customers (Sylla 2001, Cantor and Packer 1995). Robert Dun later acquired the company which became R.G. Dun and Company and published the first ratings guide in 1859. 7,000 business were covered in the 1870's, this grew to 40,000 in the 1880's and one million by 1900. A similar mercantile agency was established by John Bradstreet in Cincinnati in 1849 and merged with RG Dun and Company in 1933 to form Dun and Bradstreet.

Sylla (2001) argues that a third factor led to the emergence of credit rating agencies at the start of the twentieth century. The role of investment bankers was growing in the railroad industry. The bankers provided a large proportion of the required finance but in exchange expected to be granted access to detailed information about the company or a seat on the board. Other investors resented this access to privileged information by the bankers and there was a push to make more information publicly accessible.

The railroad bond rating agency established in 1909 by John Moody is seen as the first real credit rating agency (Sylla 2001). In 1910 they extended the coverage to utility and industrial bonds. Moody's did not rate US state and government bonds until 1919. In 1962 Dun and Bradstreet took over Moody's and disposed of them in

September 2000 when they became freestanding with a market capitalisation of $5 billion.

Fitch Publishing Company was established in 1924. Duff and Phelps entered the bond rating market in 1982 and McCarthy, Crisanti and Maffer was founded in 1975 and acquired by Xerox Financial Services before it was merged into Duff and Phelps in 1991 (see Cantor and Packer 1995). Fitch later merged with IBCA, the only UK credit rating agency, in 1997 and the combined entity was subsequently bought by a French company FIMLAC. In June 2000 Fitch IBCA bought Duff and Phelps. In December 2000 Fitch absorbed Thomson BankWatch (White 2000).

Estrella et al (2000) state that at September 1999 it was believed that there were about 130 agencies world-wide but this number may be closer to 150.

2.4 Current issues in the credit rating industry

The second part of this chapter looks at four issues that concern the credit rating industry and considers alternative views put forward by credit rating agencies and other commentators:

- Regulation and the credit rating industry
- Conflicts of interest between the agency and the issuer
- Do credit ratings have information content?
- Procyclicality and the credit rating industry

2.4.1 Regulation and the credit rating industry

The largest and most powerful credit rating agencies are based in the US. There are many smaller agencies around the world but none except Fitch Ratings come close to either the profitability or the coverage or Moody's and Standard and Poor's. The influence and wealth of the large credit rating agencies is closely linked to the position given to them by the regulators, especially in the US, but this influence may be extended in other countries by the proposals of Basel II.

> "Take ratings out of regulation altogether, and return the agencies to their role as servants not masters of the capital markets" (Economist 2003b)

Commentators such as the Economist argue strongly that the credit rating agencies should be taken out of financial regulation altogether. The argument is that regulation restricts competition and increases the risk of conflicts of interest.

> "When ratings become not just a tool for investors but the very basis for regulation, they are likely to become distorted, and conflicts of interest risk becoming sharper." (Economist 2002)

The agencies themselves argue that they serve an important function in capital markets;

> "Credit ratings are the very structure of the marketplace. They are the risk language that we all speak and rely on." (Strauss 2002)

In addition they argue that taking credit ratings out of regulation would be extremely disruptive and unnecessary as "replicating the expertise, experience, commitment and objectivity of the large agencies would be difficult if not impossible to achieve." Dominion Bond Rating Service (2003).

At present, eleven of the twelve member countries of the Basel Committee on Banking Supervision (BCBS) use credit ratings in financial regulation. Of these, seven use ratings only in their prudential supervision of banks solely to determine a qualifying debt security for the calculation of the capital requirement for specific interest rate risk. This is the market risk amendment to the original Basel Accord (Basel Committee on Banking Supervision 1988 and 1996). The remaining four countries, UK, US, Belgium and Switzerland use agency ratings in their prudential supervision of banks for purposes other than market risk (Estrella et al. 2001). To understand more about the influence that regulation has had on the credit rating agencies it is useful to look at the background of the use of agency ratings in regulation.

2.4.1.1 How credit ratings came to be used in regulation

Regulators at the US Federal and State levels started using credit ratings for regulatory purposes for the first time in the 1930s. This was a controversial step and made the front page of The Wall Street Journal because of the high level of defaults at the time (Partnoy 1999). Once better financial times arrived, which generally continued until the 1970s, there was less concern about the impact of credit ratings in regulation.

In 1930 the Federal Reserve Bank of New York devised a system to express the safety of a bank's portfolio as a single number based on credit ratings. In 1931 regulation was introduced by the Comptroller of the Currency (US Treasury department) to cover national bank's bond accounts. Bonds with a credit rating of BBB or higher could be carried at cost but all bonds with a lower rating required fractional write-offs. State banking superintendents adopted this rule in the years that followed.

In 1935 and 1936 the Comptroller tightened up the rules so that rather than having to make a fractional write-off on bonds below BBB grade it was now totally prohibited to purchase securities that fell below a certain credit rating (i.e. were speculative grade). Citing Harold (1938), Partnoy (1999) says "in one day, the Comptroller had slashed in half the universe of publicly-traded bonds banks could purchase." Harold said "it is common knowledge in bond circles that since the issuance of the Comptroller's ruling, a bond rated below that of a 'business man's investment' (BBB, Baa, B, or B1+) can almost never be sold to a bank".

Partnoy argues that regulation turns a credit rating into a valuable "regulatory licence" that can be sold by the rating agencies. Without a good credit rating an issuer cannot attract investors as purchase of the bond would be prohibited. The "licence" has great value as it reduces the costs for the issuer and the investor. He argues that regulation explains the growth in wealth and recognition of the credit rating agencies in the 1930s and their continuing success today.

Another impact of the 1930s regulation was that ratings were made public before a bond issue, this also contributed to make ratings more widely used.

> "Prior to the Comptroller's ruling the rating agencies had not rated bonds until after they were issued. The ruling created incentives for bond issuers to obtain a rating before the bonds were issued. Bond issuers were forced to look to rating agencies as sources of authority concerning their bond issues, regardless of what information the rating agencies actually generated." Partnoy (1999).

These rules still effect investment decisions of US banks today. The legislation is referred to as "safety and soundness" (prudential) regulation and has forced those institutions to make use of ratings in their purchase and holding decisions with respect to bonds (White 2002).

There was very little change in regulation concerning credit ratings between the period 1940 to 1973. Sylla (2001) argues that there is a connection between credit rating agency expansion, regulation and times of high levels of default. This certainly appears to be true for the periods 1931 – 1936 and the early 1970s and would explain why the period in between was quiet for the agencies as there were few major defaults. By the early 1970s the agencies had become small and had only a handful of analysts.

2.4.1.2 Nationally Recognized Statistical Rating Organizations

The small scale of the agencies all changed in 1973 when the first of hundreds of rules, releases and regulations were issued requiring credit ratings to be used in the regulation of banks, securities, pensions, banking, real estate and insurance regulation. The changes were driven by some liquidity crises and large defaults such as Penn Central on $82 million of commercial paper. One of the most significant regulations of this period was the adoption by the SEC of Rule 15c3-1 in 1975, a securities rule which formally incorporated credit ratings and approved the use of ratings from certain agencies know as Nationally Recognized Statistical Rating Organizations (NRSRO's). At this time the rule effectively froze the then approved credit rating agencies Moody's, Standard and Poor and Fitch. Partnoy (1999) argues that "these barriers to entry have remained insurmountable".

Other agencies sought NRSRO designation from the SEC. In 1982 Duff and Phelps received designation as did McCarthy, Crisanti and Maffei in 1983 (they were subsequently acquired by Duff and Phelps in 1991). IBCA and Thomson BankWatch gained NRSRO status in 1991 and 1992 respectively but these companies were later acquired by Fitch bringing the total number of NRSRO designated agencies back to three. Dominion Bond Rating Service (DBRS) was recognised as an NRSRO in February 2003.

The SEC's procedures and conditions for granting designation have come under substantial criticism for creating an anti-competitive environment within the industry. There are no specific conditions that have to be fulfilled, designation is very much at the discretion of the SEC and based on recognition and status of the agency within the US. This is a double edged sword as agencies cannot gain widespread usage of their ratings without NRSRO status and cannot gain the status without users already relying on the ratings. The SEC did publish proposed guidelines for NRSRO recognition in 1997 but these guidelines have never been formally adopted.

The position of the NRSRO's is currently under review as the SEC issued a Concept Release "Rating Agencies and the Use of Credit Ratings under the Federal Securities Laws" (SEC 2003). Comments were invited on a wide range of issues under review, including whether credit ratings should continue to be used for regulatory purposes under the federal securities laws, and, if so, the process of determining whose credit ratings should be used and the level of oversight to apply to such credit rating agencies. These questions tackle many of the current concerns at the core of the industry and the SEC is going so far as to question whether or not credit rating agencies should exist at all. In 2005 the SEC issued a proposed definition of an NRSRO but nothing has been finalised.

Despite this, given the position of the large credit rating agencies within US regulation it seems very unlikely that any significant changes will be made to the industry.

2.4.2 Conflicts of Interest

The second issue relevant to the credit rating industry is the potential conflict of interest between the agency and the issuer.

There are three potential areas where a conflict could arise.

1. Reliance by the agency on issuer fees could potentially lead raters to improve a rating to ensure retention of the account or in return for an additional fee.
2. Credit rating agencies also offer consultancy and other advisory services, commentators feel that seeking growth in this business could lead to conflicts of interest.
3. There has been widespread concern that the issuing of an unsolicited rating might be a way to force an issuer to pay for the full service.

2.4.2.1 Reliance on issuer fees

There is a potential conflict of interest at the core of the credit rating business. The credit rating agencies are in business to maximise earnings while the investors and other end users of the information need to use the ratings to make financial decisions. The potential problems occur when the agencies' primary source of income comes from fees paid by the issuers rather than the end users of the rating. According to Moody's 10-K it obtains more than 85% of its compensation from issuers.

Since 1973 rules depending on credit ratings have been enacted under the Securities Act of 1933, the Securities Exchange Act of 1974, the Investment Company Act of 1940 as well as banking regulations. More than a dozen financial regulations depend upon the use of credit ratings (Economist 2001). Partnoy (1999) argues that "the resulting web of regulation is so thick that a thorough review would occupy hundreds, perhaps thousands of pages."

From 1909 to the 1970's the agencies were funded from the sale of their agency reports to subscribers. After the 1970s the revenue source changed from the investors to the issuers of the securities. This became possible for two reasons. Firstly, because issuers were hoping to reassure nervous investors of the quality of their bonds after the failure of Penn Central and secondly the agencies themselves were worried that low-cost photocopying would make it hard to prevent free duplication of their information. Fitch and Moody's started to charge in 1970 and S&P followed a few years later.

White (2000) quotes "list prices" for the requested ratings: 3.25 basis points on issues up to $500 million with a minimum fee of $25,000 and a maximum of $125,000 (S&P) or $130,000 (Moody's). Both agencies charge an additional 2 basis points on amounts above $500 million. White quotes rates for Fitch and Duff and Phelps prior to their merger, these fees are lower than the two large agencies at between 2.5 and 2.75 basis points.

Estrella et al (2000) surveyed 26 agencies around the world and asked whether payments for ratings are made by the rated body or subscribers. 17 of these agencies disclosed information and of these seven receive payment from the rated body rather than the subscriber. This research suggests that, while 100% of NRSROs obtain revenue from the issuer, the majority of smaller agencies do not.

For the major agencies the vast majority of their total revenue comes from issuers fees, not from the sale of the rating information to investors. Ederington and Yawitz (1987) state that eighty percent of S&P's revenue comes from issuer fees and Partnoy (2001) gives the equivalent figure for both agencies as 95% of revenue coming from issuer fees.

The agencies argue that the risk of a conflict of interest is mitigated by a number of policies and procedures designed to guarantee the independence and objectivity of the rating process. For example, rating decisions are made by a ratings committee, there are fixed fee schedules and analysts are not compensated on the basis of the level of issuer fees.

An argument that has been used time and again to defend the agencies against any accusation of a conflict of interest over fees is that the agency's reputation is so important to the business.

"A reputation for technical competence, continuity, transparency, objectivity and impartiality comprises the principal asset of the rating agencies, without which there would be no justifiable demand for their ratings." Smith and Walter (2001)

"Apparently, [the agencies'] institutional concerns about their long-run reputations have been sufficiently strong so as to keep the moral hazard tendencies in check." White (2000)

"The reliability of ratings can be explained by reputational costs; the profitability of rating agencies is directly dependent on their reputations. Inaccurate ratings will impair, if not destroy a rating agency reputation. " Schwarcz (2002)

This appears to be the prevailing view and is widely accepted within the industry and issuers, investors, regulators and researchers alike agree that the agencies have a huge incentive to provide reliable ratings and have done a reasonably good job to date.

Partnoy (1999) takes a different view and does not agree that 'reputational capital' has been such a key driver in the success of the credit rating industry or protection against moral hazard. He argues that rating agencies are still very successful despite having made some serious mistakes in rating bonds during the troubled times of the 1930s and mid 1970s.

2.4.2.2 Consultancy and other advisory services

Credit rating agencies are increasingly offering consultancy and other services. Commentators are worried about this new business departure as it draws agencies closer to the companies that they rate. There is a risk that issuers could be pressured to purchase advisory services. The agencies have a large amount of power over issuers as the ratings have such significance to the cost of their borrowing and reputation in the market place.

Consultancy is a relatively new departure for the credit rating agencies but may already exceed one third of their income. Moody's say that 36% of revenue is now "relationship-based" (Economist 2001). The agencies argue that there are extensive guidelines and firewalls to separate the ratings services from other businesses.

2.4.2.3 Unsolicited ratings

Moody's and S&P state that they rate and make public all SEC-registered corporate bonds, whether requested by the issuer or not. If the issuer does not request a rating the agency will still issue a rating on the basis of publicly available information. In the industry this is called an unsolicited rating but Moody's and S&P do not use those terms as they believe all ratings are solicited. S&P marks unsolicited ratings with the prefix "pi" to make it clear that this is based on public information.

> "A public information credit rating is a local currency credit rating identified by the "pi" subscript and based on an analysis of the obligor's published financial information, as well as additional information in the public domain. Public information ratings are not ordinarily modified with "+" or "-" designations and are not assigned outlooks. Ratings with a "pi" subscript are reviewed annually based on the current financial statements, but may be reviewed on an interim

basis if a major event that may affect an issuer's credit quality occurs." (Standard and Poor 2002a)

Moody's state in the rating assignment press release whether a rating was unsolicited by the comment, "this rating was initiated by Moody's, the issuer did not participate in the assignment process" (Moody's 1999). Until January 2000 they did not differentiate between unsolicited and solicited ratings. Poon (2003) comments that it was impossible to establish which ratings were solicited and which were not as Moody's do not publish a list of customers. In their announcement of the policy change, Moody's say:

"Since we do not consider unsolicited ratings which lacked issuer participation to be anything less than full-fledged Moody's ratings, we had been reluctant to designate them as different. However, we recognize that market participants have shown an interest in knowing which ratings lack the issuer's participation, and we have therefore concluded that it is appropriate to do so going forward." Moody's (1999)

Moody's argue that:

"Unsolicited ratings perform a useful role. They enable us to maintain broad coverage, especially below investment grade. They are also the market's best defence against rating shopping (which occurs when issuers shop among various agencies for the highest ratings and seek to suppress lower conclusions). Under such circumstances, rating agencies risk the moral hazard of competing to provide the highest rating in order to obtain the issuer's business." Moody's (1999)

Cantor and Packer (1995) comment that "Moody's and Standard & Poor's usually receive fees for ratings they would have issued anyway because companies want the opportunity provided by the formal rating process to put their best case before the agencies." This implies that issuers believe that by giving the agencies access to company staff and internal information they will achieve a better rating than if it is based entirely on information in the public domain. A survey of 259 financial institutions in Japan (Japan Center for International Finance 2000) shows that 70% of respondents provide internal information not available to institutional investors and financial analysts for solicited ratings but less than 30% provide such information for unsolicited ratings. Harington (1997) states that some banks consider the practice of assigning unsolicited ratings as equivalent to "financial blackmail" because they feel they should co-operate and pay the agency to receive a more favourable rating.

Fitch has also stated that Moody's uses the threat of an unsolicited rating to scare reluctant customers into requesting a rating. A managing director from Duff & Phelps Credit Rating Co. stated that "unsolicited ratings are tantamount to blackmail." (House 1995)

In 1995 a lawsuit was brought against Moody's over a unsolicited rating. Jefferson County (Colorado) School District filed a lawsuit accusing Moody's of "fraud, malice, and willful and wanton conduct" for publishing a "punishment" rating on the district's bonds, because the district did not hire the agency to rate it. The motion was dismissed by the US District Court and later the US Court of Appeal on the basis that the bond market depended upon the free, open exchange of information concerning bond issues. However, the reputation of the credit rating agencies suffered and the case attracted a lot of attention to the controversial practice of unsolicited ratings.

In 1996 Moody's was the subject of an antitrust investigation by America's Justice Department. The company was suspected of issuing "unsolicited" ratings on companies to force them to pay up for a full service. No charges were brought on Moody's but there are widespread references to this practice in the literature.

In March 1996 the Justice Department's Antitrust Division investigated the possibility of anti-competitive practices in the bond rating industry, including the use of unsolicited ratings. At the time the claims were dismissed but in April 2001, Moody's was ordered to pay a fine of $195,000 as it pleaded guilty to destruction of documents demanded for this investigation. Federal authorities said "one or more of Moody's executives in addition to the one who destroyed the documents knew of, or should have known of, the destruction." CNN Money Magazine (2001)

The strong legal position of the agencies was also illustrated in the case of Orange County, California in December 1994. The county defaulted a few months after the highest short term rating had been given to $600 million of debt. In 1996 Orange Country made a complaint to the US Bankruptcy Court for breach of contract, professional negligence and aiding and abetting breach of fiduciary duty by S&P. Most of the claims were dismissed by the courts as the First Amendment protected publishers from professional negligence actions (Partnoy 1999).

There are two reasons for the strong legal position of the agencies. Firstly, that debt ratings issued by rating agencies are not financial advice but speech that is constitutionally protected under the First Amendment. Secondly, credit ratings are extensively disclaimed and are not a recommendation to buy, sell, or hold securities (Partnoy 2001).

In reality this has meant that agencies will very rarely be found to be liable. In the case of Orange Country, S&P did make a small settlement payment of $149,000. This compares to hundreds of millions of dollars paid by the investment banking defendants in the settlement. This case shows very clearly that it would be extremely hard to bring a successful case against the US credit rating agencies in the event of default of investment grade corporate, or sovereign debt.

Poon (2003) has studied the relative rating grades of unsolicited ratings relative to solicited. She finds that unsolicited ratings are generally lower but also that those issuers who choose not to obtain ratings from S&P have a weaker financial profile. However for Japanese ratings she does find that unsolicited ratings are still lower, even after controlling for differences in sovereign risk and financial characteristics. Byoun and Shin (2002) look at the price impact of unsolicited rating announcements. They find that for unsolicited new ratings and rating down-grades there are negative stock price reactions to announcements. However, for solicited ratings, there are negative effects only for rating down-grades.

Unsolicited ratings are acknowledged to be a potential problem in the draft of the New Basel Capital Accord. Basel II states that banks should use solicited ratings and can only use unsolicited ratings if national regulators allow banks to do so. They suggest that any agency that uses unsolicited ratings to put pressure on entities to obtain a full rating should lead supervisors to consider whether to continue recognising that agency under regulations (BCBS 2005).

2.4.3 Do credit ratings have information content?

A number of previous studies have examined whether debt-security ratings convey new information to the market. The findings are not consistent. For example, Partnoy (2001) discusses the paradox of the "continuing prosperity of credit rating agencies in the face of declining informational value of ratings". He states that "there is overwhelming evidence that credit ratings are of scant informational value." In contrast, Jewell and Livingston (1999) argue that "in the academic literature, the consensus is growing that bond ratings convey useful information to the market"

Research does show that agency ratings lag behind the information already available to the market. Weistein (1977), Hettenhouse and Sartoris (1976) and Pinches and Singleton (1978) examine bond returns, bond yields or stock returns at the time of announcements of ratings changes. The hypothesis of this research is that no capital market reaction at the time of the rating change suggests that ratings convey no new information to the market.

These early studies into the information content of bond ratings found that rating agency revisions do lag earlier established market perceptions. They followed the argument that in a perfect market, with no taxes, credit quality is irrelevant to the value of the firm. In those papers, rating agencies were thought to use only publicly available financial data. Consequently, it was thought that bond rating agencies did little more than certify, validate, and verify publicly available financial information and subsequently should have little impact on market value (Larrymore, Liu and Rimbey 2003). In general these researchers argue that the bond market has anticipated most of the rating process long before the rating change announcements.

For example, Weistein (1977) reported no bond price reaction at the time of a rating change and no post announcement price adjustment. He finds that bond price changes are fully anticipated during the period of 18 to 7 months preceding the bond rating revisions made by Moody's. He concluded that, in an efficient market, bond rating agency announcements do not provide any new information to the market. Hettenhouse and Sartoris (1976) support the view that there is a lag between the arrival of new information and rating changes. Pinches and Singleton (1978) found that stock price adjustments preceded the announcement of bond rating changes by several months.

Another branch of the literature argues that bond ratings do convey some useful information to the market. This seems to be especially true of bond downgrades in that there is a significant negative market reaction to falls in bond ratings. This asymmetry in the bond market's reaction to positive and negative announcements is found by many researchers.

Griffin and Sanvicente (1982) show that share prices respond negatively to bond rating agency downgrade announcements. They examined the adjustments in a firm's common stock price during the eleven months before and during the month of announcement of a bond rating change and found that bond downgradings convey information to common stockholders. Using daily data, Holthausen and Leftwich (1986) found significant negative abnormal returns associated with bond rating reductions but found that equity returns anticipate both upgrades and downgrades.

Goh and Ederington (1993) find negative stock market reaction only to downgrades associated with a deterioration of firm's financial prospects but not to those attributed to an increase in leverage or reorganization.

Cross sectional variation in stock market reaction is documented by Goh and Ederington (1999) who find a stronger negative reaction to downgrades to and within non-investment grade than to downgrades within the investment grade category. Hite and Warga (1997) also find that the strongest bond price reaction is associated with downgrades to and within the non-investment grade class. They analyse changes in ratings during the life of a bond and find some information content for downgrades at announcement, and little or none for upgrades. They show that the cumulative abnormal bond return within 6 months prior to rating changes is about two to ten times larger than that in the announcement month. This finding adds strength to the views of researchers of the 1970s such as Weistein who reported no bond price reduction at the time of a rating change and no post announcement price changes.

Wansley et al. (1992) confirm the strong negative effect of downgrades (but not upgrades) on bond returns during the period just before and just after the announcement. Their study concludes that negative excess returns are positively correlated with the number of rating notches changed and to prior excess negative returns. In contrast to the findings of Goh and Ederington (1999) and Hite and Warga (1997), Wansley et al. (1992) find that this effect is not related to whether the rating change caused the firm to become non-investment grade.

Using daily bond prices, Hand, Holthausen and Leftwich (1992) find significant abnormal bond returns associated with reviews and rating changes. A study by Steiner and Heinke (2001) uses Eurobond data and detects that negative reviews and downgrades cause abnormal negative bond returns on the announcement day and the following trading days but no significant price changes are observed for upgrades and positive review announcements.

Another thread covered by this research concerns the question as to whether the agencies are party to inside information due to the nature of their relationship with bond issuers. Ederington and Yawitz (1987) contend that bond rating agencies claim to be given inside information. Goh and Ederington (1993) argue that it is hard to ascertain whether the bond rating agencies actually receive much inside information. Nonetheless, the significantly negative market reaction to corporate bond rating downgrade announcements indicates a perception of information asymmetry. In 1974 Professon Lehn wrote to J.G. Katz, Secretary of the SEC, arguing that credit ratings must have substantial informational content because of the hundreds of stories that appear in the financial press about bond rating changes. While inclusion in the financial press is not necessarily proof of information content, it is true that you cannot scan the business news without finding some mention of credit ratings.

Ederington, Yawitz and Roberts (1987) investigate whether market participants base their evaluation of a bond issue's default risk on agency ratings or on publicly available financial information. Their results suggest that the ratings bring some information to the market above and beyond publicly available accounting variables. Danos, Holt, and Imhoff (1984) indicate that information provided to the market might be due more to bond rating agency experience in efficiently processing and analyzing public information and less due to their possession of private information. In contrast, Ederington and Yawitz (1987) survey the bond rating process and find that, at that time, there were insufficient analysts in Moody's and S&P to rate corporate bonds, they could not afford a day-to-day monitoring on thousands of corporate bonds in the market. This would provide a good explanation as to why many surveys found that there is a lag between the arrival of new information and rating changes

The reasons for these conflicting results may be to do with many problems with credit rating and bond or stock price data. In some studies only one agency was used without analysis of any of the others. Many of the studies have used monthly data which means that other information may have been released during that time that impacted the bond returns.

2.4.4 Procyclicality and the credit rating industry

Procyclicality in the financial system means that the peaks and troughs of underlying economic cycles are excessively amplified. Default and credit problems multiply in times of recession but new bond issues and total bank lending increase during the good times contributing to possible overheating of the economy. Credit ratings are cyclical in that "they look best at the top of a boom, when things are about to turn bad, and worst at the bottom of a slump, when business is about to pick up." (Economist 2003a).

A key driver of changes in regulation, accounting standards, risk measurement practices and the conduct of monetary policy is the aim to enhance both the financial system and macroeconomic stability. The worst fear is that if one bank gets into trouble during a downturn a systemic crisis can be set off leading to general panic.

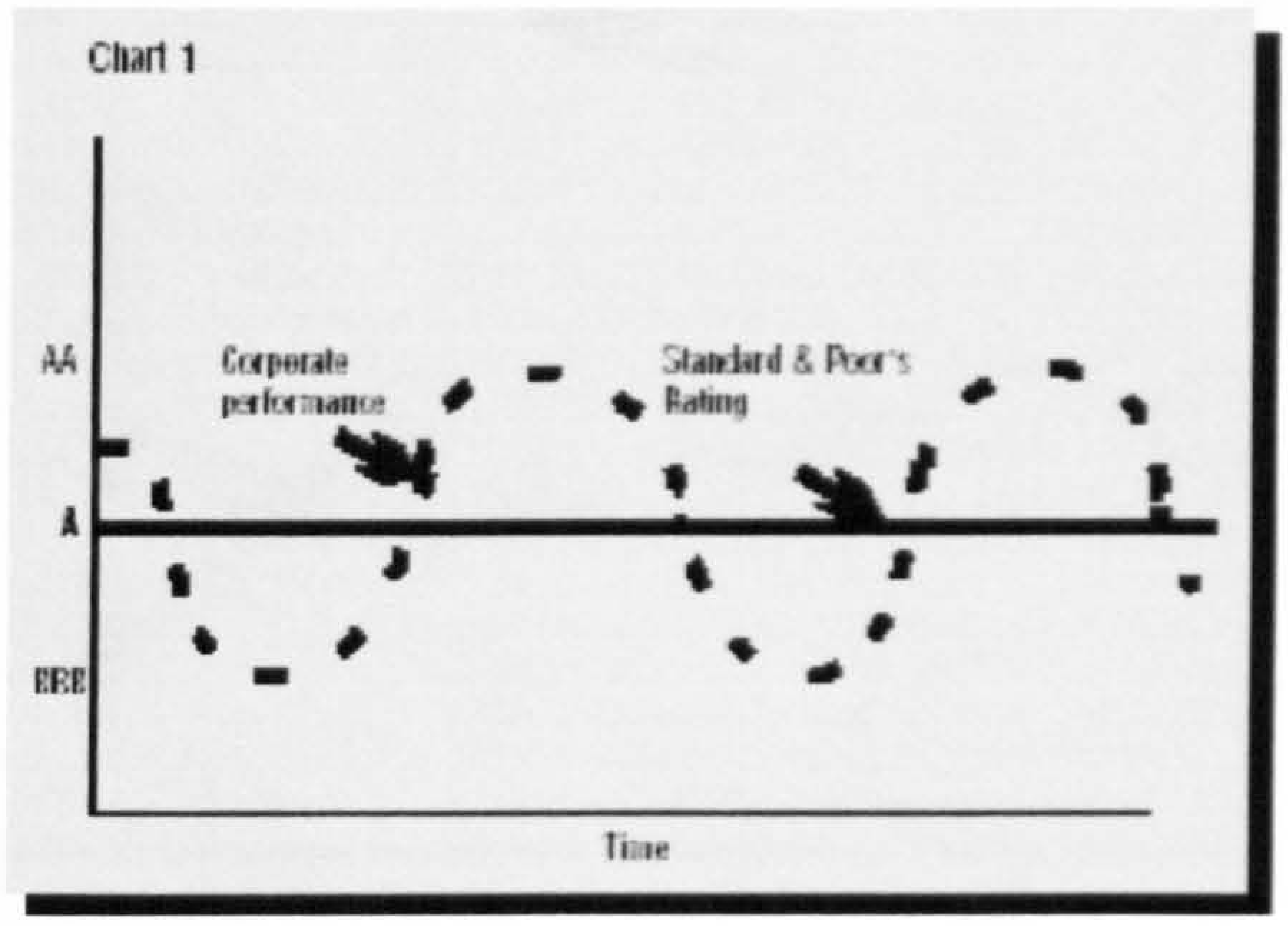
With the introduction of Basel II (BCBS 2003) the Basel Committee on Banking Supervision has a stated objective of making the capital requirements more representative of the banks' actual risk profiles. If the capital requirement is risk-sensitive, it is likely to increase during recessions and decease during expansions tending to exacerbate the business cycle waves. Since a risk-sensitive capital requirement is likely to fluctuate over the business cycle the Basel II objective is to some extent at odds with the concern about procyclicality (Pederzoli and Torricelli 2005). The extent of this problem depends on whether credit rating agencies rate "through the cycle" or at one point in time.

The major credit rating agencies maintain that their ratings should generally be stable through credit cycles (see Altman and Kao 1992, Hamilton and Cantor 2004, Altman and Rijken 2005), this is called rating "through the cycle". This means that the issuer is graded according to their expected creditworthiness over the life of the loan or entire credit cycle rather than according to current conditions. Treacy and Carey (1998) comment that only borrowers that are very weak at the time of their initial assessment would be rated according to the current condition.

Estrella et al (2000) conducted a survey of 28 international rating agencies and showed whether they use through-the-cycle or point-in-time methodology. 17 gave responses on this issue and of these 8 use through-the-cycle methodology. These are Moody's, S&P, Fitch, Thomson BankWatch (now part of Fitch), Euro Ratings AG, Japan Credit Rating Agency, R@S Rating Service and Unternehmensratingagentur AG.

"The ideal is to "rate through the cycle". There is no point in assigning high ratings to a company enjoying peak prosperity if that performance level is expected to be only temporary. Similarly, there is no need to lower ratings to reflect poor performance as long as one can reliably anticipate that better times are just around the corner." (Standard and Poor 2002a)

Figure 2.5: Credit rating "through the cycle" vs. "point in time"

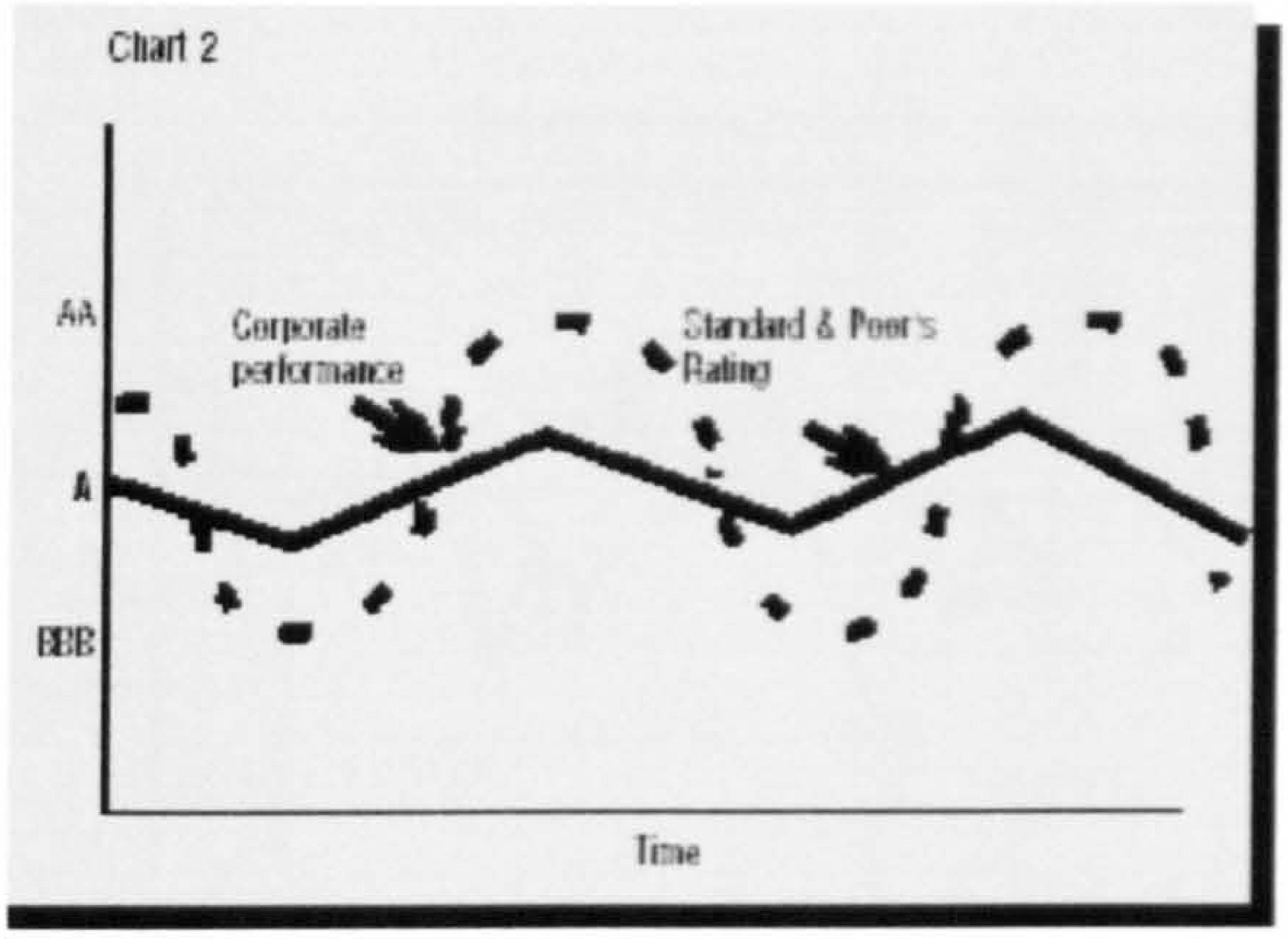


Source: Standard and Poor 2002a

In Figure 2.5, Standard and Poor's would, ideally, rate the company as an A even though its rating at a particular point in time over the cycle may range from AA to BBB. They state that this approach works well for highly stable, investment grade, major industry participants but S&P admit that may be the "incorrect model" for other issuers.

However, rating accurately through the cycle is extremely difficult. The cyclical pattern needs to be predictable, the business needs to react to the cycle in the same way and needs to survive the downturn. S&P state in their Corporate Rating Criteria (Standard and Poor 2002a) that "ratings may well be adjusted with the phases of the cycle" but "within a relatively narrow band". Figure 2.6 shows how this works. S&P emphasise that the range of ratings would not fully mirror the cyclical highs and lows, this is important as following the full range of the cycle or even amplifying this would mean the ratings are indeed procyclical. S&P comment that for non-investment grade firms cyclical fluctuations will lead to ratings changes as these firms are more volatile in nature.

Figure 2.6: Ratings adjusted with the phases of the cycle



Source: Standard and Poor 2002a

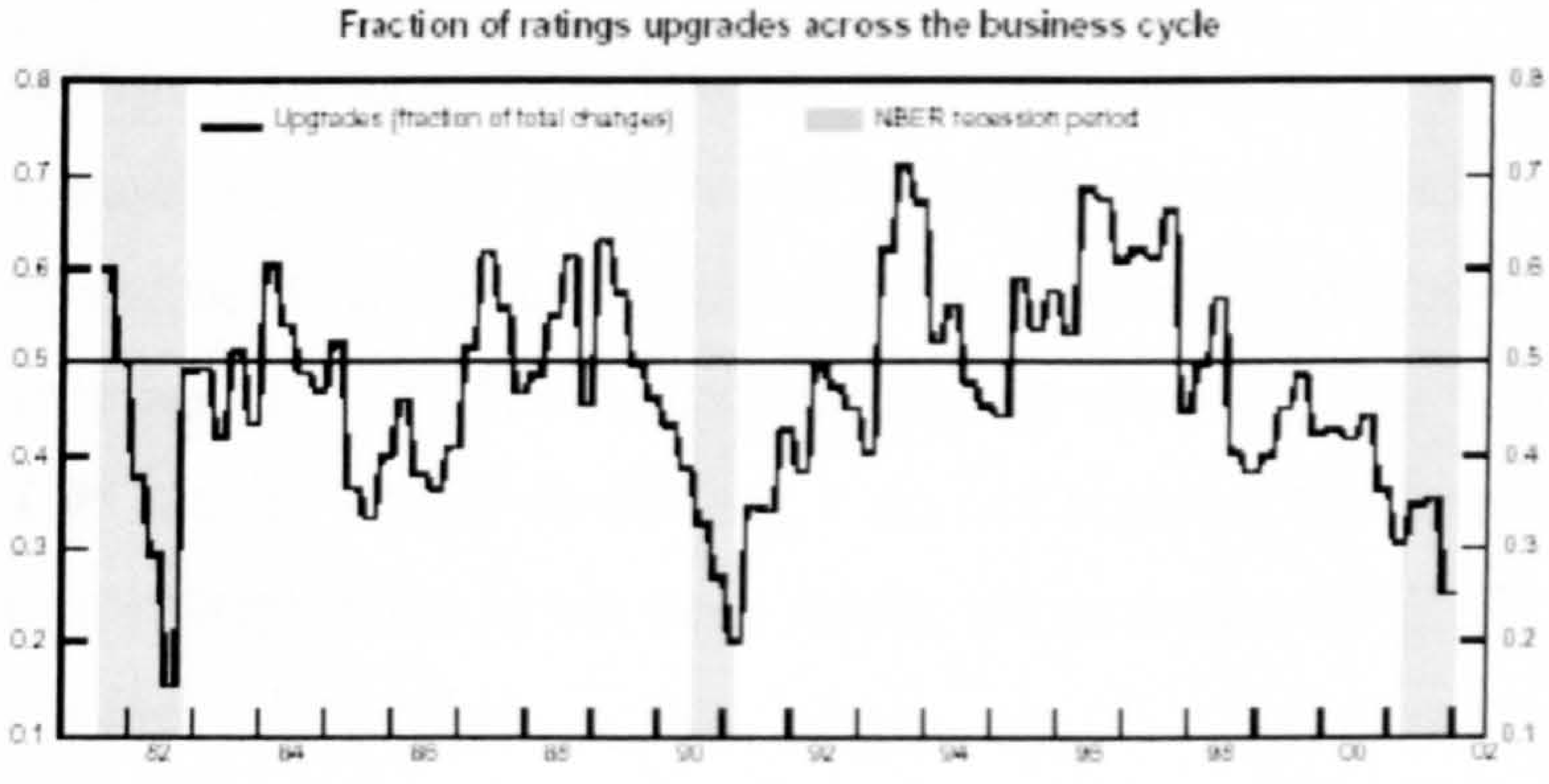
This explanation is useful as it highlights the problems with the "through the cycle" policy and how these problems are dealt with in reality.

Moody's have the same policy as S&P and state that they rate "through the cycle" but in reality their ratings are also cyclical to some extent. "While we say that we "look through the cycle" ...our rating behavior is actually cyclical", Christopher Mahoney, Credit Policy Committee, (Moody's 2003a).

The difference between "through the cycle" and "point in time" rating raises an interesting question for building models to predict credit ratings. Regression estimates of rating determinants implicitly assume that ratings adjust instantaneously to new information. This assumes a "point in time" rating policy which we have established is not the correct model to follow, at least for the three major rating agencies.

Research supports the view that credit ratings are cyclical. Ferri, Liu and Majnoni (2001), Monfort and Mulder (2000), Reisen (2000) and Amato and Furfine (2004) all find evidence that ratings agencies behave cyclically. Figure 2.7 shows the number of rating changes made by S&P that were upgrades in comparison to all changes in a given quarter. The shaded areas indicate recessions as defined by the National Bureau of Economic Research. This suggests that during recessions, rating changes are far more likely to be downgrades than upgrades.

Figure 2.7: The fraction of rating upgrades across the business cycle



Note: The solid line plots the number of upgrades as a fraction of all rating changes (upgrades plus downgrades) in each quarter.

Source: Amato and Furfine (2004)

Figure 2.7 supports the explanation of actual rating activity given by Standard and Poor as "adjustment with phases of the cycle", but can give no indication as to the level of adjustment relative to the total fluctuation of an issuer's underlying risk (or probability of default) at any point in time. Without this information it is not possible to say that credit ratings move procyclically, it can only be concluded that they are cyclical. Nickell, Perraudin and Varotto (2000) also find that there is a higher frequency of downgrades during a recession and a higher occurrence of upgrades during booms.

Many researchers have found that rating agencies move slowly and their ratings are often inflexible (Altman and Saunders 2001a). The same view is held by the market, 71% of institutional investors thought credit ratings on corporate bonds lagged behind an issuers' creditworthiness at any given moment (CFO 2002). At his testimony to the Senate hearing before the Committee on Governmental Affairs (2002) Steven Schwarcz said;

> "There is a recent internal analysis by Standard & Poor's that is publicly available which uses information extracted from its proprietary database on over 9,000 companies with rated debt that confirms the stability of investment grade ratings, finding, for example, that all A- rated companies at the beginning of a given year would have an 87.94 percent chance of maintaining that same rating by year-end" Schwarcz (2002).

The bank rating data from Moody's used for one of the studies in this thesis is shown in table 2.1. The total number of ratings in each category is split between those ratings that have changed within the last 12 months and those that have not changed in more than a year. This shows that higher grade ratings change less frequently than ratings of BBB and below. Rating transitions appear to be much more frequent around the investment grade/sub-investment grade boundary than for BBB+ and above. This is interesting as Johnson (2001) finds that the largest downgrades start from the BBB- grade. The results shown in table 2.1 do not support the findings of previous research that ratings tend to be very static, on average 38% of ratings have changed in the last 12 months.

Table 2.1: Observations of Moody's ratings showing % of ratings that have changed within the last 12 months (data for banks)

	Total no. of ratings	% of ratings that changed within last 12 months	% of ratings that changed > 12 months ago
AAA	109	7.3	92.7
AA+	118	27.1	72.9
AA	260	35.4	64.6
AA-	546	44.5	55.5
A+	437	42.6	57.4
A	422	37.0	63.0
A-	396	39.6	60.4
BBB+	260	35.4	64.6
BBB	180	60.6	39.4
BBB-	126	46.8	53.2
BB	186	44.1	55.9
B	75	61.3	38.7
C	50	52.0	48.0

Data from Moody's (FTCRI)

In a study based on US firms rated by S&P in 1981 – 2001 Amato and Furfine (2004) observe that ratings of most firms change very little and do not exhibit excess sensitivity to business cycles. They test their findings by using a second data set containing only initial ratings and ratings changes. This data does exhibit procyclicality. They also find evidence of procyclicality in investment grade firms. Their findings support the view that the ratings of existing issues are stable but when changes do occur they are procyclical.

In Japan, a review of bank credit ratings over the period 1994 to 2001 has shown a clear example of stability (1994 to the first half of 1997) despite growing concerns about the creditworthiness of some banks. When the Japanese bubble economy burst in the early 1990s confidence fell and a rapid series of downgrades took place in the second half of 1997 and 1998. Japan Center for International Finance (2001) argue that the downgrades came too late and should have taken place before the second half of 1997.

Newspaper articles also accuse the rating agencies of being slow to adjust ratings (Economist 2003a) or over reactive when changes are made (Economist 1999). Ferri et al (1999) argue that agencies failed to downgrade East Asian bonds before the crisis in that region in the late 1990s and when they did the downgrades were late and excessively conservative. This exacerbated the crisis by raising the cost of borrowing and reducing the supply of capital. The poor track record of rating agencies in less developed countries may be due to lack of investment in information gathering in comparison with the US (Ferri 2004).

The agencies and issuers aim for stability and would avoid making a change if there was a risk that the change would shortly be reversed, perhaps this factor explains the high degree of rating stability identified by Amato and Furfine (2004). It is interesting that the chairman of Moody's Credit Policy Committee states,

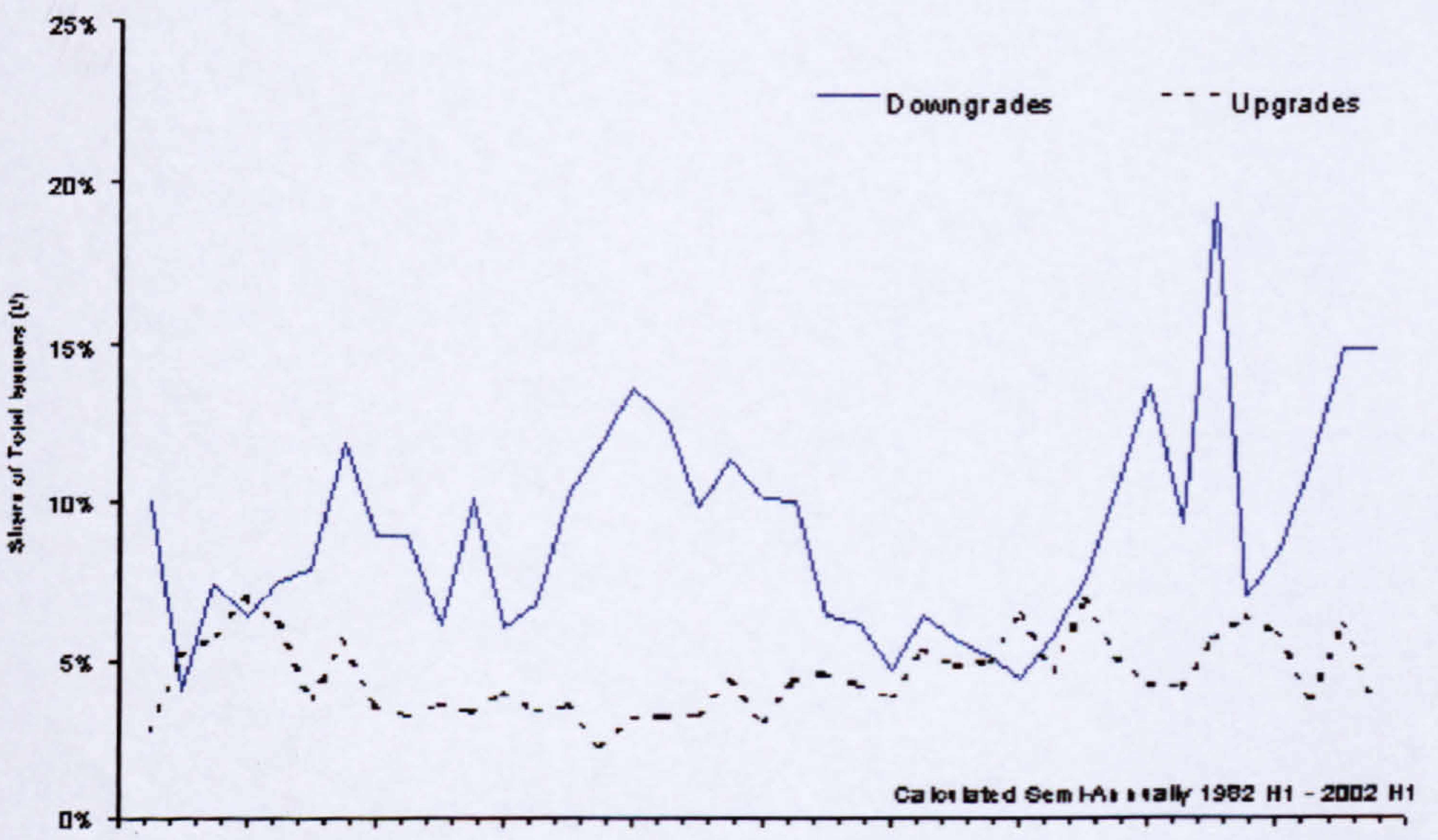
> "Ratings are observed to follow market price movement; yes, that has been empirically observed. But: ratings are intended to provide a stable signal of "fundamentally derived" credit risk. On the tradeoff between accuracy and stability, ratings offer stability." (Moodys 2003a)

Cantor and Mann (2003) demonstrate that credit ratings have been remarkably stable over past credit cycles.

Studies have also shown that rating changes tend to exhibit serial correlation (or serial dependence). Altman and Kao 1992 showed that a downgrade is more likely to be followed by a downgrade and an upgrade by an upgrade. Lando and Skodeberg (2002) also support this finding.

Figure 2.7 has already shown that the number of downgrades exceeds the number of upgrades. Evidence suggests that credit rating agencies are slow to change their ratings but when they do they tend overreact and downgrade more often than upgrade. Blume, Lim and MacKinlay (1998) find that, for the sample they studied, the trend was for credit ratings tend to fall over time as there are more downgrades on average than upgrades. Lucas and Lonski (1992) show that for Moody's, the number of firms downgraded has increasingly exceeded the number upgraded. Figure 2.8 and 2.9 from Moody's (2003a) show the number of downgrades for Moody's relative to upgrades. This supports the finding that the number of downgrades exceed upgrades. Not all studies support the view that ratings become more stringent over time, Amato and Furfine (2004) show that in some cases rating agencies have become more lenient. Feinberg et al (2004) find that Moody's and S&P generally downgrade sooner than D&P and Fitch but all the agencies tend to upgrade at the same time.

Figure 2.8: Comparison of number of downgrades to upgrades from 1982 - 2002



Source: Moody's Investors Service (2003a)

Although studies have drawn different conclusions, it appears that ratings for existing issuers generally appear to be static as agencies rate "through the cycle". However credit ratings are cyclical and when changes are made they can be procyclical and amplify business cycles.

2.5 Summary

This chapter has looked in detail at the credit rating industry, its history and current issues that face the industry. In summary, the main findings which are of most relevance to the rest of this thesis are as follows:

- Credit ratings perform well as measures of relative risk but are not intended to provide a measure of the absolute level of risk of an organisation or issue at all points through the business cycle.
- Regulation has played an important part in establishing the success of the credit rating industry. Basel II increases this regulatory importance but at the same time competition is restricted by the difficultly of obtaining NRSRO status. The credit rating market is dominated by 3 major companies.
- Credit ratings appear to be relatively stable because raters attempt to rate "through the cycle" but there is evidence that when ratings do change they are downgraded more frequently than upgraded; changes and ratings of new issues tend to be procyclical.

The Basel Capital Accord

3.1 Why regulate banks?

Banks are not like other entities because their most important product is money. A loss of confidence in a bank can lead customers to simultaneously withdraw their funds and a lack of liquidity can rapidly erode the net worth of a bank and threaten it with insolvency.

The inherent fragility of the banking system is exacerbated by the fact that there is usually heightened speculative activity by investors during the good times and without regulation banks may not make sufficient provisions for risk. When the downturn comes they could be under capitalised and poorly protected against a liquidity crisis. This contributes to procyclicality and systemic risk.

Heffernan (1996) argues that because the reputation of banks is so important a lack of confidence could subject even healthy banks to a bank run. Problems spread to other parts of the economy and carry a high social cost. She argues that the role of prudential supervision "is to minimise the possibility of financial collapse in the system, because the social costs of bank risk-taking exceed the private costs."

3.2 Banking regulation in the UK and US

Given the sensitivity of the economy to banking crises it is surprising that the first specific banking law in the UK was only introduced in 1979. Two acts in 1844 (control of the money supply) and in 1914 (establishment of the Bank of England as the lender of last resort) regulated the Bank of England but private banks were treated like other commercial concerns. The 1979 Banking Act (amended 1987) required banks and deposit takers to seek recognition from the Bank of England and it was a key factor that the banks had an excellent reputation in the financial community.

There is a far greater range of banking regulation in the US than in the UK. Regulators have sought statutory remedies to problems far more than in the UK which has led to piecemeal legislation and complex banking supervision. Small depositors have great importance in US regulation and their protection is a central pillar of legislation. Another key influence is the American philosophy of free competition in all industries. Concern about potential collusion between banks has also received much weight in the regulation.

3.3 Basel Capital Accord (1988)

In 1988, the Basel Committee on Banking Supervision of central banks and banking regulators from the Group of Ten countries introduced global standards for regulating the capital adequacy of internationally active banks. The Basle Capital Accord 1988 (Basel 1) sets down the agreement to apply common minimum capital standards to banking industries, to be achieved by the end of 1992 (BCBS 1988). The accord is almost entirely addressed to credit risk, the main risk incurred by banks.

The guiding principle of Basel 1 was that banks should have a capital cushion to cover unexpected losses. It attempted to introduce a uniform approach to credit risk and a general methodology for its measurement. Basel 1 defined four risk "buckets" and the minimum capital ratio of 8%. The aim was to minimise the so-called regulatory arbitrage, i.e. where advantages are won by one institution operating in various countries with different regulation of banking and financial activities.

Although Basel 1 represented a huge step forward towards the international harmonization of credit risk regulation it became the subject of heavy criticism. The methodology (i.e. the risk "buckets") was comparatively simple and was applied to all relevant banking institutions. There was a "one-size-fits-all" approach that did not reflect the varying level of economic risk applicable to different assets. For example, a corporate bond of a successful blue chip company is substantially less risky than that of a junk bond. Under Basel 1 a risk weight of 100% is applied to all corporates, irrespective of their relative economic risk. This means that the assets must be included in the capital adequacy calculations at their full value whether the bond is a AAA or a BB-. This did not suit more advanced institutions with a more detailed internal methods of risk analysis and internal modeling expertise.

In 1997, the market risk amendment to the original Basel Accord was adopted. Many banks now use external credit ratings in their prudential supervision solely to determine what is a qualifying debt security, or other interest rate related instrument, for the calculation of the capital requirement for specific interest rate risk. This is set out in the standardised methodology of the market risk amendment to the original Basel Accord.

3.3.1 The Basel Capital Asset Ratio

The capital asset ratio was first introduced in the UK in 1980 by the Bank of England. The Bank of England and US authorities were the first to recognise the importance of the ratio. The definition of capital to risk weighted assets that is still used around the world today was defined by the Basle risk asset ratio, introduced by Basel 1.

Basel risk asset ratio:

$$\frac{\text{Tier one and Tier two capital}}{\text{Risk weighted assets}}$$

The Bank for International Settlements define Tier one capital in their press release (BCBS 1998). It includes equity capital and disclosed reserves:

- issued and fully paid ordinary shares
- non-cumulative preference shares
- share premiums
- retained profits
- general reserves
- legal reserves

Cumulative preference shares and revaluation reserves are excluded. Tier two capital includes all other capital, revaluation and loan loss reserves, cumulative preference shares and subordinated long-term debt.

Risk weighted assets is the multiple of bank assets and one of five risk weights assigned by Basel 1. The higher the risk weight, the riskier the asset. The risk "baskets" are determined as follows (taken from Annex 2 of BCBS 1988):

0% Cash

Claims on central governments denominated and funded in national currency (sovereigns)

Claims on all OECD central governments

Claims on central banks

20% Claims on multilateral development banks and claims guaranteed by these banks

Claims on banks incorporated in OECD and loans guaranteed by these banks

Claims on banks outside OECD with maturity of up to one year

50% Loans secured by mortgage on residential property

100% Claims on corporates

Claims on banks outside OECD with maturity of more than one year

Claims on central governments outside the OECD not denominated and funded in national currency

All other assets

Off-balance sheet assets are also given risk weights and also should be included in the risk weighted asset calculations.

The risk asset ratio must not fall below 8%, an illustration of how this could be calculated is as follows:

Tier one + tier two capital: £1.6 million

On-balance sheet assets	
Cash	£5 million
Government Bonds (OECD)	£10 million
Claims on OECD banks	£7.5 million
Mortgages	£12 million
Claims on Corporates	£12 million
Total	£46.5 million

After applying the risk weights, risk weighted assets sum to:
(5 x 0) + (10 x 0) + (7.5 x 0.2) + (12 x 0.5) + (12 x 1) = £19,500,000

Risk ratio = 100 x 1,600,000/19,500,000 = 8.2% which is just inside the minimum of 8%.

3.4 Basel II: International Convergence of Capital Measurement and Capital Standards: a Revised Framework

In June 1999 the Committee released a proposal for a new Capital Accord to replace Basel 1, the progress of publications has been as follows:

June 1999	First Consultative Paper on Basel II, setting out broad overview proposals
January 2001	Second Consultative Paper on Basel II, providing detailed proposals
Since April 2001	A series of Quantitative Impact Studies (QIS) to assess the impact of the proposal on a wide range of banks
April 2003	Third and final Consultative Paper, consultation period until end of July 2003
November 2005	Latest draft of International Convergence of Capital Measurement and Capital Standards: a Revised Framework
2006	Implementation into EU law
2007	Implementation of Basel II

3.4.1 The three pillars of Basel II

The overall objective of Basel II (BCBS 2005) is to increase the safety and soundness of the international financial system by:

- making capital requirements for banks more risk sensitive while,
- maintaining the same level of overall average regulatory capital in the banking system.

Although Basel II focuses primarily on internationally active banks, the Committee expects the New Accord to be adhered to by all significant banks worldwide. However US authorities have limited the application of Basel II to about a twenty internationally active banks. The EU plans to make the New Accord applicable to all banks and investment firms in the region.

The New Accord aims to establish regulatory capital requirements that more closely reflect the true economic risks that banks face. Its sets up a system that is conceptually more in line with banks' own efforts at measuring risk. Basel II is not intended to change the aggregate level of capital in the system. Rather, the proposal aims at reallocating capital requirements, aligning regulatory capital more closely to economic risk. This means that more capital will be needed for the riskier activities and less for those where there is little risk, departing from the "one-size-fits-all" approach of Basel 1. Also, increased risk sensitivity should provide an incentive for innovation, encouraging more sophisticated risk management systems and practices.

The underlying rationale of Basel II is the Committee's conviction that safety and soundness in today's dynamic and complex financial system can be attained only by the combination of effective bank-level risk management, supervision, and market discipline. Consequently, the New Accord proposes a system based on a model of three mutually reinforcing pillars.

Figure 3.1: The Three Pillars of Basel II

PILLAR I	PILLAR II	PILLAR III
MINIMUM CAPITAL REQUIREMENTS	**SUPERVISORY REVIEW**	**DISCLOSURE**
Credit Risk (new measurement) **Market Risk** (unchanged) **Operational Risk** (new)	Additional capital requirements (discretion of national supervisors)	Increased market discipline

3.4.1.1 Pillar I: Minimum capital requirements

The rules contained in Pillar I set out the minimum ratio of capital to risk-weighted assets.

The current definition of capital and the 8% minimum capital requirement remain unchanged. However, the way that risk weights are determined will become more risk sensitive.

Regulatory Capital Under Basel II

r x A = RWA -> RWA x 8% = RC

r = risk weight	RWA = risk-weighted assets
A = assets	RC = regulatory capital

In departing from the current Accord, the Committee advances three approaches to measure credit risk and the resulting capital requirements:

- Standardized Approach
- Internal ratings-based (IRB) Foundation Approach
- IRB Advanced Approach

The standardized approach is a relatively simple method conceptually in line with the existing approach. This will be used by small banks with less sophisticated risk management tools and larger banks during the transition period.

Under the New Accord, there will be more risk sensitivity since risk weights are to be refined by reference to a rating provided by an external rating agency. For example, the 1988 Accord provides only one risk weight category for ordinary corporate lending (100%), whereas Basel II will provide four categories (20%, 50%, 100% and 150%).

Both IRB approaches are more sophisticated methods to measure credit risk and allow banks' internal estimates to serve as primary inputs to the determination of capital. Whether a bank can opt for IRB Foundation or Advanced approaches is contingent upon its supervisor's authorization and depends on whether the bank can provide internal data verifying its calculations of probabilities of default (PD) or, in the case of the IRB Advanced Approach, all relevant variables (PD, loss given default (LGD) and exposure at default).

Whereas credit risk rules are refined by Basel II, the treatment of market risk is unchanged compared with the 1996 amendment to the 1988 Accord. For the first time, an explicit treatment of operational risk (e.g. the risk of loss from IT failures) is included.

Basel II sets out three approaches to be used to determine the capital requirement for operational risk. The Basic Indicator Approach (BIA) and the Standardized Approach (STA) are based on gross income in the bank, whereas the Advanced Measurement Approach (AMA) will give banks more flexibility to develop more sophisticated methods to measure operational risk. Banks may rely on their own calculation methods for operational risk, provided these methods are comprehensive and systematic.

3.4.1.2 Pillar II: Supervisory review of capital adequacy

The second pillar of the New Accord provides for supervisory review of banks' capital adequacy and their internal assessment processes. National supervisors will be responsible for evaluating and ensuring that banks have sound internal processes in place to assess the adequacy of their capital and to evaluate their risks and can impose additional capital requirements.

3.4.1.3 Pillar III: Disclosure/market discipline

Finally, Basel II promotes market discipline through enhanced disclosure requirements for banks, e.g. regarding the risk measurement methods used. This increased transparency should give market participants a better idea of a bank's risk profile and its capital cushion. Pillar III is intended to be a complement to the minimum capital requirements and the supervisory review process.

In summary, Basel II provides for a more risk-sensitive determination for capital adequacy and, for the first time, requires capital for operational risk. It also establishes supervisory review and calls for new disclosure rules, intended to increase market discipline.

3.4.2 A detailed review of the Standardised approach

A summary of the proposals detailed in Pillar I: Minimum capital requirements are set out below:

3.4.2.1 Claims on sovereigns

Sovereigns and their central banks will have the following risk weights:

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to B-	Below B-	Unrated
Risk Weight	0%	20%	50%	100%	150%	100%

Country risk scores assigned by Export Credit Agencies can also be used and risk weights are shown in Basel II.

Under Basel 1 sovereigns and their central banks have a risk weight of 0% unless they are outside the OECD and not denominated in national currency or funded in that currency, in which case the risk weight is 100%.

3.4.2.2 Claims on banks

There are two options for claims on banks, national supervisors will decide which to apply:

(1) All banks incorporated in a given country will be assigned a risk weight one category less favourable than the sovereign of that country.

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to B-	Below B-	Unrated
Risk Weight	20%	50%	100%	100%	150%	100%

(2) The risk weighting will be based on the external credit assessment of the bank itself. Preferential rates are available for claims with an original maturity of three months or less.

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to B-	Below B-	Unrated
Risk Weight	20%	50%	50%	100%	150%	50%
Risk Weight – short term claims	20%	20%	20%	50%	150%	20%

Some special cases have been written into the accord, certain banks, such as the Bank for International Settlements and the IMF have risk weights of 0%. Public sector entities will be attributed risk weights using option 1 or 2 for banks at the regulator's discretion. Multilateral development banks (MDB's) will be given risk weights according to option 2 for banks. Certain MDBs such as the World Bank Group and European Bank for Reconstruction and Development will have risk weights of 0%.

Under Basel 1, Banks incorporated in the OECD and claims on non-OECD banks with maturity of up to one year had a risk weight of 20%, all other banks had a risk weight of 100%

3.4.2.3 Claims on corporates

Corporates, including insurance companies have risk weights as follows:

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BB-	Below BB-	Unrated
Risk Weight	20%	50%	100%	150%	100%

At national discretion supervisors may allow banks to use a uniform risk weight of 100% for all corporates.

Under Basel 1 all corporates had a risk weight of 100%.

3.4.2.4 Claims on retail portfolios

If exposure is to an individual or a small business, if it relates to credit cards or overdrafts, personal loans or leases, small business facilities, bonds or equities it will qualify as a regulatory retail portfolio and be risk weighted at 75%. Clearly, there are no requirements for external ratings for retail claims.

3.4.2.5 Claims on residential mortgages

Lending fully secured by mortgages on residential property will be risk weighted at 35%.

3.4.2.6 Claims on commercial real estate

Mortgages on commercial real estate will be risk weighted at 100%.

3.4.2.7 Off-balance sheet items

Off-balance sheet items should be converted into credit exposure equivalents and given risk weights just like on-balance sheet claims. If the commitment has an original maturity of up to one year it will be given a risk weight of 20% and if more than one year a risk weight of 50%.

3.4.2.8 Securitisation

The risk-weighted amount of a securitisation exposure is computed by multiplying the amount of the position by the appropriate risk weight determined in accordance with the table below.

For B+ assessments and below the bank is required to deduct the securitisation exposure from regulatory capital, the deduction will be taken 50% from Tier 1 and 50% from Tier 2.

Long-term rating category

External Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to BB-	B+ and below or unrated
Risk Weight	20%	50%	100%	350%	Deduction

3.4.2.9 Credit risk mitigation (CRM)

Off-balance-sheet items under the standardised approach will be converted into a credit exposure equivalents amount. There is a general principle that no asset with credit risk mitigation should receive a higher risk weight than one without CRM. The mitigation can itself give rise to a legal, operational, liquidity or market risk so controls need to be in place and supervisory review via Pillar II. Basel II details the treatment of claims were the credit risk has been mitigated by one of the following techniques:

Collareralised transactions

Two methods are available. In the simple method the risk weight of the collateral should be used in place of the risk weight of the underlying claim. In the comprehensive method a fuller offset is made of the collateral against the underlying exposure.

Guarantees by third parties and credit derivatives

The guarantee or derivative can only be taken into account if the guarantee has a lower risk weight than the underlying exposure.

Short term claims

Short term assessment may only be used for short term claims as follows.

Credit assessment	A-1/P-1[1] F1[2]	A-2/P-2 F2	A-3/P-3 F3	Others
Risk weight	20%	50%	100%	100%

On-balance sheet netting

This is where banks agree to net loans owed to them against deposits from the same counterparty. The net credit exposure should be used to assess the appropriate risk weight

Maturity mismatch

Where the maturity of the CRM is less than the underlying credit exposure there is a maturity mismatch. Where the CRM has a residual maturity of less than one year the CRM is not recongnised in the process of determining the capital requirement. Otherwise a partial recognition of the CRM is made depending on the time to maturity of the CRM and the exposure.

3.4.3 External credit assessments

External credit assessments from approved external credit assessment institutions (rating agencies) can be used to assign risk weights to sovereign, bank and corporate claims. National supervisors will be responsible for giving rating agencies agency status. They must meet the following six criteria:

- Objectivity – agencies must have a systematic and rigorous methodology for assigning credit assessments.
- Independence – the rating should not be influenced by political or economic pressures.
- International access/transparency – the rating should be available to domestic and foreign institutions at equivalent terms.
- Disclosure – methodologies, meaning of ratings and default rates should be published.

[1] Notations used by Standard & Poor's and Moody's respectively
[2] Notation used by Fitch, this has been added to this table and not included in Basel II

- Resources – agencies need to have the resources to perform a detailed, high level assessment. They should use quantitative and qualitative approaches.
- Credibility – if agency ratings are widely relied upon this shows their credibility.

If supervisors consider that an agency meets these criteria they will give them agency status and banks can use their risk assessments to determine the appropriate risk weight to be used in the calculation of capital adequacy. Many small national agencies that only operate in one country may achieve recognition in their home country which will provide a great boost to the credit rating industry outside the US. One possible problem with this is that the rating scales used in a single country are intended to reflect credit worthiness in a local context and may not be directly comparable with global agencies (Griep and De Stefano 2001).

3.4.3.1 Multiple assessments

Banks must choose the agency's that they are going to use, disclose the names of these agencies and then apply them consistently across all types of claim. It is not possible to "cherry pick" different assessments to achieve the lowest risk weighting.

If there are two assessments from different agencies that map into different risk weights the higher risk weight is applied. If there are three or more assessments with different risk weights the lowest two risk weights are compared and the higher of the two risk weights is applied.

Rating agencies usually produce an issuer rating and an issue-specific rating. If a bank holds a particular bond issue the credit rating used should be the rating for that issue-specific investment. The issuer rating typically applies to senior unsecured claims. Only senior claims on that issuer should use an issuer rating, if the claim is of a lower quality and has no issue-specific rating it should be treated as unrated.

Table 3.1 shows 14 claims in an imaginary bank portfolio, all are senior unsubordinated claims. The bank uses the credit assessments from Moody's, S&P and Fitch. Fictitious long and short term ratings have been created for each issue and are mapped to the appropriate risk weight. Note that this example only covers the type of claims which would be risk weighted using external assessments; corporate, sovereign and bank.

Using this information a risk weight has been attributed to each issue and is shown in table 3.1.

Table 3.1: Basel II risk weights for an imaginary portfolio

Issuer	Fitch	S&P	Moody's	Short-term rating	Basel risk weight	Risk weighted assets
Asda Group plc (corporate)	20%		20%		20%	2,500,000
Hanson PLC (corporate)	100%	50%	100%		100%	55,000,000
Hilton Group PLC (corporate)	50%	100%	100%		100%	12,500,000
Anglian Water PLC (corporate)	50%	50%	50%		50%	5,000,000
La Poste (corporate)	20%	20%			20%	14,000,000
Dixons Group plc (corporate)	50%		20%		50%	20,000,000
Landesbank Hessen-Thuringen Girozentrale (bank)	20%	20%	20%		20%	2,000,000
Union de Banques Arabes et Francaises (bank)				50%	50%	1,500,000
Bank of Scotland (bank)	20%	20%	20%		20%	14,000,000
Bank of Scotland (bank)	20%	50%	20%		50%	35,000,000
Alliance & Leicester (bank)				20%	20%	10,000,000
Landesbank Baden-Wuerttemberg (bank)				20%	20%	2,000,000
Bremer Landesbank (bank)	20%	50%	20%		50%	5,000,000
Poland (sovereign)	50%	50%	20%		50%	12,500,000
						191,000,000

In this simple example the risk weighted assets would require a regulatory capital for credit risk of at least:

191,000,000 * 0.08 = 15,280,000

The final level of regulatory capital under Basel II would also take into account the operational risk and market risk.

3.5 How is Basel II going to affect banks?

During the development of the Basel II proposals five Quantitative Impact Studies (QIS) have been untaken (the results of QIS 4 and 5 have not been published at March 2006). The purpose of these is to allow the Basel Committee to gauge the impact of the Basel II proposals. QIS 3 (BCBS 2003a) was published in May 2003 and involved 365 banks from 43 countries. The banks were asked to quantify the impact of the proposed capital adequacy regime on their existing portfolios.

The banks were split by region and by size. The regions were G10, EU and other; the sizes were one and two. Group one contained banks that are large, diversified and internationally active. That was defined as those having a Tier 1 capital of more than euros 3 billion. Group two banks are smaller and often more specialized. One feature of group two banks is that they often have a higher proportion of retail activity.

The variations in the results by region and by bank size are shown in table 3.2.

Table 3.2: QIS3 World-wide results – overall percentage change in capital requirements

	Credit risk			Operational Risk
	Standardised	IRB Foundation	IRB Advanced	
G10 Group 1	11%	3%	-2%	8 – 10%
G10 Group 2	3%	-19%	n/a	12 – 15%
EU Group 1	6%	-4%	-6%	8 – 10%
EU Group 2	1%	-20%	n/a	12 – 15%
Other Groups 1 & 2	12%	4%	n/a	11%

Source: Adapted from QIS 3 (2003a)

In all cases the capital requirements go up under the standardised approach. This is as the Committee intended as they want to provide an incentive for banks to apply one of the IRB approaches.

The fall in capital requirements for G10 and EU group 2 banks under foundation IRB is due to the fall in risk weights for retail portfolios from 100% to 75%. This particularly affects the smaller banks as they have a higher proportion of retail customers. The Advanced IRB (AIRB) option is only used by larger banks due to its additional complexity over Foundation IRB (FIRB). The estimates of operational risk capital requirements use the Standardised treatment. The Committee state in QIS 3 that where credit risk capital requirements have fallen using the standardised approach or the FIRB approach, the new operational risk capital requirements more than outweigh any reduction in credit risk capital requirements. This means that the overall minimum regulatory capital in the banking system will be about the same after the

implementation of Basel II as it is now. This was the goal of the Basel Committee and they seem to have achieved their target (Economist 2003c).
However there are criticisms of "cliff effects" (Royal Bank of Scotland 2003) as you move from IRB foundation to IRB advanced. Examples of this are G10 Group 1 from FIRB to AIRB or G10 Group 2 from Standardised to FIRB. RBS argue that this creates perverse incentives to adopt one method or another.

The figures in table 3.3 show the overall percentage change in capital requirements over seven different types of portfolio. These break down as follows:

Table 3.3: QIS 3 Change in capital requirements – Standardised approach

Portfolio	**G10**		**EU**		**Other**
	Group 1	Group 2	Group 1	Group 2	Groups 1 & 2
Corporate	1%	-1%	-1%	-1%	0%
Sovereign	0%	0%	0%	0%	1%
Bank	2%	0%	2%	1%	2%
Retail	-5%	-10%	-5%	-7%	-4%
SME[3]	-1%	-2%	-2%	-2%	-1%
Securitised assets	1%	0%	1%	0%	0%
Other portfolios	2%	1%	2%	-1%	3%
Overall credit risk	0%	-11%	-3%	-11%	2%
Operational risk	10%	15%	8%	12%	11%
Overall change	11%	3%	6%	1%	12%

Source: QIS 3

Table 3.3 shows that for certain banks and portfolios a reduction in the credit risk capital requirement can be anticipated under the standardised approach. For corporate, sovereign and bank claims there is very little change overall although individual banks will fluctuate greatly around these averages.

In summary, QIS 3 suggests that for the standardised approach there will be an increase in credit risk capital requirements for G10 Group 1 banks but a slight decrease for all other groups. These decreases will be more than offset by increases in capital required by the new operational capital risk requirements. In the Foundation IRB approach, Group 1 banks, on average, report only small changes to current

[3] SMEs may be treated as retail or corporates depending on the nature of their business

requirements but G10 and EU Group 2 banks show substantial reductions. This is the result intended by the Basel Committee. Group 1 banks should be incentivised to use AIRB while Group 2 banks should be encouraged to use the FIRB rather than the standardised approach.

3.6 Main concerns with Basel II

The stated objective of Basel II is to increase the safety and soundness of the international financial system. While market participants would not disagree with this goal the new regulations have not met with universal support. Six key areas which have caused controversy are discussed below.

3.6.1 Cost and rigidity

> "There is a very real risk that the current level of complexity will impact, now and in the future, the ability of banks to mange risks, the ability of supervisors to supervise, and the capacity of markets to evolve and adapt. These are not trivial flaws." Royal Bank of Scotland (2003)

Basel II is a long and complicated document. The nature of banking regulation is inherently a complex area and the final document has evolved thorough a process of interested parties providing feedback on consultative documents. As a consequence complying with the new Basel II rules will be very costly and complex. For example Royal Bank of Scotland (2003) comment that "the pillar 1 rules are highly complex and have developed beyond the level needed for sensible capital regulation".

Credit Suisse Group (2003a) estimate that the initial cost to implement Basel II will be about $100 million with considerable ongoing costs. Other estimates put the global spending related to Basel II at $7.5 billion for 2003 and $11 billion in 2005 (Sidler and David 2003).

The industry feels that the rules are too prescriptive and detailed. Regulation that aims to establish principles rather than rules may allow for a more flexible and longer lasting system. Many banks also believe that the Accord will stifle innovation in risk management. BNP Paribas's comments reflects this view;

> "We believe that Pillar I is excessively legalistic, with overwhelming data collection and validation requirements. In practice, these requirements could become a costly ceiling on risk management practices, fixing risk management into an overly rigid structure and stifling further innovation and experimentation." BNP Paribas (2003)

Implementation costs will also be substantial for supervisors. Credit Suisse Group (2003b) argue that many supervisors in non-G10 countries are not up to speed with the new rules. America's Community Bankers (2003) also voice their concern in their comments;

> "Although the most recent version of the Accord is less detailed than previous versions, it remains an extremely complex document and few industry representatives and supervisory personnel will have a good grasp of all of the provisions and intricate details. With that being the case, there is concern about how such a sophisticated and complex capital accord can be adequately implemented, supervised and enforced."

Banks in emerging markets feel that the complexity of the regulation imposes a particularly onerous burden and so places them at a disadvantage compared to banks from more developed countries. The Reserve Bank of India (2003) makes this comment;

> "The complexity and sophistication essential for banks for implementing the New Capital Accord restricts its universal application in the emerging markets. Banks in these emerging markets form a significant segment in financial intermediation and are likely to find implementation of the New Capital Accord a major challenge in the medium term. Besides banks, supervisors would be required to invest considerable resources in upgrading technology systems, and human resources to meet the minimum standards. Banks in emerging markets would, therefore, face serious implementation challenges due to lack of adequate technical skills, under development of financial markets, structural rigidities and less robust legal system."

3.6.2 The lack of a level playing field

"It came as an enormous surprise to some observers, including this writer, that only the largest 10 U.S. banks, and perhaps the next 10-20 banks in terms of asset size, would be required (top 10) or will have the option (next 10-20) to follow the advanced Internal Rate Based (IRB) version of Basel II's Accord." Altman (2003)

Altman's comment reflects the view of many observers. How can a level playing field be established when some regulators are applying Basel II, others are not and still others will be using some combination of the 44 possible areas of national discretion[4]?

The reasons why the US is only requiring the top 20 internationally active banks to apply Basel II are as follows:

- Basel II is complex and costly to introduce and enforce.
- The U.S. banking system is presently more than adequately capitalized.
- The added Basel II capital required for operating risk is highly arbitrary and based on variables that are extremely difficult to measure.
- The Federal Reserve System's, and other Bank Regulatory agencies', policy of "prompt corrective action," and maximum leveraged ratios, when bank capital falls below a certain specified level has worked well in the U.S. and is not specified as part of Basel II - even in pillar 2's regulatory oversight.

In contrast, in the EU Basel II will be written into law to be applied to all banks and investment firms regardless of size and scope. China and India have opted out entirely. Japan may apply Basel II in a less stringent way as their banks presently have a relatively weak capital buffer. Emerging market countries will struggle to apply the Accord in full as they lack resources as discussed above.

As supervisors in local markets adopt their own approaches and strategies the principle of a level playing field is seriously undermined.

There is also a level playing field issue between banks and non-banks. Other financial institutions are not subject to rules and requirements along the lines of Basel II. There

[4] "The leaning Tower of Basel", Financial Times June 19, 2004 p. 14

is an argument that this will place banks at a relative disadvantage compared to non-bank competitors.

3.6.3 Procyclicality

The issue of procyclicality has already been discussed in some detail in chapter two. There is a concern that banks will lend large amounts of money in the good times but not provide enough capital for the bad times. When recession comes banks will be undercapitalized and finance will not be available just at the time customers need it.

This is not a new phenomenon but research by Credit Suisse has suggested that Basel II will greatly exacerbate the problem:

> "We have analyzed this effect over the last 20 years of credit cycles. Our calculations suggest that the impact on required bank capital will be substantial. In particular, the new Basel II calculations could require much more bank capital during economic recessions than the current system. " Ervin (2003)

The reason for this increase is that the current system is relatively insensitive to downgrades but under the new accord additional capital will be required if credit assessments are downgraded. In theory credit ratings should be steady through the cycle, as discussed in chapter two, but in reality agencies can be slow to change ratings and then overreact and downgrade more often than upgrade. Between 2000 and 2002 many companies have been downgraded and Ervin goes on to say;

> "My personal estimate is that my bank [CSFB] would have cut back its lending by perhaps an additional 20% to 30% if the Basel II rules were in place during 2002. If all banks cut back at the same time, the potential adverse impact on the real economy could lengthen and deepen the recession. "

Some commentators have suggested that capital requirements are tightened in the upswings and eased in downswings (Borio 2003). Altman (2003) makes a similar comment, "I suggest that the FED consider a more smoothed capital allocation system to even out the normal fluctuations in bank reserves, capital allocations and lending behavior. This would require more capital to be set aside in good times and less during periods of stress."

Altman and Saunders have written several papers in response to the first two consultative documents for the New Accord (Altman and Saunders 2001a, 2001b and Altman and Saunders 2002). In the first they argue strongly that relying on traditional agency ratings could produce procyclical effects as agency ratings lag capital requirements. They show that the percentage of issuers in the higher risk buckets peaks at the bottom of the economic cycle exactly when problems would be exacerbated by belated hikes in capital requirements. They also argue that the corporate risk buckets are too broad and do not reflect the relative risk of unexpected losses on loans in each bucket. Their concern is that the size of relative risk weights could induce banks to risk-shift towards riskier borrowers.

3.6.4 Expected and unexpected losses

Under Basel II there are capital charges for unexpected and expected losses. Expected losses are covered by provisions but unexpected losses cannot be anticipated by their very nature. Existing practice requires banks to make capital charges only for unexpected losses. Expected losses are dealt with differently, through provisions and pricing.

The Americans have raised an objection about this definition of capital under Basel II and therefore the amount that banks will have to set aside. In particular, they are concerned about capital charges for expected losses. Partly as a result of QIS3, the magnitude of this new charge has become clear. American banks, which have a large amount of business from credit-card and small-business loans, on which expected losses are high, pushed for a revision to Basel II.

Examples of respondents to the Basel II consultative document who expressed this view were Citigroup, Fortis Bank, Risk Management Association and Bank One.

In their press release of 11 October 2003 the members of the Basel Committee announced that they were "changing the overall treatment of expected versus unexpected credit losses" (BCBS 2003b). Which means that they are accommodating the American view and using a definition of capital that only includes unexpected losses. American approval of the Accord is essential and the Basel Committee has little choice but to review this issue.

3.6.5 Operational risk charge

One of the most controversial areas of the New Basel Accord is the operational risk charge. Opponents to the inclusion of this risk in Pillar 1 say that it is a fundamentally different risk from capital and market risk. It is the risk of IT problems or internal control failures. It can be argued that these types of risk are mainly driven by the control environment of the bank so could be dealt with as part of Pillar 2.

The comments to Basel II appear to be split, for example "Citigroup strongly supports [the] inclusion [of operational risk] within Pillar I, as the only way to achieve consistency and transparency in the banking system for a very real risk area" (Citigroup 2003).

In contrast, the Credit Suisse Group (2003b) argues strongly that operational risk should be included as part of pillar II as does the Hong Kong Association of Banks (2003), Merrill Lynch & Co (2003) and many other of the 200 banks that replied.

The issues concerning operational risk are not dealt with in detail in this thesis as the key area of concern is external credit assessments and split credit ratings.

3.6.6 Disclosure requirements

Generally banks are in agreement that market discipline could be enhanced by increased public disclosure so the principle of Pillar III is supported. However there is a general feeling that the emphasis should be on quality not on quantity and the balance of Pillar III is still too strongly weighted towards quantity.

3.7 Annex 2: Standardised approach - implementing the mapping process

Basel II gives details of the way in which credit assessments should be mapped to particular risk weights for use in the standardised approach. However, different rating agencies have different rating scales so how should agency ratings be mapped to particular credit assessments?

Annex 2 of Basel II details how supervisors should check and monitor this mapping process. A study presented in chapter six shows that even using a broad scale of letter grades[5] only 63% of credit ratings agree. If the level of agreement between agencies is low there are inherent problems with taking ratings from a wide variety of different agencies and mapping them to the same risk assessments.

One of the main findings to have emerged from the literature to date is that split ratings arise because the rating scales of agencies differ (Beattie and Searle 1992a, Cantor and Packer 1997). For example, an A- given by Moody's is not the same as an A- given by Japan Credit Rating Agency (JCR). These studies have shown that some agencies assign systematically higher ratings than others. This finding is very important for Basel II as the Committee and supervisors have to decide on broad tolerance levels based on cumulative default probabilities, i.e. at what point an A- given by one agency is not the same as an A- given by another.

Tolerance levels will be based on default rate statistics published by the agencies. The following section considers the annual probability of default and cumulative default ratings which are used in the mapping process.

3.7.1 Default rate statistics

3.7.1.1 Annual probability of default

Moody's and S&P calculate the annual probability of default as the ratio of defaulted issuers during a year divided by the number of issuers that could have defaulted during the year (measured at the beginning of the year). Moody's state that the issuer is the unit of study rather than outstanding dollar amounts because the likelihood of default is the same for all of a firm's debt issues (Moody's 2002). Alternative methodologies weight default rates either by the number of bond issues or their par amounts. The argument for this is that weighted average techniques correctly bias results toward the larger-issue years (Caouette, Altman and Narayanan 1998).

The issuer rating is used rather than an issue rating. The rating that is considered is the company's senior unsecured debt, if there is no such rating a statistically derived rating is used. This is referred to as the "implied senior rating".

[5] Letter grades used for this comparison are AAA,AA,A,BBB,BB,B,CCC,CC/C,D. The map used is shown in Appendix 2.

3.7.1.2 Cumulative default rates

A cumulative default rate is the sum of default experience over successive years. Moody's and S&P calculate their cumulative rates using slightly different methodology.

Moody's employs a dynamic cohort approach to calculating multi-year default rates. A cohort consists of all issuers at the start of a given year. These issuers are then followed through time, keeping track of when they default or cease to be rated (i.e. when they mature). These cohorts are dynamic and allow the estimation of cumulative default risk over many years. For each year the default rates are calculated as the ratio of issuers who did default to those bonds that were outstanding at 1 January of that year and therefore members of that cohort.

Standard and Poors employs static pools. A static pool is formed at the start of each year and followed from that point on. The pools are called static because their membership remains constant over time. This is where they differ from the dynamic cohorts which are updated on 1 January of each year. S&P form a new static pool each year. It is possible to aggregate cohorts across years (Bessis 2002) but not static pools (Standard and Poor 2002b).

The clearest definition of how cumulative average default rates (CDRs) are calculated is contained in Standard and Poor's 2002 Ratings Performance. Default rates are calculated for all static pools, these are split into sub-portfolios by rating grade and weighted by the numbers of issuers per rating per pool. Cumulative average default rates are derived from accumulating these results.[6] Caouette, Altman and Narayanan 1997 give and example of the calculation of CDRs.

> "For instance, the average first-year default rate on 'A'-rated companies for all 22 pools [the study is over 22 years] was 0.05%. Similarly, the second- and third-year averages were 0.10% for the first 21 pools and 0.13% for the first 20 pools [the number of pools will drop as each year passes]. Accumulated, these percentages produced ... 0.05%, 0.15%, and 0.28%. As these cumulative average default rates are a distillation of default experiences across all pools,

[6] There are alternative methods to calculate cumulative default rates, these are detailed in full in Chapter 15 of Caouette, Altman and Narayanan 1997

they could be used by an investor to assess the default expectation associated with particular ratings over different time horizons."

3.7.2 The Standardised approach and mapping risk weights

Annex 2 to Basel II proposes a system to check that the rating scale of an approved rating agency lies within an acceptable tolerance. The intention of this is to ensure that the mapping of credit assessments to risk weights is applied consistently whichever agency is used. It is of particular concern if a rating agency's current default experience for a particular credit assessment is markedly higher than international default experience.

Figure 3.2: Comparisons of Cumulative Default Rate (CDR) measures

International experience (derived from the combined experience of major rating agencies) *Set by the Committee as guidance*	Compare to ◀————▶	**External Credit Assessment Institution** *Calculated by national supervisors based on the agency's own default data*
Long-run "reference" CDR	◀————▶	Ten-year average of the three-year CDR
CDR Benchmarks Monitoring level and trigger level		Two most recent three-year CDR

There are two comparisons that need to be made, these are both comparing the international experience of major agencies with the individual default data of the rating agency. The international experience is measured by reference rates and benchmarks recommended by Basel II.

The Long-run "reference" cumulative default rate (CDR) is based on the Committee's observations of the default experience reported by major rating agencies internationally. Ten-year average of the three-year CDR is calculated from default rates published by the agency. This measure is for guidance only rather than a strict target.

Supervisors should also look at the CDR benchmarks set by the Committee and compare these to the two most recent three-year CDRs of the agency. There will be a monitoring level and a trigger level set by the Committee. Exceeding the monitoring level implies that the agency's current default experience for a particular credit assessment is markedly higher than international experience. However, it would not be necessary to change the associated risk weights unless they considered the default rates to be caused by the agency's weak standards in assessing credit risk. Exceeding the trigger level implies that the default experience is considerably higher and a change to the risk weights should take place if the trigger level is exceeded for two consecutive years.

The benchmarks suggested in Annex 2 are static and there is no provision for these to change over time or with an economic downturn. In their response to Basel II, Fitch Ratings suggest that the reference CDRs and Benchmark CDRs should move and be updated annually. They point out that ratings are not static or absolute but are a relative measure of risk. Studies such as Cantor and Packer 1995 support this view. Therefore the CDRs should not be static and if an agency does not meet the benchmarks in one year their default rates should be checked against the figures for the last two years; if there has been an economic downturn that may have increased default rates. They argue that there is a risk that agencies could be delisted during prolonged recessionary periods under the existing draft of Annex 2 (Fitch Ratings 2003). However, agencies state that they rate "through the cycle" so ratings should not be affected by short term economic fluctuations.

There are detailed data requirements for this process. The Czech National Bank makes the observation in their comment to Basel II that some smaller agencies do not have the data available to calculate these CDRs and suggest an alternative method (Czech National Bank 2003).

3.7.3 Comparison of agency CDRs

Using Moody's as an example and using the latest published cumulative default figures (Moody's Investor Service 2006) the ten year average of the three-year CDR and two most recent three-year CDRs would be calculated as follows:

Table 3.4: Moody's ten year average of the three-year CDRs

10 year average of the 3 year CDRs	2003	2002	2001	2000	1999	1998	1997	1996	1995	1994	10 yr Avg.
Aaa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Aa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A	0.00	0.32	0.66	0.35	0.18	0.09	0.00	0.00	0.00	0.00	0.16
Baa	0.20	1.58	1.99	2.23	1.41	1.10	0.74	0.17	0.00	0.20	0.96
Ba	1.82	3.89	4.89	4.64	6.60	6.02	5.28	2.34	2.04	2.05	3.96
B	6.38	13.31	25.59	25.41	26.07	18.93	12.01	9.25	10.11	12.49	15.96
Caa-C	37.06	51.85	57.68	54.40	52.96	41.32	40.29	27.85	21.04	24.31	40.88

Table 3.5: Comparison of Moody's Long-run "reference" CDR per Annex 2 and ten-year average of the three-year CDR

%	Long-run "reference" CDR	Moody's ten year average of 3-year CDR
AAA - AA	0.10	0.00
A	0.25	0.16
BBB	1.00	0.96
BB	7.50	3.96
B	20.00	15.96

This shows that the long-run "reference" CDR exceeds Moody's ten year average three-year CDR in all cases so, on the basis of this first test, supervisors would be satisfied with risk assessments based on this agency. This means that the letter scale as used by Moody's could probably map straight to the risk assessments used in the Standardised approach of Basel II[7].

Table 3.6: Comparison of three-year CDR benchmarks and Moody's two most recent three-year CDRs

%	Three-year CDR benchmarks		Moody's two most recent three-year CDRs	
	Monitoring level	Trigger level	2003	2002
AAA - AA	0.8	1.2	0.00	0.00
A	1.0	1.3	0.00	0.32
BBB	2.4	3.0	0.20	1.58
BB	11.0	12.4	1.82	3.89
B	28.6	35.0	6.38	13.31

As you would expect, Moody's recent three-year CDRs sit comfortably below the monitoring level. This is no surprise as figures from Moody's would have formed the averages used by the committee to set the reference levels. Chapter six shows that Moody's is one of the least generous agencies and rates most issuers lower than other

[7] There is a change in the letter scale of Moody's needed to map to the scale as shown in Basel II, this map is detailed in Appendix II.

agencies, on average. This means that the default rates at each grade would be expected to be lower than for other agencies.

A more interesting test would be to review the published CDRs for the Japanese agency Rating and Investment Information (Rating and Investment Information 2005). Studies are included in chapters six and seven that show that the Japanese credit rating agencies consistently rate more generously than Moody's and S&P. This, and other studies, find that R&I rates companies, on average, one letter grade more generously than Moody's. Consequently for a given credit assessment you would expect R&I to report higher default rates than Moody's.

10 year cumulative average default ratings are given by R&I as show below:

Table 3.7: Comparison of long-run "reference" CDR and R&I cumulative average default rates

%	Long-run "reference" CDR	R&I's 10 year average of 3 yr CDR 1993 - 2002
AAA - AA	0.00	0.09
A	0.25	0.43
BBB	1.00	1.21
BB	7.50	8.38
B	20.00	35.37

These reference CDRs are exactly that, reference only and a guideline for supervisors. This would indicate that default rates for all rating grades issued by R&I have a higher default rate than expected but it is down to the local supervisor as to what action to take.

Table 3.8: Comparison of benchmark CDRs and R&I average three-year CDR 1991 - 1997

%	Three-year CDR benchmarks: Monitoring level	Three-year CDR benchmarks: Trigger level	R&I's most recent three-year CDR 2002 - 2001	
AAA - AA	0.8	1.2	0.00	0.00
A	1.0	1.3	0.00	0.39
BBB	2.4	3.0	0.00	1.16
BB	11.0	12.4	11.32	11.67
B	28.6	35.0	41.67	37.50

All the CDRs for R&I fall comfortably below the monitoring level except for BB and B grade. BB grade issues show a default rate of below the trigger level so this would not be a cause for immediate concern but the B grade shows a default rate above the trigger level for the last two years and there is a likelihood that this would be considered seriously by supervisors. Japan Credit Rating Agency also publish default ratings (Japan Credit Rating Agency 2005).

3.8 Basel Committee's Market Risk Amendment and split ratings

Banks already have experience in dealing with differing credit rating scales and split ratings. With the implementation of the Basel Committee's Market Risk (BCMR) Amendment (BCBS 1998) to the Capital Accord in 1988 (BCBS 1988) seven out of the eleven Basel Committee on Banking Supervision members already use agency credit ratings in their banking supervision. This amendment required that an institution with significant trading activity must now calculate a capital charge for market risk using either its own internal risk measurement model (the "internal models approach") or a "standardised" process developed by the Committee.

Estrella et al (2000) reports that a variety of methods are used to deal with split ratings in relation to the requirements on BCMR Amendment. The US follows a policy similar to that now specified in the New Accord, others follow the wording of the BCBS market risk amendment which is primarily concerned with a cut off to find the minimum level of acceptable ratings.

One interesting case is Hong Kong Monetary Authority where efforts are specifically made to discount some agencies' ratings relative to others. They map the different ratings assigned by the recognised credit rating agencies by looking at the definitions they use for each ratings category and by comparing the ratings they assign to some selected corporations.

To give a minimum acceptable rating for the purpose of the liquidity ratio the comparable ratings are as follows:

Credit rating agency	Minimum acceptable Long-term rating
Moody's	A3 (equivalent to S&P A-)
S&P	A-
Fitch	A-
Thomson Bank Watch	A+
R&I	A+

This approach implies a belief that the rating scales are not equivalent.

3.8 Summary

This chapter considers banking regulation in the light of Basel II. The Standardised approach to calculating credit risk is reviewed in detail along with the reliance placed on external credit assessments and procedures to be followed when split ratings arise. The results of Quantitative Impact Study 3 are reviewed which assess the likely impact of the Basel II proposals on banks' capital requirements and comments from a wide variety of respondents to the Third Consultative Paper are summarised. The final part of this chapter provides worked examples of the guidelines given to supervisors under Annex 2 of the Basel II which suggest how mapping of agency grades to risk assessments under the Standardised approach should take place. The purpose of these guidelines is to ensure that the cumulative default probabilities of different agencies are equivalent before agency grades are mapped directly to risk assessments.

Literature review: Split credit ratings and bond rating prediction models

Chapter one of this thesis provided a introduction to the credit rating industry and chapter two discussed Basel II and the place of credit ratings within the legislation. The purpose of this chapter is to review previous studies that directly relate to the research presented the next six chapters of this thesis. Two areas are covered; split credit ratings and bond rating prediction models.

4.2 Split credit ratings

4.1.1 What is a split credit rating?

A split credit rating arises when different ratings are assigned to the same organisation or issuer by different credit rating agencies. A study into the frequency and reasons for split ratings is of interest because market participants generally use the ratings of the major agencies as if they are equivalent to one another. Subject to Annex 2, Basel II recommends the use of external ratings in such a way that implies the ratings of agencies approved by the regulators will be equivalent. Regulations also use credit ratings to determine other cut-off points for investment purposes such as investment grade and sub-investment grade ratings.

Neither investors, issuers nor agencies would expect ratings to be the same all the time. Griep and Stefano (2001) clarify this by saying "it should be understood that ratings are opinions and not audits." Each agency establishes it own policies, methodologies, ratings scales and determines the mix of quantitative and qualitative inputs so it is to be expected that some differences will arise. However a study of the frequency and degree of split ratings is relevant in the light of the Standardised approach to credit risk measurement under Basel II. The studies in this thesis add to the findings of previous research by extending the data sample to over 51,000 matched pairs of ratings for ten agencies and over 36 countries for the period May 1999 – March 2004.

4.1.2 The frequency of split ratings

One of the first studies to collate data on rating differences between a number of different rating agencies was Beattie and Searle 1992a and 1992b. Using a large sample of long term credit ratings reported by twelve of the leading international rating agencies from the publication, Financial Times Credit Ratings International, they found more than 5,000 cases when two or more agencies rated the same issue. Less than half (44%) of these pairs of ratings agreed precisely and more than 20% differed by two or more notches.

Beattie and Searle asked whether there are systematic differences in the rating scales of the agencies. They addressed this question by computing the mean rating differences across jointly rating companies for every possible pair of rating agencies.

The two agencies with the largest number of jointly rated companies are Moody's and S&P. The average difference in their ratings for the 1,398 jointly rated companies was only 0.05 of a notch suggesting that these agencies assign very similar average ratings. The equivalence between Moody's and S&P ratings has also been identified by Perry 1985, Ederington 1986, Ederington and Yawitz 1987, Cantor and Packer 1995, 1996, 1997, Jewell and Livingston 1998.

However the equivalence in rating scales does not necessarily extend to other rating agencies. For example, when the ratings of eight other agencies were compared to those given by Moody's to the same borrowers, the ratings of five of them were significantly higher than Moody's. The ratings of the third and fourth largest US agencies (Fitch and Duff and Phelps) each rated about a third of a notch higher than Moody's and two of the Japanese rating agencies rated on average between one to two notches higher than Moody's. Ederington 1986, Cantor and Packer 1995, Jewell and Livingston 1998 and 1999 have also identified D&P and Fitch as consistently rating higher than Moody's and S&P.

Cantor and Packer 1995 made a comparison between the senior debt ratings assigned by Moody's and S&P and found 64% were assigned the same rating, 16% were rated higher by Moody's and 20% rated higher by S&P. They used 1,398 bonds jointly rated by Moody's and S&P, 524 bonds jointly rated by Moody's and D&P and 295 bonds rated jointly by Moody's and Fitch from the end of 1990. They also used data from the Financial Times quarterly publication, Credit Ratings International. In 1997 Cantor and Packer updated the results using data at the year-end 1993 (see Cantor and Packer 1997). The results were as follows:

Table 4.1: Comparison of split ratings between Moody's, S&P, D&P and Fitch

	D&P relative to				Fitch relative to			
	Moody's		S&P		Moody's		S&P	
D&P/Fitch	1994	1997	1994	1997	1994	1997	1994	1997
Rated higher (%)	47.6	49.7	39.9	43.2	55.3	58.7	46.0	49.7
Rated same (%)	42.3	39.6	46.5	44.0	37.9	35.5	43.5	43.2
Rated lower (%)	10.1	10.7	13.5	12.8	6.8	5.8	9.9	7.1
Mean difference in rating (notches)	0.57	0.6	0.16	0.46	0.74	0.74	0.56	0.56

Cantor and Packer 1997

The table shows that mean ratings of D&P and Fitch are considerable higher than Moody's and S&P. The authors interpret these differences as evidence that Fitch and D&P have more lenient ratings scales than Moody's and S&P.

Cantor and Packer (1995) also compared the split ratings for speculative grade (or "junk") bonds. They found the ratings of Moody's and S&P to be nearly identical on average. However, the third and fourth largest agencies disagree with Moody's with greater regularity and on a greater scale in the junk bond sample than in the comparable study of the whole spectrum of bond ratings by Beattie and Searle. The ratings of the smaller agencies were between one and one and a half notches higher than those of Moody's and S&P.

4.1.3 The causes of split ratings

Split credit ratings may arise for a variety of reasons:

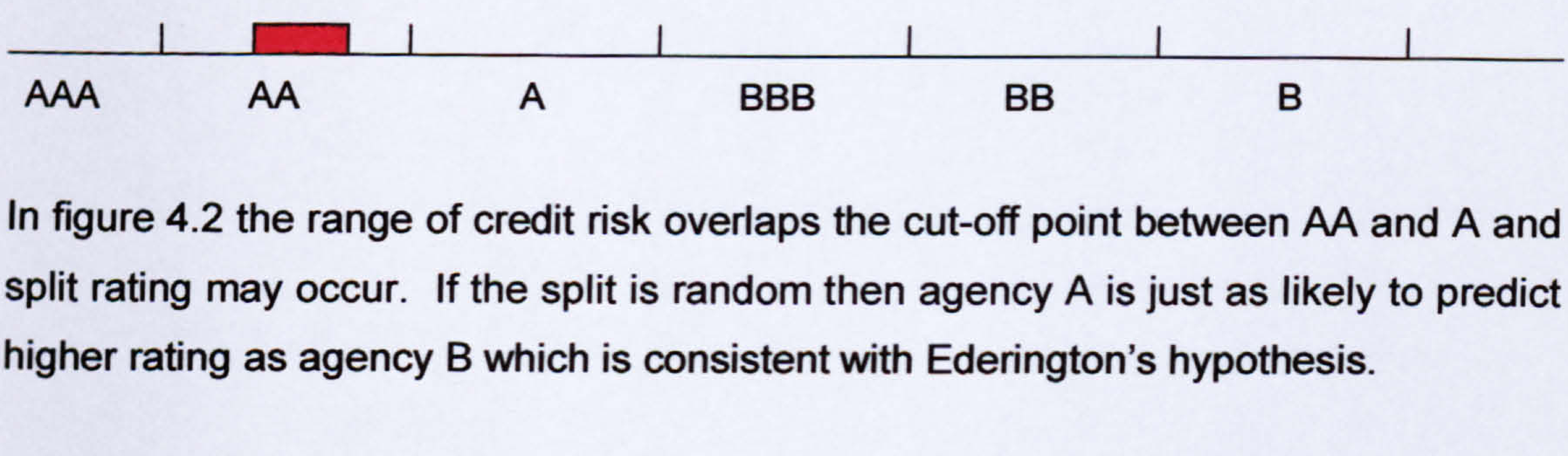
- Individual rating scales may differ meaning that the default risk that underlies each rating is different for each agency.
- Agencies use different methodology to generate ratings.
- There is a random judgement element in the selection of a rating, specified policies may not be applied consistently giving rise to random differences.
- There is a rating lag, i.e. split ratings will arise as there are timing differences in the release of new ratings or response to new information by different agencies.
- Agencies may have access to different information. Some ratings are unsolicited and based only on publicly available information while others have been solicited and information that is not publicly available has been provided by the issuer.
- The credit risk of some issuers or industries is harder to assess than others due to their opacity or due to poor credit quality.

Beattie and Searle 1992a suggest that differences in rating scales are the primary cause of rating differences. Ederington 1986 argues that split ratings are caused by the random errors of the two ratings agencies, implying that issues with split ratings are likely to have credit risks bordering the rating cut-off points. Morgan 1997 and 2002 finds that issuers whose assets are hard to judge due to their opacity are more likely to receive split ratings. He focuses his research on banks as he finds the highest level of split ratings to be for this industry.

Livingston, Naranjo and Zhou (2005) present a diagrammatic explanation of split ratings in terms of a range of credit risk that is assessed by the agencies. They argue that the hypotheses of Ederington and Morgan are not necessarily mutually exclusive.

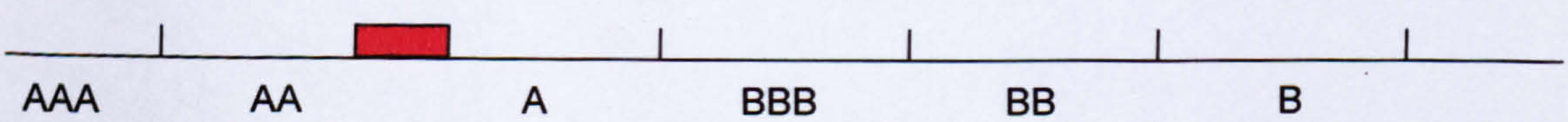
Figure 4.1 shows the range of credit risk for an issuer over which agencies agree. Two or more agencies may not be able to pin point the exact credit risk but have confidence that the risk lies within the boundary as shown by the red lozenge. In figure 4.1 the range of credit risk does not overlap the rating scale cut-off point and there is no split rating.

Figure 4.1: No split rating - the credit risk range for an issuer



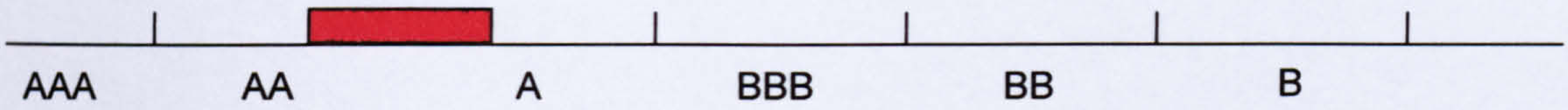
In figure 4.2 the range of credit risk overlaps the cut-off point between AA and A and a split rating may occur. If the split is random then agency A is just as likely to predict a higher rating as agency B which is consistent with Ederington's hypothesis.

Figure 4.2: A split rating – the credit risk range for an issuer



Morgan argues that with more opaque assets the credit risk range will increase as in figure 4.3 as it is more difficult for agencies to estimate the precise risk. This implies that it is more likely for two agencies to select a different credit risk within this range and hence a split rating is more likely to arise.

Figure 4.3: A split rating – a wide credit risk range



It is likely that a variety of the factors listed above influence the ratings of individual agencies and therefore, split ratings. The diagrams above imply an equivalence in rating scales but chapter five and six and Beattie and Searle 1992a show that there do appear to be systematic differences in the rating scales of different agencies. This could add to the likelihood that the credit risk range of an issuer falls over a cut-off point. Ederington argues that split ratings are caused by random errors but chapter five shows that there is a statistically significant ranking of the agencies' rating scales and the tendency for some agencies to be more or less lenient than others does not appear to be random.

The diagrams of Livingston, Naranjo and Zhou (2005) offer clarity in explaining two of the possible causes of split ratings but ignore the impact of differences in the scales of rating agencies.

Figure 4.4: Split ratings and differences in rating scales

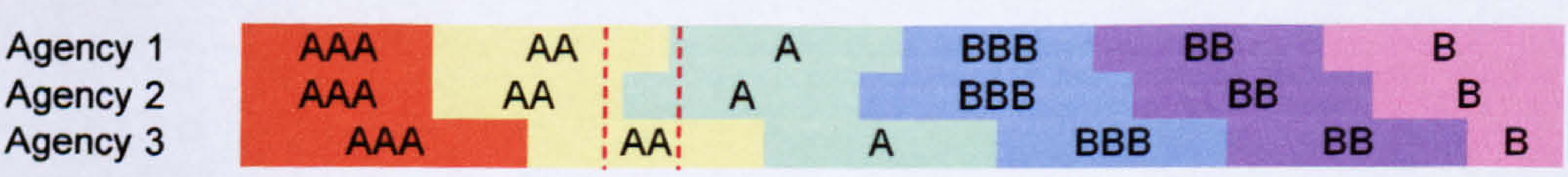


Figure 4.4 shows three different agencies that have different ratings scales. Agency 1 and 2 have different cut-off points at different parts of the ratings scale, i.e. agency 1 is sometimes more generous and sometime less generous with its ratings. The rating scale of agency 3 is entirely skewed above that of the other agencies so at all points it is more generous in its ratings.

The dotted red lines show a range of credit risk determined by the agencies. Split ratings may arise because the agencies allocate a different risk within the hypothetical credit risk band, because the risk is the same but the rating scale is different or a combination of both causes.

4.1.4 Regional differences between rating agencies

Most studies use data for the major rating agencies; Moody's, S&P, Fitch and D&P (which was acquired by Fitch in 2000). Outside of the US, Japanese rating agencies are among the oldest and most active and have attracted the interest of researchers. Beattie and Searle 1992b have found that Japanese rating agencies consistently give higher ratings to the same bond issues than Moody's and S&P. On average, Japanese agencies rate between one to three notches higher than Moody's and S&P.

Japan Centre for International Finance (JCIF1999) finds that Moody's ratings of Japanese firms may be relatively tough, since fewer defaults have been observed over time in Japan than would have been predicted by Moody's ratings in conjunction with US default rates.

Japanese entities have also complained that US rating agencies are unduly harsh towards Japanese firms because they do not take sufficient account of the Keiretsu form of organisation. A keiretsu means that the group is structured with cross-holdings of shares and mutual appointment of corporate directors. However, Shin and Moore (2003) used a ordered probit model to assess the impact of keiretsu affiliation on agency ratings and found that the affiliation of an entity was not the cause of rating differences between Japanese and US agencies. Instead they argued that home bias of Japanese agencies causes them to rate Japanese issuers more favourably.

Shin and Moore are not the only authors to have cited home bias as the main driver of differences between US and Japanese rating agencies. Home bias means that Japanese rating agencies appear to rate issuers from their own country more leniently than issuers from overseas. An examination of split ratings by Beattie and Searle (1992b) suggests that agencies judge issuers from their own country more leniently. They also find that relative consensus is greater between agencies from the same country than between agencies from different countries. Nevertheless, Nickell, Perraudin, and Varotto (2000) find that higher rated Japanese firms are more likely to be downgraded by Moody's and that Japanese firms with low ratings were less likely to be upgraded. Li, Shin and Moore (2006) find that Japanese bond prices are influenced by downgrades by global agencies more than by local Japanese agencies.

However, Cantor and Packer (1995) find that, for ratings of international banks, observed differences between home and foreign ratings principally reflected differences in the scales of individual ratings agencies, rather than home-country bias.

4.1.5 Issuer sectors and split ratings

Morgan (1997 and 2002) measured the frequency of credit rating agency disagreement in the banking versus other sectors. Consistent with Cantor and Packer (1995) he finds that split ratings tend to be more frequent in banking than other sectors. He argues that the risk of banks is hard to judge because the risk of their financial assets is hard to measure. He finds that bond raters disagree more over opaque assets like loans and easily substitutable assets like cash and trading assets.

Ammer and Packer (2000) support this finding and note that ratings are not always consistent across issuer sectors. They find that US banks experienced significantly more defaults than US industrial firms between 1983 – 1998. Beattie and Searle (1992b) found that ratings in the banking and utilities sectors exhibit a lower level of absolute agreement than those in other sectors. They also find that the level of agreement for supranationals is higher than for any specific geographic sector.

Cantor and Packer (1995) find that split ratings are more common in the banking sector, for lower-rated sovereigns than lower rated US corporates and less common for higher rated (AAA/AA) sovereigns than higher-rated US corporates. These results suggest greater opacity in the measurement of credit risk for banks relative to corporates, for lower-rated sovereigns relative to corporates and less opacity for higher rated sovereigns relative to corporates.

Nickell, Perraudin and Varotto (2000) focus on rating transitions and find that banks tend to have less stable ratings than industrials. Higher rated banks have more downgrades but lower rated banks are upgraded more often than lower-rated industrial issuers. Jackson and Perraudin (1999) report that over one year horizons, banks rated B suffer fewer bond defaults than B- rated industrial issuers, although the difference was not statistically significant.

4.1.6 Economic rationale for using different rating agencies

One possible pitfall of simple comparisons of average rating levels (or of the observed frequency of higher or lower ratings) arises from differences in ratings policies of the rating agencies. Moody's and S&P rate all taxable corporate bonds publicly issued in the United States, regardless of whether a rating has been solicited by the issuer. Both Moody's and S&P also frequently issue unsolicited ratings to issuers from outside the United States as well.

Most of the other rating agencies in the United States have a longstanding policy of rating bonds only on the request of the issuer, which involves a fee being paid for the ratings (solicited ratings). It is possible that the smaller agencies' ratings are only purchased (and thus reported) when there is a strong expectation of improvement upon Moody's and S&P ratings, while when the smaller agencies rate lower, their ratings are not purchased. This implies a potential bias in the mean rating and in the frequency comparisons, which is known in the econometric literature as sample selection bias.

Cantor and Packer have contributed a number of studies to the literature on the theme of the economic rationale for purchasing an additional credit rating. The authors attempt to find out what types of firms are more likely to seek out a third (or fourth) bond rating (Cantor and Packer 1995). They find that 46% of firms in their sample with one investment grade rating and one non-investment grade rating from the two major agencies seek a third rating. Of these firms, approximately 85% (29 of the 34) receive an investment grade rating from the third agency. Firms with ratings from Moody's and S&P that are a number of notches away from the investment grade cut-off are less likely to obtain a third rating. The authors conclude that third ratings are more likely to be purchased if the firm is close to a sub-investment grade rating. Combined with the evidence from the same study that Fitch and D&P have more lenient ratings scales than Moody's and S&P, this was very suggestive of rating shopping on the part of some firms.

Cantor and Packer (1996) revisited the issue of rating shopping by firms. The authors test two theories on the existence of third ratings. The first theory is that third ratings are more likely to be obtained when there is great uncertainly about the default risk of the firm. Baker and Mansi 2002 support the view that issuers obtain multiple ratings to increase the probability of a true credit risk evaluation emerging. If this is the case, the third rating could provide valuable additional information to the market about the default risk. There are several factors that would support this theory. First, third ratings would be more common for firms that have split ratings from Moody's and S&P. Second, the likelihood of a third rating should increase as the difference (in rating notches) between Moody's and S&P grows. Finally, the authors believe that default risk should be inherently more uncertain for small firms and firms with high leverage. However, probit regressions revealed that none of the above factors increased the likelihood of a third rating.

The second theory the authors investigate is that third ratings are more likely when the debt-issuing firm is shopping for a better rating. According to this theory, a third rating should be more likely when the existing ratings of the firm are close to important regulatory cut-off ratings, such as the investment grade cut-off. However Cantor and Packer used regression analysis to find that this was not the case. Therefore, rating shopping does not appear to explain the existence of third ratings.

Cantor and Packer (1997) find, once again, that mean ratings for D&P and Fitch are consistently higher than those for Moody's and S&P. They control for the existence of potential sample selection bias using an approach pioneered by Heckman (1979). The authors find that selection bias can account for about 40% - 50% of the observed difference in ratings between the major agencies and the third agencies. They find limited evidence for significant sample selection bias and thus much stronger evidence for differences in ratings scales. While sample selection bias may explain some pair-wise ratings differentials, most is attributable to rating scale differentials.

The studies by Cantor and Packer make several useful contributions to the literature on rating agencies. They document the higher average ratings of the "third" rating agencies compared to the two major agencies. In addition, they find no evidence to support the theory that only firms with greater default risk engage in rating shopping to obtain a stronger third rating. However it is not clear from this research what the major motivation for obtaining third ratings may be, nor is the study extended to a review of other rating agencies.

Jewell and Livingston (1998, 2000) focus primarily on the impact of ratings on bond yields but their studies make an interesting addition to and also a disagreement with the work of Cantor and Packer. They split their study into analysis of a full sample of all ratings made by S&P, Moody's and Fitch and a 3-rater sample which contains only those bonds rated by all three agencies. In the full sample the average rating for Fitch is considerably higher than the average rating for Moody's and S&P. In the 3-rater sample Fitch is only marginally higher (0.3 rating notches). Their results show that firms with publicly available Fitch ratings have higher ratings from Moody's and S&P than firms without Fitch ratings. They find that about 85% of the difference in mean ratings between the full and 3-rater sample is caused by this selection bias. This finding is in contrast to Cantor and Packer who find limited evidence for sample selection bias. The typical firm releasing a Fitch rating has a lower yield (controlling for Moody's and S&P rating), a more stable rating and is more likely to receive an upgrade. They find that Fitch ratings have an impact on yields and serve as a tie breaker when Moody's and S&P disagree on a rating.

Jewell and Livingston repeat their study in 2000 to include data for D&P as well as Fitch. Their findings are consistent with their earlier paper.

Poon (2003) studies unsolicited ratings in comparison to solicited ratings. Poon finds that S&P ratings are lower for unsolicited ratings than solicited ratings. This is interesting with respect to the observation that Japanese credit rating agencies rate higher than Moody's and S&P. S&P attempted to enter the Japanese market in 2000 and assigned 150 unsolicited long-term credit ratings to Japanese issuers, this represented 63% of S&P ratings in the country (Standard and Poor's 2000). This could have had the effect of biasing the S&P ratings downwards although the low level of S&P and Moody's ratings has been identified in research prior to 2000.

Estrella et al (2000) find that banking supervisors do not distinguish between solicited and unsolicited ratings, although many express unease about unsolicited ratings. In practice both ratings are used as if they are equivalent.

Japan Center for International Finance (2000) publish the results of a survey of Japanese financial institutions and include some information about their experience of the process of assigning an unsolicited rating. If an entity requested a solicited rating, management was interviewed by the agency in 90% of cases for a total period of 2 – 4 days, on average. The comparable percentage of entities that were asked for interviews when an unsolicited ratings was being assigned was 66% taking a total of half a day, on average. When a rating had been requested, top level management was involved in these meetings 40% of the time compared to 20% of the time for unsolicited ratings. Finally, for solicited ratings 70% of respondents said that they provide internal information to the agency not available to investors and analysts, this was the case for less than 30% of unsolicited ratings.

4.1.7 Comparing default probabilities

Tabakis and Vinci (2002) extend their review of split ratings to a comparison of default probabilities. They found that when comparing the ratings, (i.e. AAA, AA etc.) S&P ratings were lower then those of Moody's and Fitch. When comparing the same split ratings using estimated default probabilities, no significant differences were found. They conclude that the rating scales are not equivalent. They find that, when comparing the five-year default rates in S&P's AAA grade with those of Moody's there is a significant difference which implies that an AAA from S&P is better than a Aaa from Moody's. The authors argue that this result is important as it validates the use of the available historical estimates of default probabilities by rating grade in studies of split ratings, instead of the grades themselves.

4.2 Bond rating prediction models

The second area of literature reviewed in this chapter covers bond rating prediction models. For at least 40 years studies have been published attempting to model agency credit ratings using financial ratios, non-financial data and sometimes, qualitative information. A wide range of different methodologies have been used which have evolved and become more sophisticated over time.

4.2.1 Choice of methodology

Table 4.2 shows a summary of studies predicting bond ratings along with the methodology used, important independent variables and data samples. Horrigan (1966) performed the first study to estimate and predict bond ratings based on financial ratios of the rated company and characteristics of the bond. Since this time scores of studies have extended his initial research using more sophisticated statistical techniques and a wider range of accounting and non-accounting variables. Horrigan used ordinary least-squares (OLS) regression on 9 grades of bond ratings with various combinations of variables. West (1970) and Ang and Patel (1975) also used OLS analysis to predict corporate bond ratings. The models estimated in these studies predicted the correct credit rating in the holdout sample for 55% of cases for Horrigan (1966) and 62% for West (1970). Ang and Patel reran the same models on credit rating data from an early period and the zero notch classification accuracy was lower at 30.1% and 34.8% for Horrigan and West models respectively.

One problem with these early studies was that the regression analysis was attempting to code the ordinal bond ratings onto an even interval scale but different rating grades do not fall at equal intervals on a scale from a low to high probability of default. To try to overcome this problem Pogue and Soldofsky (1969) used only two of four rating categories at a time using a 0 – 1 dummy dependent variable for the two categories considered. However this study was based on small sample sizes of 10 bonds in each rating category.

Subsequent research used multiple discriminant analysis (MDA) to classify bonds into rating classes. With MDA a series of functions are computed to maximise the ratio of between-group deviation sum of squares to within-group deviation sum of squares. Since MDA concentrates on differences between categories of variables, an interval scale is not imposed on the data but neither is the ordinal nature of the bond ratings reflected. MDA classifies the bond ratings into different categories but ignores the fact that these categories are partitions of the total probability of default, divided at different intervals (see Kaplan and Urwitz 1979). The other disadvantage of MDA is that it requires multivariate normality for the independent variables.

Throughout the late 1970's and 1980's a variety of studies used MDA to predict bond ratings. The first was Pinches and Mingo (1973, 1975). Other examples include Altman and Katz (1974), Baran et al (1980), Belkaoui (1980), Peavy and Edgar (1983, 1984), Perry, Henderson and Cronan (1982). On average these models correctly predicted between 50 – 60% of the holdout sample.

Table 4.2: Previous studies modelling the determinants of bond ratings

Study	Independent variables	Methodology	Independent variables	
Horrigan 1966	Financial ratios + subordination	Linear regression/ OLS	Subordination status, total assets, working capital / sales, net worth / total debt, sales / net worth	USA, Moody's & S&P, 567 industrial bonds, split between stable, new ratings and changes.
West 1970	Financial ratios and non-accounting data	Linear regression/ OLS	Earnings variability, period of solvency, equity / debt ratio, bonds outstanding	USA, Moody's, 313 industrial bonds over 6 years (this could include the same company upto 5 times)
Pogue and Soldofsky 1969	Financial ratios	Regression (dependent variable 0-1) OLS	Debt/total capital, net income / total assets, coefficient of variation of net income / total assets, net total assets, (net income + interest) / interest	USA, Moody's, approx 62 industrial bonds
Pinches and Mingo 1973 1975	Financial ratios + subordination	MDA Linear discriminant function Quadratic discriminant function	Subordination status, issue size, net income + interest / interest, years of consecutive dividends, long-term debt / total assets, net income / total assets	USA, Moody's, 180 industrial bonds,
Altman and Katz 1974	Financial ratios	Quadratic discriminant function	Interest coverage, standard error of interest coverage, cash flow	USA, Moody's
Ang and Patel 1975	Financial ratios and non-accounting data	Regression	Compared models of Horrigan, West, Pogue and Soldofsky and Pinches and Mingo.	USA, Moody's, 424 industrial bonds.
Kaplan and Urwitz 1979	Financial ratios and non-accounting data	Linear regression and ordered probit	Cash flow interest coverage, long term debt / total assets, Net income / total assets, total assets, subordination, systematic and unsystematic risk	USA, Moody's, 327 industrial bonds.
Baran et al 1980	Financial ratios + beta	MDA	Cash / sales, total earnings, current asset / current liabilities, standard deviation of accounting rate of return, cash / total assets, net working capital / total assets, payout ratio, long term debt / total assets, beta	USA, S&P, 202 industrial bonds. Financial data from Compustat
Belkaoui 1980	Financial ratios and market data and subordination status	MDA	Total assets, total debt, long term debt / total invested capital, short term debt / total invested capital, current assets / current liabilities, (net income + total interest expense) / (interest expense + preferred dividend requirement), stock price / common equity per share, subordination status	
Peavy and Edgar 1983, 1984		MDA	Banks: Net income, return on assets, shareholders' equity / total assets, return on equity, reserve for loan losses / loans, net charge-off / loans, growth rate of	USA Moody's, 83 Bank Holding Companies with commercial paper ratings

			assets over last 5 yrs. Industrial: total assets, long term debt / investment capital, net sales / cash, receivables / total assets, net income / total assets, sales / total assets	USA, S&P, 244 industrial companies with commercial paper ratings
Perry et al 1985	Financial ratios & Industrial classification		Ratios reflecting profitability, debt and capital structure, SIC codes for industry classification.	USA, Moody's, 152 industrial bonds. Financial data from Comupstat.
Ederington 1985	Financial ratios + subordination	Linear regression, ordered probit, linear discriminant, unordered logit	Subordination, average total assets, long term debt / total capitalization, forecast interest coverage.	USA, Moody's, 346 industrial bonds. New issues.
Gentry, Whitford and Newbold 1988	Financial ratios especially cash flow	Ordered probit model	Subordination status, issues size, cumulative years of dividends, net income / total assets, funds flow data; inventories, other current liabilities, dividends, long term financing, fixed coverage charges	USA, Moody's 206 industrial bonds, split between new issues and reclassifications. Financial data from Comupstat.
Dutta and Shekhar 1988	Financial ratios + forecast + qualitative aspect	Neural networks compared with linear regresssion	Liabilities / (cash + assets), debt ratio, sales / net worth, profit / sales, financial strength, earnings / fixed costs, past five years' revenue growth rate, projected next five years' revenue growth rate, working capital / sales, subjective company prospect	USA, S&P and Value Line Index, 47 industrial bonds.
Singleton and Surkan 1991	Financial ratios	Neural networks	Debt / total capital, pre-tax interest / income, income / shareholders' equity, coefficient of variation of ROE, total assets, construction costs / total cash flow, local toll revenue / long distance toll revenue.	18 Bell Telephone companies divested by AT&T
Reiter and Emery 1991	Financial ratios + qualitative measures	OLS, ordered probit analysis and conjoint analysis	Cash flow / construction expenditure, debt / equity, property funding ratio, permanent capitalisation, coefficient of variation of return on equity, pretax interest coverage	Moody's and S&P, 281 newly issued utilities bonds
Kim 1993	Financial ratios + market data + subordination status	Neural networks compared with linear regression, discriminant analysis, logistic analysis and a rule-based system	Total assets, Total debt, Long term debt / Total invested capital, Short term debt / Total invested capital, Current assets / Current liabilities, (Net income + Total interest expense) / (Interest expense + Preferred dividend requirement), Stock price / Common equity per share, Subordination status	USA, S&P, 228 industrial bonds. Financial data from Compustat.
Moody and Utans 1995		Neural Networks	Not specified	Credit rating data and financial ratios from major financial institution.
Mar Molinero, Gomez, Cinca 1996	Financial ratios	Multidimensional Scaling models, cluster analysis,	24 financial ratios reflecting profitability, debts, capital structure and number of employees.	Spain, S&P, 10 short term foreign currency bank bonds

		property fitting and discriminant analysis		
Maher and Sen 1997	Financial ratios + risk measures	Neural networks and logistic regression	Cash flow interest coverage, long term debt / total assets, net income / total assets, total assets, subordination, systematic and unsystematic risk, net pension liability, net income (loss) from discontinued operations.	USA, Moody's, 299 industrial bonds. New issues. Financial data from Compustat.
Poon, Firth and Fung 1999	Financial ratios + long term bond ratings + country risk	Ordinal logistic regression	Risk, profitability, loan provision ratios, long term and short term bond ratings, country risk	Worldwide, Moody's BFSR for 130 banks. Financial data from S&P.
Daniels and Kamp 1999	Financial ratios	Neural network	Leverage, coverage, liquidity, profitability and size.	S&P, 256 industrial bonds. Financials from Datastream.
Shin and Han 1999	Financial ratios	Case based reasoning supported by genetic algorithms	Firm types (e.g. conglomerate), total assets, shareholders' equity, sales, gross profit / sales, net cash flow / total assets, financial expenses / sales, total liabilities / total assets, depreciation / total expenses, working capital turnover.	Korea, National Information ad Credit Evaluation Inc. 3886 companies, commercial paper ratings.
Trevino and Thomas 2000	Financial ratios and economic indicators	Ordered probit and OLS	Economic indicators, debt / borrowing, country debt / total bank lending, credit commitments, foreign exchange reserves, use of IMF credit, total borrowing / bank deposits.	Worldwide, 11 international rating agencies, 55 sovereign borrowers, 1003 observations.
Laruccia and Revoltella 2000	Financial ratios and country risk	Linear regression, logistic regression and neural network	Country risk (Bank Deposit Country Ceiling), loan loss reserve / gross loans, equity / total assets, cost to income ratio, net loans / total assets. Country dummy variables.	Moody's BFSR, 212 banks. Developing countries in Latin America, South East Asia (excl Japan), Eastern Europe. Financial data from Bancscope
Kamstra, M., Kennedy, P. and Suan, T.-K. 2001	Financial ratios + subordination status	Ordered logit combining technique to combine several forecasting methods	Interest coverage, debt ratio, return on assets, total firm assets, subordination status.	USA, Moody's, 354 transportation and industrial bonds, new issues.
Huang,Chen, Hsu, Chen, Wu 2004	Financial ratios	Support vector machines and neural networks	Total assets, debt / invested capital, debt ratio, EBIT / interest, profit margin, return on assets, return on equity, earnings per share, net income before tax / sales, cash flow from operating activities / total assets	USA and Taiwan. 74 Taiwan Ratings Corporation for financial institutions. USA 36 banks ratings from S&P.
Griffiths and Beynon 2005	Financial ratios	Variable precision rough sets model (VPRS)	Total assets, net income, capital funds / liabilities, net interest margin, return on average assets, return on average equity, cost to income ratio, net loans / total	European and North America, Moody's BFSR 435 banks.

			assets, liquid assets / customer & short term funds	
Kim 2005	Financial ratios	Artificial intelligence	Ratios to represent cash reserves, leverage, liquidity, profitability, market value, standard deviation of key earnings and leverage.	Dun and Bradstreet, S&P and Compustat. 1,080 industrial companies (excluding utilities, transportation and financial)
Bennell, Crabbe, Thomas and Gwilym 2006	Macroeconomic variables	Neural networks and ordered probit	External debt / export, fiscal balance, external balance, rate of inflation, GDP per capita, GDR growth, development indicator.	Worldwide 1383 observations, 70 Sovereign borrowers, Moody's, S&P, Thomson BankWatch, Duff & Phelps, Fitch, IBCA, CBRS, DBRS, R&I, JCR, Nippon Investors Service. Data from FT Credit Ratings International

Kaplan and Urwitz (1979) predicted bond ratings with an ordered probit method (N-chotomous probit) with a specialisation of the categorical dependent variable to the case where it is ordinal in nature (see McKelvey and Zavoina 1975). This avoided the problem of the OLS method which assumed an interval scale of the dependent variable and MDA which assumes a nominal scale. Interestingly, although the N-probit technique is theoretically more appropriate, the results were not significantly better than using OLS. Reiter and Emery (1991) and Iskandar-Datta and Emery (1994) supported this finding. Jackson and Boyd (1988) modelled bond rating behaviour using probit analysis and Gentry, Whitford and Newbold (1988) also used probit analysis to estimate a model with a high classification accuracy using ratios and cash flow components. These models generally classify 55% to 65% of the holdout sample correctly.

Ederington (1985) used an unordered multinomial logit model in his comparison of bond rating models comparing this to each of the statistical methods discussed so far. An unordered model allows the relative importance of different independent variables to vary across rating classifications but does not make use of the a priori knowledge that bond ratings are ordered. Ederington found that the ordered probit and unordered logit outperformed the models estimated using OLS and MDA. The logit model performed best in the estimation sample where 70% of ratings were correctly classified, on average probit and logit analysis correctly classified about 14% more of the ratings than OLS or MDA. Gentry, Newbold and Whitford (1985) also compared these three methods in the analysis of bankrupt firms using cash flow data.

Other examples of studies using logistic regression are Poon et al (1999) and Laruccia and Revoltella (2000). Results show classification accuracy of between 50% - 70% depending on the study, data sizes and independent variables used. Back et al (1996) compared MDA, logistic regression and neural networks and note that the amount of variables included in the model varies with methodology used and logit consistently chose the smallest number of variables in that study. Kamstra et al (2001) used an ordered-logit regression combining method. This combines together the results of several different forecasting methods.

In the late 1980s the first bond rating studies using Neural Networks were published. Neural networks are algorithms that are patterned after the structure of the human brain. They contain a series of mathematical equations that are used to simulate biological processes such as learning and memory. In a neural network, one has the same goal as in logistic regression modelling, predicting an outcome based on the values of some predictor variables. However, the approach used in developing the model is quite different.

Artificial neural networks were first developed several decades ago but it was only in the late 1980s with the rediscovery of the back-propagation training algorithm did widespread interest in this technique develop within the scientific community. Neural networks have the ability to "learn" mathematical relationships between a series of input (independent, predictor) variables and the corresponding output (dependent, outcome) variables. This is achieved by "training" the network with a training (or derivation) data set consisting of predictor variables and the known or associated outcomes. Networks are programmed to adjust their internal weights based on the mathematical relationships identified between the inputs and outputs in a data set. Once a network has been trained, it can be used for pattern recognition or classification tasks in a separate test (or validation) data set.

Dutta and Shekhar (1988) used financial ratios and a qualitative measure to model bond ratings and compared results using a neural network and linear regression model. They estimated a model to distinguish between two groups of bonds; AA and non-AA. This study differed from most earlier research as other studies usually predicted a wide range of rating categories. The neural network classified more correct bond ratings than the linear regression model. In addition, whenever the neural network model misclassified a bond, it was off by at most one rating class whereas the regression model was often off by several rating classes.

Singleton and Surkan (1990) compared the performance of a neural network using 7 financial ratios with an MDA model. As above, the neural network outperformed the MDA model. Maher and Sen (1997) compared the results of a neural network with ordinal logistic regression and also found that the neural network outperformed the logistic model. Other examples of studies using neural networks include Moody and Utans (1995) and Daniels and Kamp (1999). Many of these studies show that neural networks can classify 60% – 70% of the observations correctly. Where the same data has also been used to estimate models using logistic regression the results range from 60% – 62%.

These studies generally show that using neural networks gives some improvement in classification accuracy. An exception to this result is Chaveesuk et al (1997). The authors argue that of the available statistical approaches logistic regression is best suited to modelling bond ratings. They compared results using a neural network with logistic regression and found that there is not much difference between the best neural network design and the best logistic regression model. As with Dutta and Shekhar (1988) they show that a neural network performs slightly better than the logistic regression in terms of correct classification. When the methods misclassify a bond, the logistic regression misses by more classes slightly more often than the network.

Some detailed analysis of the advantages and disadvantages of neural networks has been carried out in other fields such as Tu (1996). The advantages of neural networks are that they can detect complex nonlinear relationships between independent and dependent variables and they have the ability to detect interactions or inter relationships between all of the input variables by using the hidden layer. They also can be developed using multiple different training algorithms such as back propagation or radial basis function.

However neural networks do have some significant disadvantages as well. Neural networks are a "black box" and have limited ability to explicitly identify possible causal relationships. In logistic regression it is possible to determine which variables are most strongly predictive of an outcome and through a stepwise selection process it is possible to eliminate a number of independent variables that are not related to a particular outcome. Within a neural network it is not possible to determine which variables are the most important contributors and a model may contain a number of unimportant variables. This is a significant problem with relation to the use of the neural network within banks as data is expensive and time consuming to collect.

Neural networks are more difficult to use in the field as specialist software must be purchased, staff need to be trained and greater hardware resources are required. In contrast, the estimates for a logistic regression model can be entered into a standard spreadsheet and applied to the relevant independent variables to generate probabilities that are easy to interpret.

Overfitting is also a problem with neural networks. The network is trained using a set of training examples which will be used to predict the correct output for validation data set. However, especially in cases where learning was performed too long or where training examples are limited, the network may adjust to very specific random features of the training data. In this process of overfitting, the performance on the training examples still increases while the performance on unseen data becomes worse. Finally as neural networks are a relatively new technique there are still some important methodological issues to be resolved. For example, credit ratings are not allocated evenly between the different rating classes and neural networks are limited in dealing with the ordinal nature of bond ratings (Kim 2005).

Other methodologies have also been used in recent years to predict bond ratings. Examples are variable precision rough sets model (Griffiths and Beynon 2005), case based reasoning supported by genetic algorithms (Shin and Han 1999), support vector machines and artificial intelligence (Kim 2005), expert systems (Kim and Lee 1995) and neurofuzzy systems (Piramuthu 1999).

4.2.2 Studies of bank credit ratings

Only a small amount of the research shown in table 4.2 focuses on bank ratings. Several studies look specifically at Moody's Bank Financial Strength Ratings (BFSR). Poon et al (1999) use logistic regression to model the determinants of BFSR. They find that a model including Moody's traditional long term ratings as one of the independent variables performs much better than a model built from ratios alone. The long term rating is the most significant input into the model. This is an interesting finding as it suggests that BFSRs may not be adding very much information over and above the traditional debt rating. Although Moody's claim that BFSRs are independent from traditional ratings it appears that factors that go into BFSRs are similar to the factors that underlie debt ratings. Variamax rotation factor analysis was used to reduce the number of independent variables and three factors were identified which represented risk, loan provision ratios and profitability.

Laruccia and Revoltella (2000) also model Moody's BFSR in developing economies in the Far East, South America and Eastern Europe. They compare results using linear regression, logistic regression and a neural network and use independent variables representing country risk, bank efficiency, assets quality, liquidity and capitalisation (for more detail see table 4.2). The linear regression model explains 73.5% of the variance of the dependent variable and the equivalent figure for the logistic model is 71%. The R-square statistic for the neural network is 76.7%. It is interesting that this study does find a country risk measure to be highly significant in the models while Poon et al (1999) do not find that a county risk proxy is significant.

Molinero et al (1996) modelled S&P short term bond ratings for Spanish banks. Using a multidimensional scaling technique (chosen because of the small sample size of 10 banks) they found that both accounting ratios (bad debts and profitability) and the type of ownership were significant in determining the short term bank ratings in Spain.

To the author's knowledge no studies have been made into the prediction of long term bank ratings. These are the main focus of this study.

4.2.3 Selection of independent variables

Table 4.2 shows a summary of important independent variables and data samples. The independent variables used in the different studies are shown. Where a large number of variables were used, only the ones that were significant to the prediction of the ratings are shown.

The majority of studies use financial ratios and values from the income statement or balance sheet as independent variables but there are examples of research using non-accounting data such as market values, risk measures, forecast values, subordination status, industry or country classifications and subjective aspects such as company prospects. Although credit ratings agencies do take qualitative and non-accounting information into consideration when rating bonds it is not clear that the inclusion of non-accounting independent variables in bond rating models significantly improves the results.

The financial ratios that appear the most frequently in these studies of industrial bond ratings are: size (measured by total assets or debt) e.g. Horrigan (1966), Kaplan and

Urwitz (1979), Ederington (1985), Maher and Sen (1997). Profitability (often measured as net income/total assets) e.g. Pogue and Soldofsky (1969), Pinches and Mingo (1973, 1975), Kaplan and Urwitz (1979), Ederington (1985). Gearing (long term debt/total assets) e.g. Pinches and Mingo (1973, 1975), Kaplan and Urwitz (1979), Ederington (1985), Maher and Sen 1997. Interest coverage e.g. Altman and Katz (1974), Pogue and Soldofsky (1969), Pinches and Mingo (1973, 1975), Kaplan and Urwitz (1979), Maher and Sen (1997), Daniels and Kamp (1999).

Table 4.2 also shows that the majority of the studies focus on industrial data for the USA and that ratings from Moody's are the most commonly used. The average sample size for most of the studies is about 260 companies. In the study in chapter ten most models are estimated based on more than 1,000 observations.

4.2.3.1 Independent variables for banks analysis

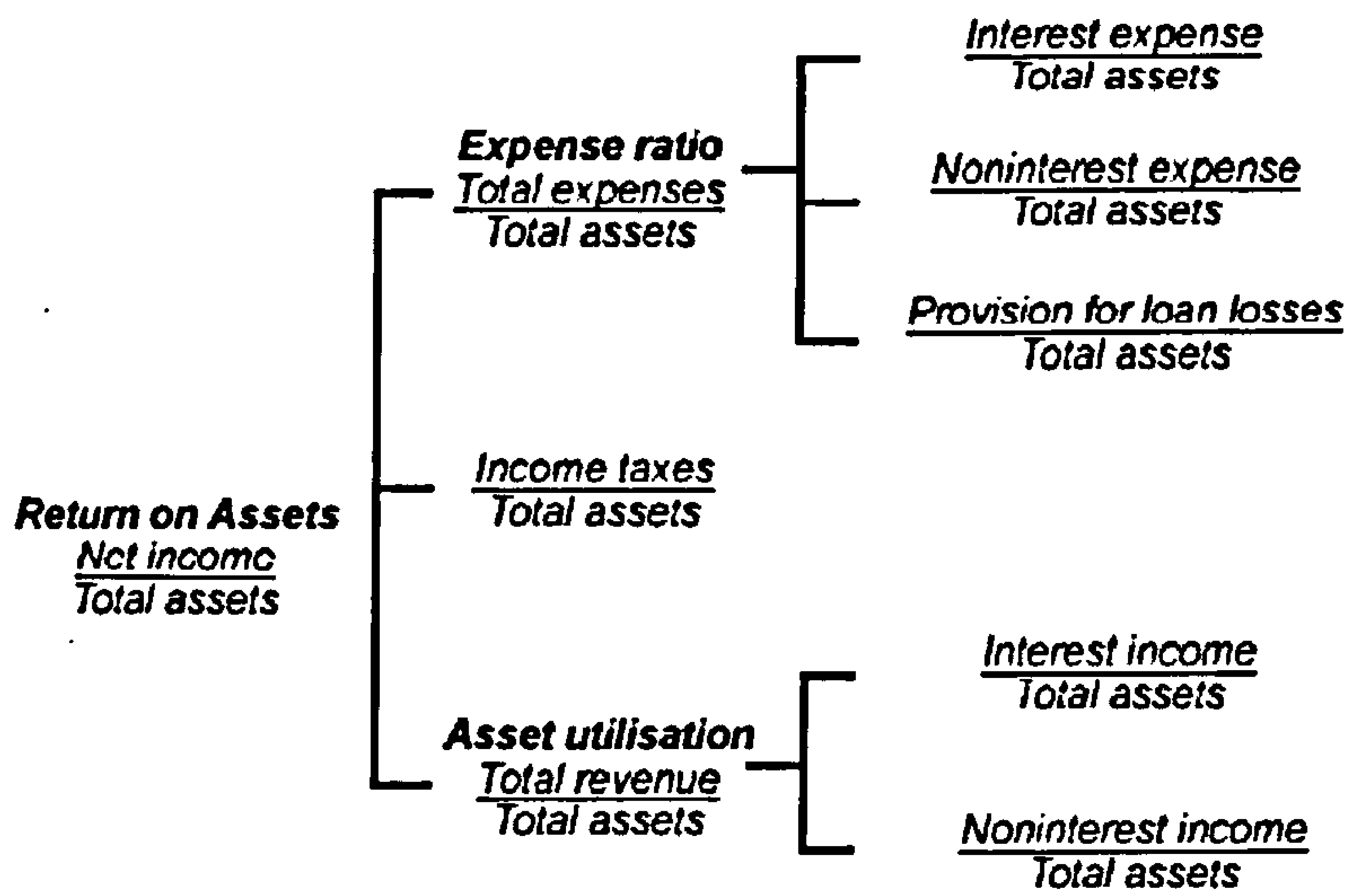
The range of independent variables that have been used in models predicting credit ratings are discussed above. In the majority of cases the data used for this research is taken from samples of US industrial bonds. The independent variables selected are suitable for industrial companies but not for banks. The following section considers ratios traditionally used in the analysis of banks.

Cole (1972) introduced a procedure for evaluating bank performance by ratio analysis which he adapted from the DuPont system of financial analysis (see Foster 1986 and Reid and Myddelton 1992 for summary of traditional financial analysis and Koch and MacDonald 2000 for bank analysis). The starting point of the analysis is return on equity (ROE) which is the multiple of return on total assets (ROA) and total assets/shareholders equity. The ROE measures the return on the shareholder's investment while the ROA measures the return on the total assets invested so gives an indication of the effectiveness of management to generate income from the assets under their control.

$$\underset{\textit{Return on Equity}}{\frac{\textit{Net income}}{\textit{Shareholder's equity}}} = \underset{\textit{Return on Assets}}{\frac{\textit{Net income}}{\textit{Total assets}}} \times \underset{\textit{Equity multiplier}}{\frac{\textit{Total assets}}{\textit{Shareholder's equity}}}$$

Total assets/shareholders equity (also called the equity multiplier) breaks down the relationship between the bank's assets and equity. The difference between these two items will be the sum of deposits and debt, as total assets equals total liabilities which is made up of deposits, debt and shareholders' equity. A bank with a high level of deposits and debt relative to equity will have a high equity multiplier so this is a useful ratio to compare a bank's financial structure. This ratio will also give an indication of risk as a high level of deposits and debt will increase the bank's risk of illiquidity and insolvency.

Figure 4.1: Assessing bank profitability



The return on assets can be broken down in turn into the expense ratio (total expenses/total assets, asset utilisation (total revenue/total assets) and income tax/total assets. On the expense side, the expense ratio can be broken down to analyse interest expense, noninterest expense and loan loss provisions. The asset utilisation can be split into interest income and non-interest income. Each of these ratios is important in the analysis of profitability, asset utilisation and expenses and are found in Standard and Poor's list of bank ratios used for the assessment of credit ratings (Standard and Poor's 2004).

Several other profitability measures are commonly used by bank analysts. The net interest margin (net interest income/earning assets) is a summary measure of the net interest returns on income-producing assets. The Burden ratio, (noninterest expense – noninterest income)/total assets, shows the proportion of net noninterest expenses that are covered by fees, service charges, securities gains and other income as a percentage of total assets. A low ratio is favourable as this indicates a low level of noninterest expense relative to income. The efficiency ratio, noninterest expense/(net interest income – noninterest income), measures the bank's ability to control noninterest expense relative to net operating income. It shows how much a bank pays in noninterest expense for each unit of operating income, a smaller ratio indicates a more profitable bank.

Asset quality is another essential part of the bank analysis process. Raters are interested in the values of loan loss provisions, loan loss reserves, non-performing loans and net charge-offs relative to loans. Ratios have also been included which indicate a bank's leverage and liquidity. Unfortunately much of this data was poorly populated in the database used for the study in chapter ten but the ratio for which there was good coverage was loan loss reserves/loans. Some studies such as Poon et al (1999) have included ratios incorporating risk weighted assets. It was found that this data was available for a very small number of banks and was not used in this study. Restricting the sample to those banks for which risk weighted assets were available in the database would have biased the sample to large and predominantly US banks.

Poon et al. (1999) provide a detailed list of 100 financial variables and ratios used in their study of Bank Financial Strength Ratings. Three factors were identified from this list after using varimax rotation factor analysis which represented dimensions of risk, loan provision ratios and profitability. Molinero, Gomez and Cinca (1996) identified 24 financial ratios to be included in their study of short term Spanish bond ratings. Most of these ratios are also included in the study in chapter ten with the exception of ratios based on the number of employees or number of bank branches as that data was not available. The full list of independent variables used in the bank rating prediction models in this thesis are shown in Appendix 5.

A strongly performing bank will obtain higher yields than its competitors by taking on increased risk or lowering operating costs. Increased risk can be measured in terms of greater volatility of net income or market value. Independent variables reflecting volatility of earnings and variability of net income/total assets were used by West (1970) and Pogue and Soldofsky (1969) respectively. Kaplan and Urwitz (1979) included two measures of earnings instability in their research. They used a systematic risk measure, the market beta, to reflect the covariation of a firm's earnings with a market-wide index of earnings and an unsystematic risk measure to reflect firm-specific random phenomena. Equivalent measures of earnings instability have not been included in chapter ten as the purpose of this study is to review the importance of financial values in the determination of bank credit ratings.

4.3 Summary

This chapter has provided an extensive literature review in two areas; split credit ratings and bond rating prediction models.

Previous research in the area of split credit ratings has established that the rating scales of different agencies appear to differ with some agencies consistently rating issuers higher than others. The results are reasonably consistent between different studies. Agencies also appear to be more generous on issuers from their home country and differences arise between the ratings of issuers from different countries and industries.

Much of the research into split ratings dates from the 1990s so this thesis updates earlier findings with an extensive data sample including over 51,000 split rating observations. It also looks in detail at ten different rating agencies rather than focusing on ratings for Moody's, S&P and Fitch.

Modelling bond ratings from financial ratios and other variables is an area that has attracted numerous studies during the last forty years. The literature review analysed many of these different studies in detail and showed how the methodologies used have become more complex over time as researchers strived to achieve higher classification accuracy for corporate bond prediction. The study in chapter ten uses ordinal logistic regression analysis to model bank bond ratings. The number of studies which have covered bank ratings is small compared to industrial bonds and very little work has been performed in the area of long term bank bond ratings.

Data used for the analysis of split credit ratings and bank credit rating models

The purpose of this chapter is to describe the data used in the studies which are presented in the following chapters. Chapters six to nine present the results of research looking at the level of agreement between credit rating agencies and split credit ratings. The results of a study modelling bank credit ratings are presented in chapter ten.

Three different databases were brought together in order to provide the necessary data for these studies;

- Credit ratings data from Financial Times Credit Ratings International (FT-CRI)
- Fitch Individual Bank ratings from Fitch Ratings
- Bank financial accounting data from Fitch Ratings

Credit rating data used for the split credit ratings study will be discussed first, followed by the bank accounting and credit rating data used to model bank credit ratings.

5.1 Credit rating data from Financial Times Credit Ratings International

The data used in these studies was kindly provided by Financial Times Information from the Financial Times Credit Ratings International (FT-CRI) database and covers the period from May 1999 to March 2004 (Dale and Thomas 1999 – 2004). This database contains over 15,000 credit ratings assigned to long-term senior unsecured or senior subordinated debt by major credit rating agencies. These ratings are representative of the issuer rating and this study is not attempting to compare the ratings of individual bonds.

Credit ratings for companies and institutions from 37 different industries are represented in the data. These range from banks and financial institutions to sovereigns and industrial companies. Issuers from 132 countries are included in the database. The database compares credit ratings from ten different rating agencies, seven live and three dead agencies.

Table 5.1: Credit rating agencies included in the FT-CRI database

Agency name	Abbreviation used throughout this study
Live agencies	
Capital Intelligence	CI
Dominion Bond Rating Service	DBRS
Fitch Ratings	Fitch
Japan Credit Rating Agency	JCR
Moody's Investors Service	Moody's
Rating & Investment Information	R&I
Standard & Poor's	S&P
Moody's Bank Financial Strength Ratings	BFSR
Dead agencies	
Canadian Bond Rating Service	CBRS
Duff & Phelps	D&P
Thomson BankWatch	TBW

The scope of the FT-CRI database allows this study to be the largest of its type undertaken to date. It uses a total of 51,342 matched pairs of agency ratings. This compares to 5,284 matched pairs from 12 agencies studied by Beattie and Searle (1992a), 2,217 matched pairs from the four main agencies by Cantor and Packer (1995) and 1,766 from Moody's and Standard & Poor by Jewell and Livingston (1999).

The data sample covers the period May 1999 to March 2004. This data contains the issuer name, industry, country, agency providing a rating, the initial rating in 1999 and any subsequent changes. New issuer credit ratings and changes in existing ratings are updated in the database on a monthly basis. All database changes in a given month relate to changes made by the agencies in the previous month, e.g. all changes recorded in the database during May are to bring it up to date as of the end of April.

The FT-CRI database does not include Fitch Individual Bank ratings. These were kindly supplied by Fitch Ratings in electronic format.

5.1.2 Rating definitions used by different agencies

All agencies have a system of letter grades to represent an opinion on the future ability and legal obligation of an issuer to make timely payment of principal and interest. The definitions of rating grades and the letter scales that are used to represent these grades are different for each agency. In some cases the differences are very striking, for example, the letter scale used by Moody's is different to that used by all other agencies. In other cases, such as Fitch and S&P, the letter scales appear to be identical but there are more subtle differences in the definition of each category once you read the descriptions. Full rating definitions for all the agencies used in this study are included in Appendix 1.

Investment grade rating definitions used by different rating agencies are remarkably similar but there are more discrepancies for sub-investment grade debt. For example, Fitch describes the rating CCC as "high default risk. Default is a real possibility". JCR describes the same rating as "there are factors of uncertainly .... and a possibility of default." Moody's definition is "obligations of poor standing. Such issues may be in default...". S&P's definition is "a currently identifiable vulnerability to default... In the event of adverse business, financial or economic conditions, it is not likely to have the capacity to pay interest and repay principal." Although S&P's definition effectively captures the flavour of the CCC rating, in that the issuer is unlikely to survive an economic downturn, there are different emphasises in each of the definitions that could result in different internal interpretations and allocation of ratings.

5.1.3 Mapping agency ratings to a common scale

In order to compare the ratings of one agency with another it is critical to be able to map the ratings of different agencies onto a common scale. In this study a number of maps are used. These are all referred to as rating correspondences.

5.1.3.1 Investment/sub-investment grade correspondence

The most straightforward way to map agency ratings would be to divide ratings between those that are investment grade and those that are sub-investment grade. All agencies have a clear cut-off between these grades. This map is referred to as investment/sub-investment grade correspondence. Although this map avoids the problem of mapping detailed ratings to a common scale it ignores a huge amount of the richness available within the database. The percentage of investment grade and sub-investment grade ratings in the database is 64% and 36% respectively.

Table 5.2: Investment/sub-investment grade correspondence

	CBRS	CI	DBRS	D&P	Fitch	JCR	R&I	Moody's	S&P	TBW
Investment grade	All ratings BBB- and above							All ratings Baa3 and above	All ratings BBB- and above	
Sub-investment grade	All ratings BB+ and below		All ratings from BB H and below	All ratings BB+ and below				All ratings from Ba1 and below	All ratings from BB+ and below	

5.1.3.2 Letter grade correspondence

Another method of mapping agency ratings would be to compare agencies at the level of a letter grade but ignoring the + or – suffixes. This is called the 'letter grade correspondence'.

Table 5.3: Letter grade correspondence

	CBRS	CI	DBRS	D&P	Fitch	JCR	R&I	Moody's	S&P	TBW
Investment grade										
1	AAA	AAA	AAA	AAA	AAA	AAA	AAA	Aaa	AAA	AAA
2	AA	AA	AA	AA	AA	AA	AA	Aa	AA	AA
3	A	A	A	A	A	A	A	A2	A	A
4	BBB	BBB	BBB	BBB	BBB	BBB	BBB	Baa	BBB	BBB
Sub-investment grade										
5	BB	BB	BB	BB	BB	BB	BB	Ba	BB	BB
6	B	B	B	B	B	B	B	B	B	B
7	C	C	CCC	CCC	CCC	CCC	CCC	Caa	CCC	CCC
8	D	D	CC/C/D	CC/DD	CC/C/ DDD/DD/D	CC/C/D	CC/C	Ca/C	CC/C/D	CC/C/D

5.1.3.3 11-notch correspondence

The FT-CRI database compiles ratings and generates an average quarterly rating for each issuer called the FT Composite index. To do this the editors map all ratings onto a numerical scale of one to ten and include all sub-investment grade ratings in a single "speculative" category. Beattie and Searle (1992a and 1992b) used the same scale in their study to allow comparison of ratings in order to assess the number of split ratings. The way in which investment grade ratings are compared between agencies has become reasonably accepted and the rating correspondence set out below is used in many studies. Tabakis and Vinci (2002) refer to this way of mapping ratings as "a well established and agreed upon equivalence between rating grades of different assessment institutions."

Table 5.4: 11-notch correspondence

	CBRS	CI	DBRS	D&P	Fitch	JCR	R&I	Moody's	S&P	TBW
1	AAA	AAA	AAA	AAA	AAA	AAA	AAA	Aaa	AAA	AAA
2	AA+	AA+	AA H	AA+	AA+	AA+	AA+	Aa1	AA+	AA+
3	AA	AA	AA	AA	AA	AA	AA	Aa2	AA	AA
4	AA-	AA-	AA L	AA-	AA-	AA-	AA-	Aa3	AA-	AA-
5	A+	A+	A H	A+	A+	A+	A+	A1	A+	A+
6	A	A	A	A	A	A	A	A2	A	A
7	A-	A-	A L	A-	A-	A-	A-	A3	A-	A-
8	BBB+	BBB+	BBBH	BBB+	BBB+	BBB+	BBB+	Baa1	BBB+	BBB+
9	BBB	BBB	BBB	BBB	BBB	BBB	BBB	Baa2	BBB	BBB
10	BBB-	BBB-	BBB-	BBBL	BBB-	BBB-	BBB-	Baa3	BBB-	BBB-
11 Sub-investment grade	All ratings from BB+ and below		All ratings from BB H and below	All ratings from BB+ and below				All ratings from Ba1 and below	All ratings from BB+ and below	

The difference between two adjacent grades such as AA and AA- or BBB+ and BBB is referred to as a 'notch'.

5.1.3.4 20-notch correspondence

In table 5.4 all issuers rated below BBB- have been mapped into one category called a 'sub-investment grade'. As noted above, the rating definitions of sub-investment grade debt given by different agencies vary more widely than those for investment grade ratings. Ignoring categories of sub-investment ratings has the advantage of reducing the number of split ratings caused by this wider range of definitions. The distribution of ratings across the sub-investment grades was reviewed to determine whether certain ratings are used infrequently and can be combined to avoid very small sample sizes at certain rating levels.

As the ratings CC/C and D have few observations, relative to the average for sub-investment grades, they are combined to form one group. Also Moody's does not disclose a D grade, the equivalent is CC or C so it is useful to combine this group so that Moody's and S&P ratings can still be compared in a meaningful way. The resulting '20-notch correspondence' is shown in table 5.5. The use of this scale adds to existing literature which does not discuss matched pairs of sub-investment grade issuers in detail.

Table 5.5: 20-notch correspondence

	CBRS	CI	DBRS	D&P	Fitch	JCR	R&I	Moody's	S&P	TBW
1	AAA	AAA	AAA	AAA	AAA	AAA	AAA	Aaa	AAA	AAA
2	AA+	AA+	AA H	AA+	AA+	AA+	AA+	Aa1	AA+	AA+
3	AA	AA	AA	AA	AA	AA	AA	Aa2	AA	AA
4	AA-	AA-	AA L	AA-	AA-	AA-	AA-	Aa3	AA-	AA-
5	A+	A+	A H	A+	A+	A+	A+	A1	A+	A+
6	A	A	A	A	A	A	A	A2	A	A
7	A-	A-	A L	A-	A-	A-	A-	A3	A-	A-
8	BBB+	BBB+	BBBH	BBB+	BBB+	BBB+	BBB+	Baa1	BBB+	BBB+
9	BBB	BBB	BBB	BBB	BBB	BBB	BBB	Baa2	BBB	BBB
10	BBB-	BBB-	BBB-	BBBL	BBB-	BBB-	BBB-	Baa3	BBB-	BBB-
11	BB+	BB+	BB H	BB+	BB+	BB+	BB+	Ba1	BB+	BB+
12	BB	BB	BB	BB	BB	BB	BB	Ba2	BB	BB
13	BB-	BB-	BB L	BB-	BB-	BB-	BB-	Ba3	BB-	BB-
14	B+	B+	B H	B+	B+	B+	B+	B1	B+	B+
15	B	B	B	B	B	B	B	B2	B	B
16	B-	B-	B L	B-	B-	B-	B-	B3	B-	B-
17		C+			CCC+	CCC+	CCC+	Caa1	CCC+	
18	C	C	CCC	CCC	CCC	CCC	CCC	Caa2	CCC	CCC
19		C-			CCC-			Caa3	CCC-	
20	D	D	CC/C/D	CC/DD	CC/C/ DDD/DD	CC/C/D	CC/C	Ca/C	CC/C/D	CC/C/D

5.1.3.5 Watch grade correspondence

A more detailed rating correspondence could potentially be used to incorporate the watch grades. Watch grades provide valuable information about the expected direction of the agency's next rating change. A 'u' stands for 'up' so the next change is expected to be an improvement. An 'e' stands for emerging, this means that the agency is not saying which way the rating will change but it is anticipated that there will be a change either up or down. A 'd' watch stands for down so these ratings can be expected to fall. This rating correspondence is very detailed and has been included in Appendix 2.

5.1.3.6 Basel II correspondence

For Basel II, it is useful to understand how many split ratings will arise under the risk weight categories specified in the New Basel Capital Accord. A correspondence based on these risk weights has been designed for this study. This allocates risk weights as follows:

Table 5.6: Basel II correspondence

	Corporates	Banks	Sovereigns
AAA to AA-	20%	20%	0%
A+ to A-	50%	50%	20%
BBB+ to BBB-	100%	50%	50%
BB+ to BB-	100%	100%	100%
B+ to B-	150%	100%	100%
C+ and below	150%	150%	150%
Unrated	100%	50%	100%

Split ratings arise where the ratings given to an issuer by different agencies do not fall into the same category and would be given a different risk weight under the Basel II proposals.

In summary, the matched pairs of agency ratings can be compared based on the common scales of:

(1) Investment grade/sub-investment grade correspondence
(2) Letter grade correspondence
(3) An 11-notch correspondence
(4) A 20-notch correspondence
(5) A watch grade correspondence
(6) Basel II correspondence

5.1.4 Bank credit ratings

The individual bank ratings provided by Moody's and Fitch have separate rating scales that are shown in detail in Appendix 1. These ratings have been mapped to the rating scales of the long term credit ratings as shown in Appendix 2.

There are shortcomings involved in mapping long term or individual ratings to a common scale. Research performed by Beattie and Searle (1992), Cantor and Packer (1997) and Tabakis and Vinci (2002) has shown that rating scales of different agencies are not equivalent. It may be more useful to map the scales of individual agencies to their respective probabilities of default if they are available. Detailed Statistics for cumulative average default rates are available for Moody's, Standard & Poors and Fitch at a notch level. For R&I and JCR this information is available at the letter grade level.

5.1.4.1 Correspondence used for modelling bank ratings

Chapter ten gives details of a study modelling bank credit ratings. The credit rating is the dependent variable in this study and four categories of ratings were chosen. Table 5.7 shows the mapping of agency ratings to the one to four numeric scale used for this study. The table includes Moody's, S&P, Moody's BFSR and Fitch individual ratings.

Table 5.7: Credit ratings categories used in chapter ten models

Dependent variable	Moody's long term rating	S&P long term rating (and all other agencies)	Moody's BFSR	Fitch Individual rating
1	Aaa, Aa1, Aa2, Aa3	AAA, AA+, AA, AA-	A, A-	A, A/B
2	A1, A2, A3	A+, A, A-	B+, B, B-	B, B/C
3	Baa1, Baa2, Baa3	BBB+, BBB, BBB-	C+, C, C-	C, C/D
4	Sub-investment grade	Sub-investment grade	Sub-investment grade	Sub-investment grade

Previous studies which have built models to predict bond ratings use a range of categories of dependent variables from four to ten different rating categories. Many studies use six different categories. A smaller number of categories were used in this sample because the data sample relates to banks rather than industrial companies and these ratings incorporate a support element which does not apply to industrial companies. A crucial part of the rater's assessment of a bank consists in considering whether, and in what circumstances, a bank in trouble would be rescued and by whom. This is referred to as the support element. Consequently bank ratings are more difficult to model accurately than industrial ratings and a smaller number of rating categories were modelled.

5.1.5 Calculation of matched pairs of agency ratings

To assess the level of agreement between agencies, the credit ratings of all issuers rated by more than one agency must be compared. For example, BAE Systems plc is rated by Moody's, Standard and Poor (S&P) and Fitch. Table 5.8 shows the credit rating information for this company taken from the FT-CRI database.

Table 5.8: Credit rating information for BAE Systems plc

Agency	Ratings	Date change recorded in database
Moody's	A3 (~A)[1]	November 1999
Moody's	A2 (~A)	December 1999
Moody's	A2 (~A)	January 2003
S&P	A-	November 1999
S&P	A	December 1999
S&P	A-	September 2002
S&P	A-	January 2003
Fitch	A-	November 1999
Fitch	A-	February 2003

Using the example in table 5.8, at the end of February 2003 there were three matched pairs of ratings:

Table 5.9: Matched pairs of credit ratings for BAE Systems plc: February 2003

Date	Agency 1	Agency 2	Rating 1	Rating 2	Difference
February 2003	Moody's	S&P	A2 (~A)	A-	One notch
February 2003	Moody's	Fitch	A2 (~A)	A-	One notch
February 2003	S&P	Fitch	A-	A-	None

Two of these ratings are one notch apart and one is the same.

The data across the whole available history is now considered to show the following matched pairs:

Table 5.10: Matched pairs of credit ratings for BAE Systems plc: Nov 1999 – March 2003

Date	Agency 1	Agency 2	Rating 1	Rating 2	Difference
Nov 1999	Moody's	S&P	A3 (~A-)	A-	None
Nov 1999	Moody's	Fitch	A3 (~A-)	A-	None
Nov 1999	S&P	Fitch	A-	A-	None
Dec 1999	S&P	Fitch	A	A-	One notch
Dec 1999	Moody's	S&P	A2 (~A)	A	None
Dec 1999	Moody's	Fitch	A2 (~A)	A-	One notch
Sept 2002	S&P	Moody's	A-	A2 (~A)	One notch
Sept 2002	S&P	Fitch	A-	A-	None
Jan 2003	S&P	Moody's	A-	A2 (~A)	One notch
Jan 2003	S&P	Fitch	A-	A-	None
Jan 2003	Moody's	S&P	A2 (~A)	A-	One notch
Jan 2003	Moody's	Fitch	A2 (~A)	A-	One notch
Feb 2003	Fitch	S&P	A-	A-	None
Feb 2003	Fitch	Moody'	A-	A2 (~A)	One notch

[1] Using the mapping of agency ratings shown in Appendix 2 , an A3 in Moody' credit rating scale is equivalent to an A- in S&P and Fitch's scale and an A2 is equivalent to an A in S&P and Fitch's scale.

In this example for BAE Systems plc there are 14 matched pairs, 7 agree and 7 disagree by one notch.

If watch grades are appended to the credit ratings the process of comparing pairs of agency ratings would be exactly the same but would be more complex with a higher chance of split ratings.

5.1.6 Treatment of dates on which ratings are updated in the FT-CRI database

If an agency has made several rate changes in one month, sometimes all the changes may be recorded in the FT-CRI database individually but at other times they may be combined into just one change. For example, if in June 2002 S&P changed a rating from AAA to AA+ and then to AA, both changes may be recorded in the database but it is also possible that just the final rating of AA was recorded. The month end ratings are always correct (as determined by the rating with the latest monthly date on the database) but the detail of movements may or may not be included. If the full detail of multiple changes that took place within a month by one agency were included in data, this would introduce bias as additional matched pairs would be generated in some instances but not in others. For the purposes of this study the credit rating AA+, in the example above, would have been deleted and only the move from AAA to AA considered in the analysis of matched pairs.

From time to time an issue is deleted from the database. Where the database gives a date of deletion this issue is excluded from the sample of matched pairs. Sometimes an issue may be deleted in one month and reinstated a few months later, when new debt is issued. In this case the issue would not be included in any matched pairs during the period between its deletion and reinstatement.

5.1.7 Industry and country categorisations

The FT-CRI categorises issuers into one of 37 industry categories. These were allocated into 13 broader categories for the purpose of this study. Where possible, these categories were based on S&P's groupings as disclosed in Standard and Poor's (2002a).

- Banks
- Finance and real estate

- Automotive and manufacturing
- Consumer
- Energy
- Forestry and building
- Technology and computers
- Leisure
- Transport
- Utilities
- Sovereigns
- Healthcare
- Insurance

Several other studies have broken down split ratings by industry. The banking industry has been studied by Cantor and Packer (1995) and Morgan (1997, 2002). Beattie and Searle (1992) focused on a wider range of industries and split the FT-CRI categorisations into 9 groups. These were sovereigns, banks finance, (including insurance and real estate), energy, utilities, transport and storage, consumer goods/services, capital goods and basic industries. The impact of the industry in which an issuer operates on the level of split ratings is explored in detail in chapter seven.

The FT-CRI contains data for 131 countries. As the coverage in some of these countries is very small, the data was split into nine country groups. These are:

- UK
- Europe
- USA
- Canada
- Japan
- Far East
- South America
- Middle East and other
- Supranationals

The Supranational group only contains 104 matched pairs (the next smallest country group contains 2,762 matched pairs) so this group is included within Middle East and other for most of the studies performed. Beattie and Searle (1992b) also studied the impact of geographic sector on fixed ratings.

5.1.8 Software designed to interrogate the database

Computer software was used to integrate the FT-CRI database and generate matched pairs as illustrated in table 5.10 above. The software allows a wide range of comparisons to be made, for example:

5.1.8.1 Comparing all matched pairs of ratings between all agencies

The software allows comparison of all matched pairs of ratings for all agency pairs in comparison with each other on an overall basis. A specific time period can be chosen, such as the most recent ratings only or the whole period of the database. The same analysis is possible with only specified agencies. Industries and countries can also be specified to restrict the analysis. This functionality is used to assess the overall level of inter-rater agreement (chapter five) and industry and geographic characteristics (chapter seven).

5.1.8.2 Comparing matched pairs between specified agency's

It is possible to compare a reference agency with one or more target agencies. For example matched pairs can be calculated between Moody's and S&P or Moody's and both S&P and Fitch etc. where Moody's is the reference agency and S&P and Fitch the target agencies.

The software shows the number or percentage consensus between the agencies for all pairs chosen (e.g. Moody's vs. S&P and Moody's vs. Fitch) as well as the count and breakdown of the level of split ratings. The level of split ratings is analysed according to the correspondence being used, for example if a letter grade correspondence is used the split ratings would be shown in terms of the size of the difference between ratings in terms of letter grades. The combined results from comparison of the agencies are also show in an overall column. This analysis is used in the second part of chapter five where the matched pairs from individual credit rating agencies are compared.

This comparison can also be broken down to review all industry or country groups or individual industries or countries can be chosen for detailed analysis as appropriate. A breakdown of these results can also be made by rating category so the relative consensus and split ratings at each rating grade can be analysed.

5.1.8.3 Changes in matched pairs between specified agencies over time

The software allows the results of the comparison of matched pairs between specific agencies to be broken down over specified time periods so that the movement in split ratings over time can be observed. This is used wherever an analysis is performed of changes in rating consensus over the period of the database, i.e. between May 1999 and March 2004.

5.1.8.4 Analysis of the Basle risk weight that would be attributed by the least and most generous rating agency

The findings of the next four chapters show that there is an approximate ranking of credit rating agencies due to differences in the rating scales used by each agency. These differences are shown to be statistically significant. Using these findings, and refining them for industry and geographic sectors, a detailed ranking of agencies was generated in terms of those that are, on average, the most generous through to those that are the least generous.

Using these findings the software estimates the Basel risk weight that would be attributed to the issuer if the credit rating of the most and least generous agency was used under the standardised approach. Only issuers rated by all the selected agencies are compared. The average risk weights are presented by industry and sector. This functionality is used in chapter nine.

5.1.8.5 Correlation matrix

Correlation co-efficient can be calculated for any combination of agency pairs. This functionality is used in chapter five.

5.1.8.6 The distribution of ratings grades for each agency

This shows the distribution of rating grades for each of the agencies selected and allows an analysis of the quality of the issuers rated by each agency. The overall column combines the results for each individual agency selected and summarises the combined results.

5.1.8.7 Analysis of issuers rated by more than one agency

A body of the literature examines the issue of "window shopping" by issuers and asks whether issuers choose a buy a rating from a third agency (i.e. Fitch) so that they can obtain a better rating grade. The principle is based on that fact that US issuers will be rated by Moody's and S&P automatically if they are listed by the SEC. Issuers may also choose to request a third rating from Fitch or another agency but only pay for this rating if it is an improvement on those of Moody's and S&P. In other words there will be a selection bias as only the higher Fitch ratings will be purchased and enter the public domain. Previous work by Cantor and Packer (1996 and 1997) looks into this theory in detail but finds no evidence for window shopping by issuers.

The software allows issuers rated by specified agencies to be analysed. The rating level for these jointly rated issuers is of particular interest so that analysis can be performed around the investment grade/sub-investment grade cut-off point. For example if an analysis is performed for Moody', S&P and Fitch the software will show the distribution of rating grades for issuers rated by all three agencies for each of the three agencies. This would show whether the rating grades issued by Fitch, for the same group of issuers, are higher than those of Moody's and S&P.

5.2 Database biases and errors

> "The presence of erroneous data can destroy a research effort and seriously damage the management decisions based upon research." Rosenberg and Houglet (1974).

Rosenberg and Houglet conclude in their study of CRSP and Compustat data that it is "difficult to escape the conclusion that data error will be a problem in all the large databases in the social sciences and, in particular, in the several large machine readable repositories of economic and financial data."

Although nearly 30 years has passed since this study and many more databases are available to researchers, there is still a risk that errors in the data contained within large databases go undetected and invalidate research.

To check the accuracy of the FT-CRI data, one daily electronic feed from Fitch was compared to the database. Unfortunately the two database are not truly independent as the FT-CRI data ultimately comes from the same source as the electronic feed with which it was being compared. However, the FT-CRI is not fed from this particular electronic Fitch feed but it is updated manually from a paper copy report provided by Fitch. This means that checking against an electronic Fitch feed was a good way to ensure that the data used in this study does not contain a large number of errors that could invalidate the results.

The daily Fitch feed contains 2,900 issuers in a separate issuer file (separate to the issues file which contains ratings for about 45,000 individual issues). It was taken for 30/4/2001 as this date fell in the middle of the period covered by the FT-CRI database used in this study. If a Fitch feed file was chosen from the end of the period there would be a risk that updates would not yet have been processed and a large number of unexplained differences would arise.

Of the 2,900 issuers in the Fitch feed, only 1,949 contained ratings data (i.e. 951 contained blank fields and were ignored). 1,863 of these were matched with names in the FT-CRI database and 86 (4%) had no name match. Of the matched names, 199 did not have ratings for Fitch, they matched with the FT-CRI database because it contains ratings for those named issuers for Moody's, S&P or another agency.

Checking the FT-CRI database for issuers not contained in the daily Fitch feed revealed 429 companies in FT-CRI but not in the Fitch feed. A random sample of 82 of these 429 companies was checked to understand why they are in the FT-CRI database but not in the daily Fitch feed. 18 (21%) has either been missed in the matching process and had not been matched. Name matching between different rating databases is not straightforward. Problems are caused by differences in punctuation, common synonyms such as 'corp', 'co', 'comp', 'ltd' etc. and qualifiers such as local, forex or deposit.

50 issuers (62% of the random sample) were not found in the FT-CRI database up to or including the date of the Fitch feed file (31/4/2001) so it was concluded that they had not been rated at that time. 5 issuers (6%) had ratings in FT-CRI prior to the Fitch feed but none at or after 30/4/2001 so it appears that these issuers should have been deleted from the FT-CRI.

9 unmatched issuers (11%) appeared to be more ambiguous. There were ratings in the FT-CRI both before and after 30/4/2001 but nothing in the Fitch feed. The possible explanations for this are that the ratings should have been deleted from the FT-CRI as they were no longer current. Alternatively they may have been missing from the Fitch feed.

In summary, valid explanations were found for 83% of the sample of ratings in the FT-CRI but not in the Fitch feed, other problems seem likely to have been caused by problems in the Fitch feed, rather than the FT-CRI database.

For the remaining 1,669 issues that match with the FT-CRI and for which there is credit rating data available for Fitch, the issues were compared to check that the credit ratings are consistent, i.e. the FT-CRI has been updated correctly. The FT-CRI rating current one month after the date of the Fitch feed (May 2001) was used for the comparison. This was because updates are entered into the FT-CRI database approximately one month after they are issued by the rating agency.

Using the 20-notch correspondence, 95% of the ratings match exactly. In other words, at the end of May 2001 1,252 FT-CRI ratings matched those taken from the Fitch feed for April 30. Of these that did not match, 36 (70%) were no more than one notch apart.

The time taken to update ratings was also checked by comparison to the date at which the FT-CRI ratings were changed to align with the matched ratings from the Fitch feed. The majority of ratings were updated within 4 weeks which is consistent with our understanding of this database.

This analysis shows that in general the consensus between the FT-CRI database and a daily feed from Fitch is very high. This gives confidence that there are no major errors in the database that would invalidate the results of this study.

5.3 Bank financial data

Accounting data was kindly provided by Fitch Ratings for the years 1999 - 2003 for approximately 14,500 banks[2]. Financial information is collected by Fitch Ratings from the annual report and accounts at a high level of detail. The same data is used to generate the Bankscope database by Bureau Van Dijk. The data was provided in country specific templates and in an 'as reported' format so that the data closely resembled the original annual report and accounts.

For 36 countries the country specific templates were mapped into a standardised template. The full list of countries for which bank financial information was available is included in Appendix 3 and the standardised template into which the data was mapped is shown in Appendix 4. Standardisation of the data was essential as the raw data was very rich in detail. This would have made meaningful comparison between the banks from different regions very difficult and comparison of equivalent ratios would not have been possible. A validation system of cross checks was designed to ensure that the mapped data summed correctly to total assets, total liabilities, profit before tax and net income as disclosed in the original data. Every effort was taken to ensure the accuracy of the database in the knowledge that erroneous data would invalidate the findings (see Rosenberg and Houglet 1974).

[2] The author is very grateful to the London office of Fitch Ratings for providing bank financial data and individual credit ratings, especially Robin Munro-Davies and David Andrews.

Values from the template shown in Appendix 4 were mapped into ratios and absolute values to be used as independent variables in the credit rating models. The full list of ratios and variables used is shown in Appendix 5. Where absolute values were used, foreign currencies were translated into sterling at the rate in force at 31.12.02. One rate was used to avoid distortions from foreign currency movements. Standardised profit and loss account, asset and liability data (cash flow information was not available) was collected for 10,273 companies for the periods 1999 – 2003 (not all periods are available for all companies). Missing values were removed from the database to provide a total sample of 8,901 banks for which complete accounting data was available.

5.4 Matching accounting and credit rating data

5.4.1 Long term credit ratings

Long term credit ratings were provided by Financial Times Interactive Data's quarterly publication, FT Credit Ratings International. Exactly the same database is used for the study of inter-rater agreement and split credit ratings.

The banks rated by the rating agencies for which data is available from FT-CRI were matched to the database of accounting data. After the combination of credit rating and accounting data the final data samples were as follows:

Table 5.11: Sample sizes of matched bank financial and credit rating data for long term ratings

Agency	Total number of banks	Total number of financial periods*
Live agencies		
Moody's Investor Service	1,159	3,165
Standard and Poor's Rating Group	1,001	2,556
The Fitch Group	1,000	2,652
Dominion Bond Rating Service Ltd	279	424
Capital Intelligence Ltd	183	381
Japan Credit Rating Agency Ltd	194	343
Rating and Investment Information	286	484
Dead agencies		
Canadian Bond Rating Service	57	101

Duff and Phelps Credit Rating Co	207	384
Thomson Financial BankWatch Inc	565	1101

* This is the total number of observations, one bank may have financial data for up to 5 years so it would be included from one to five times in the sample depending on the accounting and credit rating data available.

5.4.2 Individual bank ratings

Individual bank ratings from Moody's (Bank Financial Strength Ratings) and from Fitch Ratings were also matched to the accounting data as above. Sample sizes were as follows:

Table 5.12: Sample sizes of matched bank financial and credit rating data for bank individual ratings

Combination of agencies	Total number of banks	Total number of financial periods*
Moody's Bank Financial Strength Ratings	1,167	2,944
Fitch Individual Ratings	914	2428
Moody's BFSR and Fitch Individual Ratings	1,281	3,660

* This is the total number of observations, one bank may have financial data for up to 5 years so it would be included from one to five times in the sample depending on the accounting and credit rating data available.

5.5 Summary

This chapter has described the different databases used for the studies that are presented in the following chapters. Credit ratings data is taken from Financial Times Credit Ratings International (FT-CRI), Fitch Individual bank ratings and bank financial accounting data were supplied by Fitch Ratings.

As this study compares the ratings of a number of different rating agencies it is necessary to map ratings to a common scale for comparison purposes. The full range of credit ratings and alternative rating correspondences is discussed in this chapter. Sophisticated software has been designed for and used in this study to allow a detailed analysis of split credit ratings. The functionality of this software is outlined in this chapter. The problems of database biases and errors are also considered and the database is tested for significant errors.

The process of standardising the detailed bank fundamental data provided by Fitch Ratings is explained as is the matching of accounting and credit rating data for use in modelling bank credit ratings.

The level of inter-rater agreement

This chapter considers the level of agreement and split ratings between different credit rating agencies when they rate the same issuer. It looks at tendencies for particular agencies to agree or disagree over ratings and considers whether these trends change over time. Finally, the distribution of the level of credit ratings assigned by different agencies is considered and split ratings are compared for investment and sub-investment grade ratings.

The findings of previous studies into split ratings, especially Beattie and Searle (1992a) and Cantor and Packer (1995) are revisited. This study adds to previous research by using updated data, a larger sample size and data for a four year period. In addition, previous studies did not investigate splits between the sub-investment grade ratings in detail.

6.1 Overall level of inter-rater agreement

The overall level of inter-rater agreement can be found by comparing matched pairs of agency ratings across the available history of the FT-CRI database. Table 6.1 shows the overall level of agreement and disagreement for May 1999 – March 2004. The final column reproduces the results of the same study performed by Beattie and Searle in 1992, based on FT-CRI data from 1990.

Table 6.1: Overall levels of rating agreement and split ratings between agencies (based on the 11-notch correspondence)

	FT-CRI database All periods May 1999 – March 2004	**FT-CRI database 6 months ending Dec 2002**	**FT-CRI database 6 months ending Dec 2001**	**FT-CRI database 6 months ending Dec 1999**	**Beattie and Searle results (1992) FT-CRI 1990**
Numbers of matched pairs Agreement - rating at same notch	26,568 (51.7%)	8,327 (51.5%)	7,971 (52%)	7,362 (48.1%)	2,315 (44%)
One notch apart	15,786 (30.7%)	5,066 (31.3%)	4,719 (30.8%)	5,117 (32.6%)	1,905 (36%)
Two notches apart	5,500 (10.7%)	1,753 (10.8%)	1,634 (10.7%)	1,711 (11.6%)	746 (14%)
Three notches apart	2,137 (4.2%)	610 (3.8%)	598 (3.9%)	685 (4.6%)	228 (4%)
Four notches apart	818 (1.6%)	249 (1.5%)	251 (1.6%)	266 (1.9%)	90 (2%)
Five or more notches apart	533 (1.0%)	168 (1%)	163 (1.1%)	186 (1.2%)	Not reported
Sample size	*51,342*	*16,173*	*15,336*	*15,327*	*5,284*

In total there are 51,342 matched pairs of credit ratings over the whole period. Using the 11-notch correspondence[1], 51.7% of the matched pairs agree completely, 30.7% disagree by one notch and 10.7% by two notches, as shown in table 6.1.

Overall consensus has increased since 1990 from 44% to 51.5% in the latest period. There is a corresponding fall in split ratings, especially one and two notches apart. The number of differences of three or more notches is relatively small and has remained at similar levels across the whole period. However, only half of all pairs of credit ratings actually agree to within a notch. For the period May 1999 to March 2004 credit rating agencies appear to assign different ratings to the same issuer approximately half of the time.

A review of the results for the 6 months ended 31/12/99, 31/12/01 and 31/12/02 shows the same trends as discussed above. Overall consensus has increased above the 1990 level and one and two notch differences have reduced. On average ratings that were split by one or two notches in 1990 tend to show more consensus over time.

As you would expect, there is a higher level of consensus when comparing ratings by the letter grade correspondence, rather than the 11-notch correspondence used in table 6.1. Table 6.2 shows that 63.2% of credit ratings agree to within one letter grade. Only 3.3% of matched pairs differ by two or more letter grades.

Table 6.2: Overall levels of rating agreement and split ratings between agencies

FT-CRI database - all periods	Letter-grade %	20-notch %	Watch grades %
Agreement - rating at same notch/letter grade or "score"	63.2	32.9	31.5
One apart	32.9	38.7	11.2
Two apart	3.3	16.1	7.5
Three apart	0.5	6.9	24.9
Four apart	0.1	2.8	3.2
Five apart		1.3	3.0
Six apart		0.6	8.7
Seven apart		0.3	1.2
Eight apart		0.2	1.2
Nine apart		0.1	3.3
Ten apart		0.1	4.3

[1] See Chapter five for detailed descriptions of 'rating correspondences'.

As the 20-notch correspondence is considerably more detailed than the 11-notch the level of consensus has dropped to 32.9%. The comparable figure was 51.7% on the 11-notch scale. The difference of 18.8% (a fall of 57%) between the 11-notch and 20-notch correspondence is entirely due to the lack of consensus between sub-investment grades as this is the only difference between these scales. The watch grade correspondence is extremely detailed as it takes into account, not only the '+' and '-' identifiers but also the watch grades, u, d, and e. 31.5% of ratings agree to the same watch grade, the peaks at three and six notch differences arise because many ratings do not have a watch grade so, on this scale, they would frequently be three notches apart. The distribution of ratings is examined later in this chapter to see if there is relatively more agreement between investment grade ratings than there is between sub-investment grade ratings.

6.2 Comparison of matched pairs from individual credit rating agencies

So far, the results discussed in this chapter have been shown on an overall basis and matched pairs between each of the different agencies have not been compared. This section will consider which rating agencies show the most and least consensus, whether these results are consistent over time and if the mean differences between the agencies are statistically significant.

6.2.1 Which rating agencies show the most and least consensus?

To assess the level of agreement between each of the rating agencies, matched pairs for each pair of agencies were compared. The mean difference between each pair of agencies was calculated and tested for significance. If the agency ratings are the same the mean level of split ratings between two agencies will not be significantly different from zero.

Table 6.3 shows the results of this comparison. The pairs of agencies shown in table 6.3 are listed in order of consensus with the highest level of agreement at the top of the table. As noted in the literature review, the high level of agreement between Moody's and S&P has been well documented in other studies. This study shows that S&P and Moody's agree 60% of the time out of a sample of 22,752 matched pairs. Beattie and Searle (1992a) found that the level of consensus between Moody's and S&P was 64% out of a sample of 1,398 matched pairs.

Where the mean is positive this indicates that the average rating for agency 2 is higher than for agency 1. If the mean is negative then the mean rating of agency 1 is higher than agency 2. Table 6.3 shows that S&P tends to rate a little higher than Moody's, this finding is consistent and highly statistically significant. On average, S&P rates 0.07 of a notch higher than Moody's. This result is very similar to a mean difference identified by Beattie and Searle (1992a) of 0.06 of a notch and they also found that S&P rates a little higher than Moody's on average.

Table 6.3: Consensus between pairs of agencies (11-notch correspondence)

Agency 1	Agency 2	Consensus %	Matched pairs	Mean difference	Standard deviation	Correlation coefficient
Fitch	D&P	67.5	797	0.12**	0.84	0.961
S&P	CI	63.7	292	-0.06	0.89	0.909
CI	D&P	63.3	30	0.13	0.92	0.928
Fitch	TBW	61.5	620	0.2**	0.82	0.980
DBRS	D&P	61.1	36	0.14	0.82	0.983
Moody	S&P	60.0	22752	0.07**	1.04	0.940
Moody	CI	57.4	479	-0.46**	1.25	0.841
CI	TBW	55.5	128	0.39**	1.19	0.827
Fitch	CI	55.0	569	-0.10	1.46	0.687
S&P	Fitch	51.8	5630	0.31**	1.02	0.936
TBW	D&P	51.4	175	-0.37**	1.06	0.963
Moody	Fitch	50.3	5837	0.21**	1.16	0.921
S&P	DBRS	49.6	977	0.29**	0.97	0.945
S&P	D&P	48.9	1812	0.42**	1.06	0.933
R&I	D&P	48.8	43	-0.72**	0.92	0.977
Moody	TBW	48.3	631	0.5**	1.26	0.934
Fitch	DBRS	46.3	203	-0.13	0.97	0.898
Moody	DBRS	46.0	790	0.25**	0.99	0.946
Moody	D&P	44.5	1695	0.55**	1.13	0.919
CBRS	D&P	43.9	41	-0.88*	1.61	0.904
CI	JCR	41.9	43	1.09**	1.05	0.883
R&I	JCR	41.8	1188	0.68**	1.03	0.932
CBRS	DBRS	39.8	623	-0.61**	1.28	0.895
JCR	TBW	39.1	46	-1.11**	1.09	0.965
JCR	D&P	38.5	26	-0.96**	0.94	0.968
R&I	TBW	38.2	89	-0.67**	1.13	0.959
S&P	TBW	38.2	519	0.76**	1.21	0.942
S&P	CBRS	34.9	504	0.83**	1.43	0.871
Moody	CBRS	32.1	396	0.81**	1.39	0.899
Fitch	JCR	32.0	197	1.34**	1.43	0.912
Fitch	R&I	31.4	325	0.92**	1.22	0.909
Fitch	CBRS	26.4	53	0.92**	1.43	0.792
S&P	JCR	26.2	416	1.9**	1.86	0.895
CI	R&I	25.5	51	1.35**	1.22	0.886
S&P	R&I	24.4	745	1.72**	1.57	0.900
Moody	R&I	19.2	1593	1.78**	1.69	0.844
DBRS	R&I	16.7	30	1.37**	1.30	0.879
Moody	JCR	12.3	913	2.62**	1.88	0.778

a Results for pairs of agencies with less than 25 observations were excluded from the results.

* significant at 0.05 level (two tailed test), ** significant at the 0.01 level (two tailed test)

Fitch and D&P is another pair of agencies that show a consistently high level of agreement . The overall level of agreement is 67.5% out of 797 matched pairs. On average D&P rates higher than Fitch by 0.12 of a notch. Beattie and Searle 1992a also found that D&P rates a little higher than Fitch on average but found a lower mean and consensus of 0.03 notches and 43% respectively. Fitch acquired D&P in June 2000, it was excluded from the database from 15/8/2000.

Table 6.4: Summary of relationship between pairs of agencies

		Agency 2									
		Moody	S&P	Fitch	DBRS	CI	JCR	R&I	D&P	CBRS	TBW
Agency 1	Moody	-	< /1%	< /1%	< /1%	> /1%	< /1%	< /1%	< /1%	< /1%	< /1%
	S&P		-	< /1%	< /1%	=	< /1%	< /1%	< /1%	< /1%	< /1%
	Fitch			-	=	=	< /1%	< /1%	< /1%	< /1%	< /1%
	DBRS				-	No data	No data	< /1%	=	< /1%	No data
	CI					-	< /1%	< /1%	=	No data	< /1%
	JCR						-	> /1%	> /1%	No data	> /1%
	R&I							-	> /1%	No data	> /1%
	D&P								-	< /5%	< /1%
	CBRS									-	No data
	TBW										-

<	Mean rating of agency 1 is less than agency 2
>	Mean rating of agency 2 is less than agency 1
1%	Statistically significant at the 1% level (two tailed test)
5%	Statistically significant at the 5% level (two tailed test)
=	No statistically significant difference between the means of the agencies
No data	Less than 25 observations for this pair of agencies

Table 6.4 summarises the relationship between the mean ratings of the pairs of agencies and shows the results of significance testing. The table effectively shows a rank of the mean difference between pairs of agency ratings starting with Moody's as the least generous agency and showing the Japanese agencies as the most generous. 84% of the matched pairs have means that are significantly different from one another at the 1% level. One pair is significantly different at the 5% level (D&P and CBDR) and a further five pairs show no significant difference between means.

The null hypothesis could not be rejected for five pairs of agencies: Fitch and CI, S&P and CI, Fitch and DBRS, DBRS and D&P and CI and D&P. This finding is generally consistent with Beattie and Searle 1992a as they found that in 17 out of 25 cases there was a significant difference between the means at a 1% level. None of the five pairs identified above were included in their study. Pairs which showed no significant difference between means in Beattie and Searle's study, and are also included in my study, were Fitch and D&P, Moody's and DBRS, S&P and DBRS.

Particular pairs of credit rating agencies show the lowest level of consensus, this holds true whether the comparisons are made using data from the whole database or for specific six month periods between May 1999 – March 2003. These are:

- Moody's and JCR
- S&P and JCR
- Moody's and R&I
- S&P and R&I

Table 6.5: Mean differences in notches between Moody's, S&P, JCR and R&I

Agencies	6 months to Dec 1999 – mean difference (notches)		6 months to Dec 2001 – mean difference (notches)		6 months to Dec 2002 – mean difference (notches)	
	11-notch	20-notch	11-notch	20-notch	11-notch	20-notch
Moody's & JCR	2.79**	3.25**	2.56**	3.00**	2.41**	2.83**
S&P & JCR	1.77**	2.02**	1.76**	1.94**	1.84**	2.06**
Moody's & R&I	2.00**	2.32**	1.84**	2.10**	1.63**	1.97**
S&P & R&I	1.7**	1.87**	1.55**	1.64**	1.45**	1.68**

** significant at the 0.01 level (two tailed test)

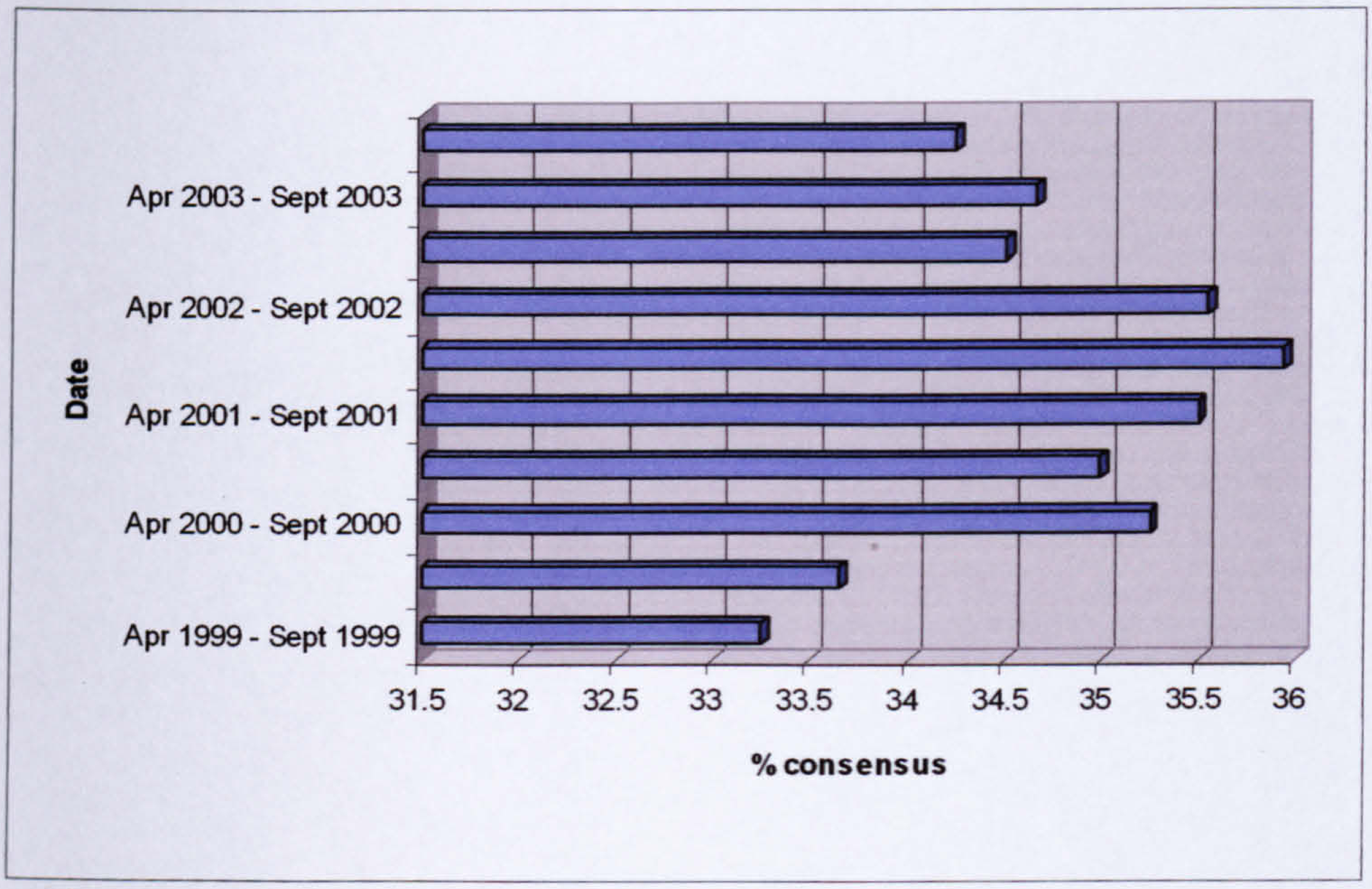
These four pairs of agencies consistently show the lowest levels of overall consensus of any combinations of rating agencies. Moody's and JCR shows the lowest level of consensus for all periods; there is an average difference of 2.6 notches using the 11 notch correspondences and 3 notches using the 20 notch correspondence.

The literature covering Japanese rating agencies finds that, on average, they rate between one to two notches higher than Moody's and Standard & Poor's. Beattie and Searle find that the mean differences in notches between S&P and R&I and Moody's and R&I are 1.18 and 1.75 respectively where the Japanese agencies rating higher than US agencies. This study uses an equivalent rating correspondence and shows higher mean notch differences between these agencies than in 1990.

6.2.2 Does the level of consensus change over time?

Figure 6.1 shows the consensus between matched pairs of agencies for the 6 months ended December 1999 to 2003. Only pairs of agencies that feature throughout the history of the database have been included so any combination that includes D&P, TBW and CRBS is not shown.

Figure 6.1: Change in consensus over time - 20 notch correspondence



The level of consensus has fluctuated over time but the overall trend appears to be an increase in consensus.

6.3 Distribution of rating grades and rating consensus

The final section of this chapter examines the relative levels of consensus for investment grade and sub-investment grade issuers. Cantor and Packer (1995) found that there is generally less consensus between agencies for sub-investment grade ratings than for investment grade.

Figure 6.2: Quality distribution of major rating agencies

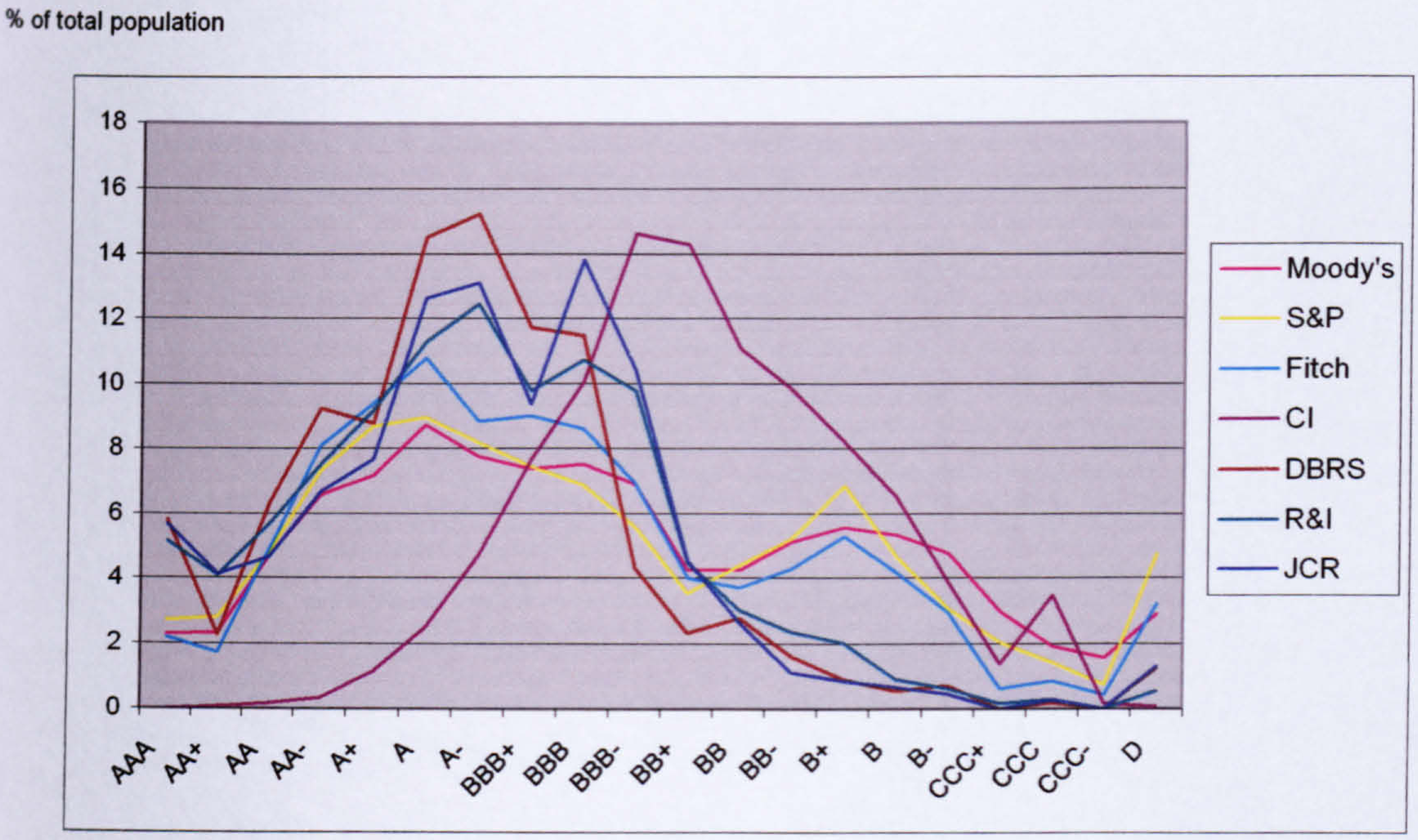


Figure 6.2 compares the quality distribution of the FT-CRI database for the seven major agencies reviewed in this chapter. The ratings of Moody's, S&P and Fitch appear have a similar distribution, with a peak in investment grade ratings at the A grade and for sub-investment grade ratings at B grades. DBRS, R&I and JCR show a similar peak at around A- and each agency has a higher proportion of AAA grades than the three largest agencies. The number of AAA grades is not higher in absolute terms but does appear to be relatively high as the smaller agencies have a smaller population of sub-investment grade ratings.

In general, figure 6.2 shows that the quality distribution of DBRS, R&I and JCR appears to be higher, on average, than Moody's, S&P and Fitch. They have far fewer rated issuers than the three larger agencies[2] but we also know from this research that they each appear to rate a little higher than Moody's and S&P so this will impact the quality distribution.

2 DBRS, R&I and JCR have 1,115, 2,424 and 1,526 ratings in FT-CRI respectively. This compares to 23,810 ratings for Moody's and 25,821 for S&P)

Figure 6.3: Distribution of investment grade vs. sub-investment grade ratings

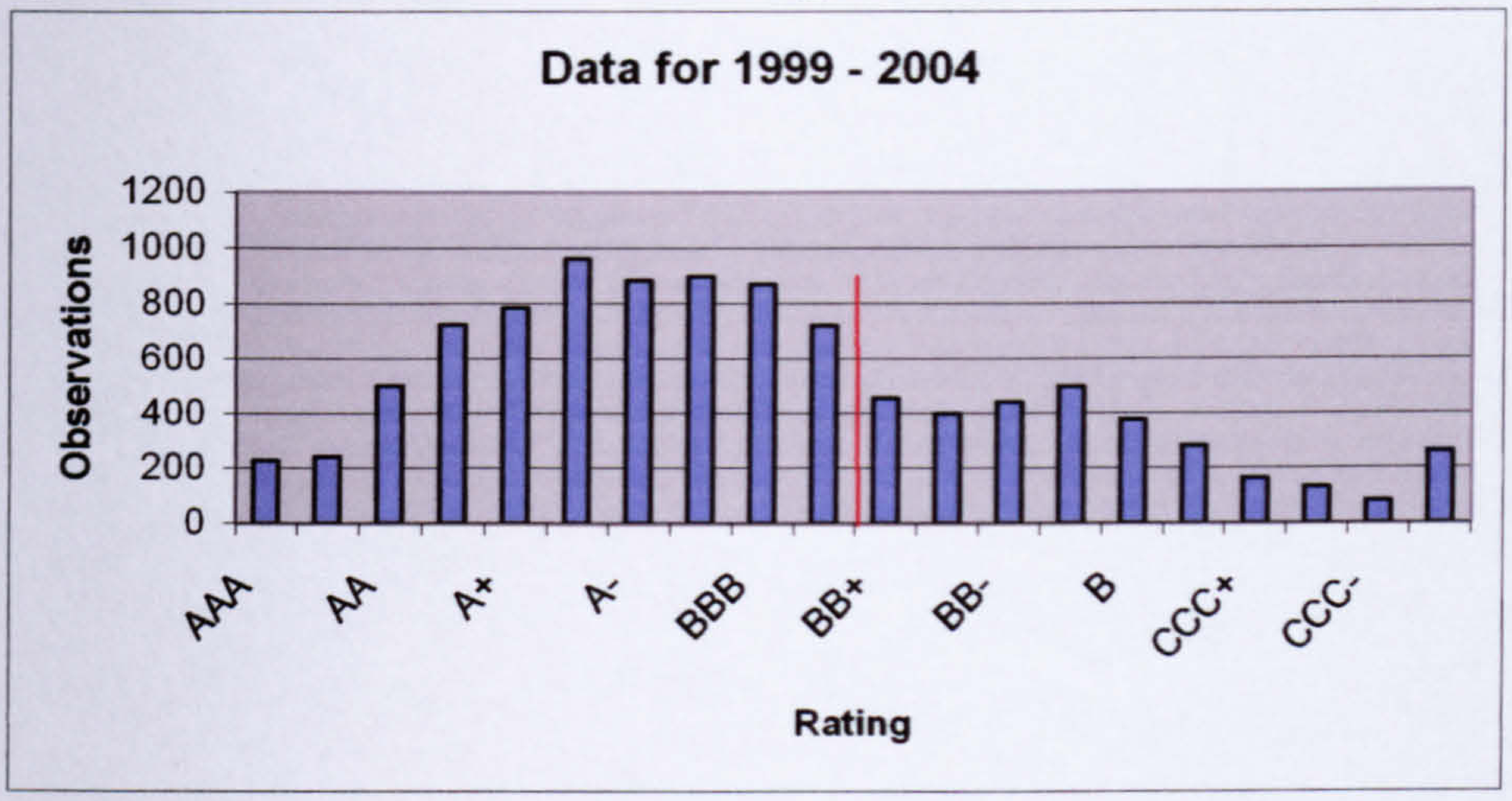
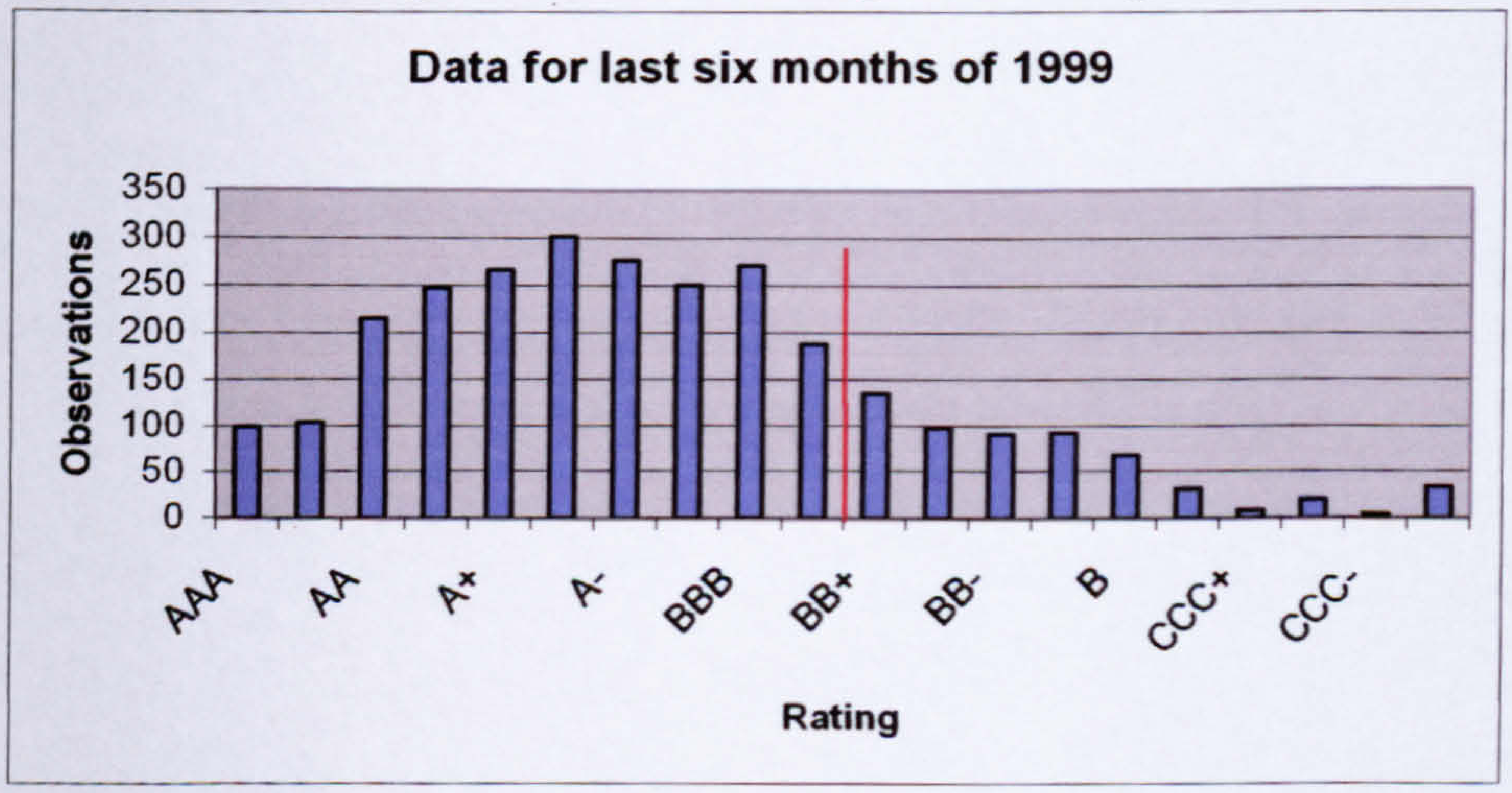


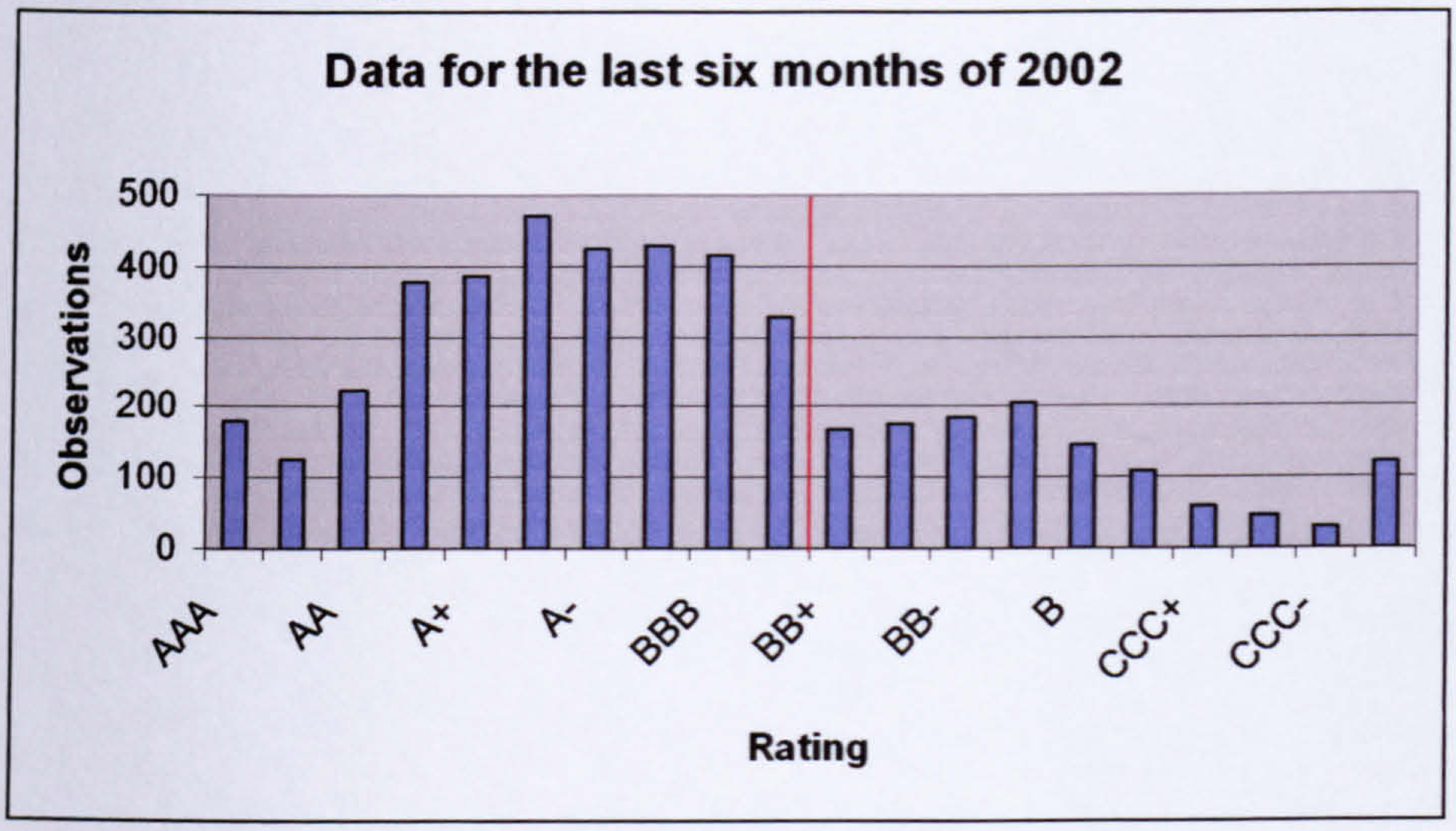
Figure 6.3 shows that there are fewer rating observations for sub-investment grade issuers than for investment grade issuers. However the average number of observations for each category of sub-investment grade ratings is approximately 300. Only for the grade CCC- does the number of observations fall below 100.

Figure 6.4: Average number of ratings of each grade – last six months of 1999



Data for the last six months of 1999 shows that for the early periods of the database there are fewer observations of sub-investment grade ratings, especially for B- where observations fall to below 35 on average.

Figure 6.5: Average number of ratings of each grade – last six months of 2002

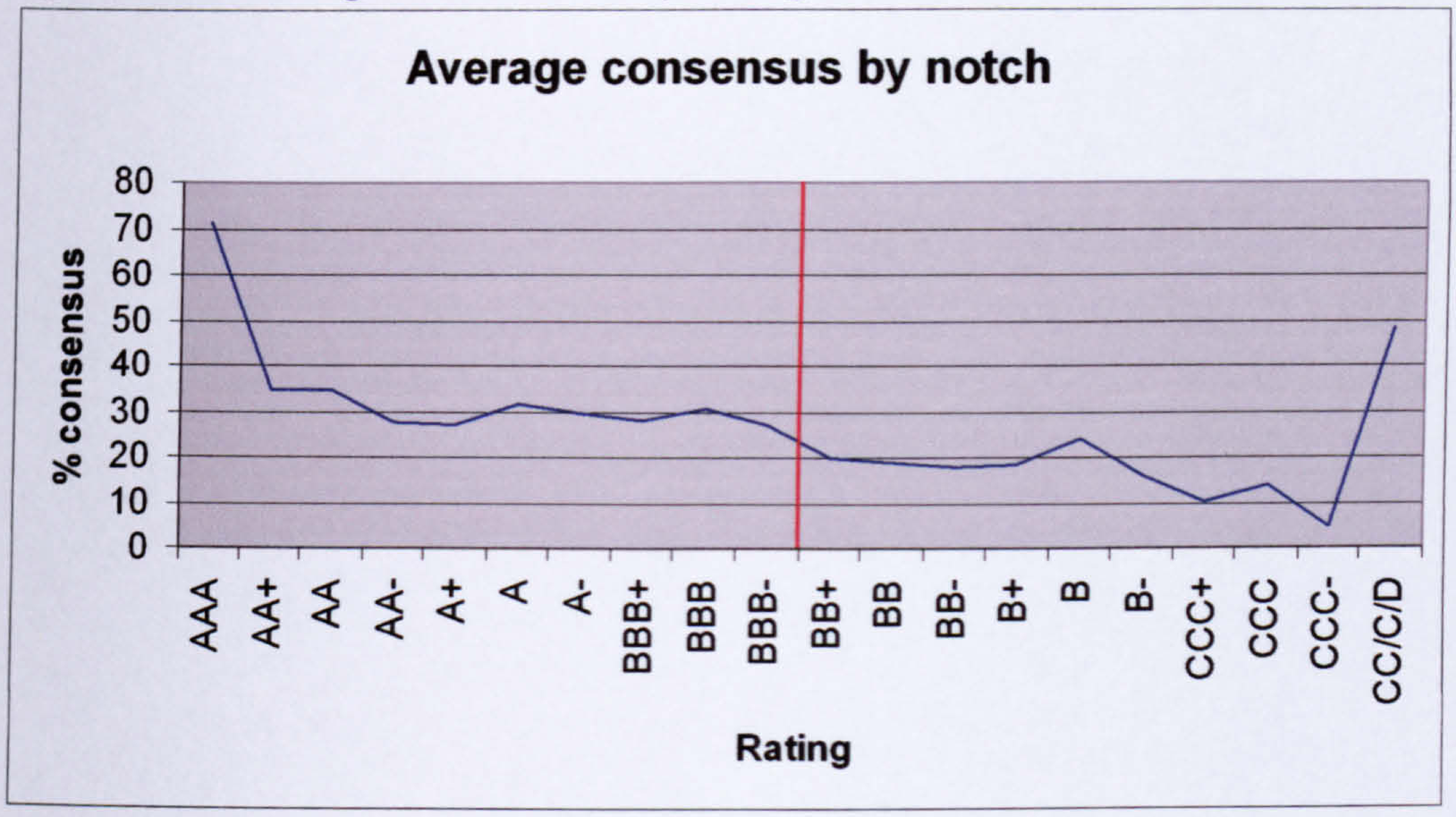


A comparison of figures 6.4 and 6.5 shows that the number of sub-investment grade ratings in the database has increased over time. The majority of sub-investment grade ratings in this sample are issued by the three larger agencies. These agencies use the full range of available ratings while the smaller agencies do not use the grades CCC+ and CCC-. This means that there will inevitably be more split ratings around these grades when the smaller agencies are compared to Moody's, S&P and Fitch.

6.4 Split credit ratings and changes in the credit risk of the issuer

Figure 6.6 shows the level of consensus for each rating grade, this data is calculated from the average of the seven live agencies in the data sample. The average level of consensus drops as the perceived credit risk of the issuer increases. The level of consensus over the rating of AAA grade bonds is very high at 71% but this falls to 16% on average for sub-investment grade issuers that have not yet defaulted. This graph clearly demonstrates that credit rating agencies disagree over ratings far more frequently as the quality of the issuer falls and the probability of default increases.

Figure 6.6: Average consensus by rating notch



6.5 Summary

The overall level of consensus between the rating agencies is approximately 50%. This result treats sub-investment grade ratings as one band and the consensus is considerably lower (33%) when split ratings between sub-investment grades are also taken into account. The level of consensus appears to have increased over time.

There are statistically significant differences between most pairs of agency ratings and mean differences show that a ranking exists between the agencies where some tend to rate more or less generously than others. The results are consistent for the period 1999 – 2004. Consistent with previous research, Japanese agencies are shown to have the widest split ratings when compared to the major US credit rating agencies.

The final section of this chapter presents the level of consensus for each rating grade and shows that as the credit quality decreases so the level of split ratings increases.

Differences between agency ratings scales and home country bias

Chapter six presented evidence to support the view that rating scales used by different agencies are not equivalent. Statistically significant mean differences between ratings for the same issuer indicate that either the cut-off points between rating grades are systematically different between agencies or the whole rating scale is skewed up or down for some agencies in comparison to others. The objective of this chapter is to examine this question in more detail and to understand the rating characteristics of the major rating agencies.

Previous studies have shown that agencies show home country bias in that they are more lenient on issuers from their own country and also that they are more likely to agree with rating agencies based in the same country. The second part of this chapter investigates these issues.

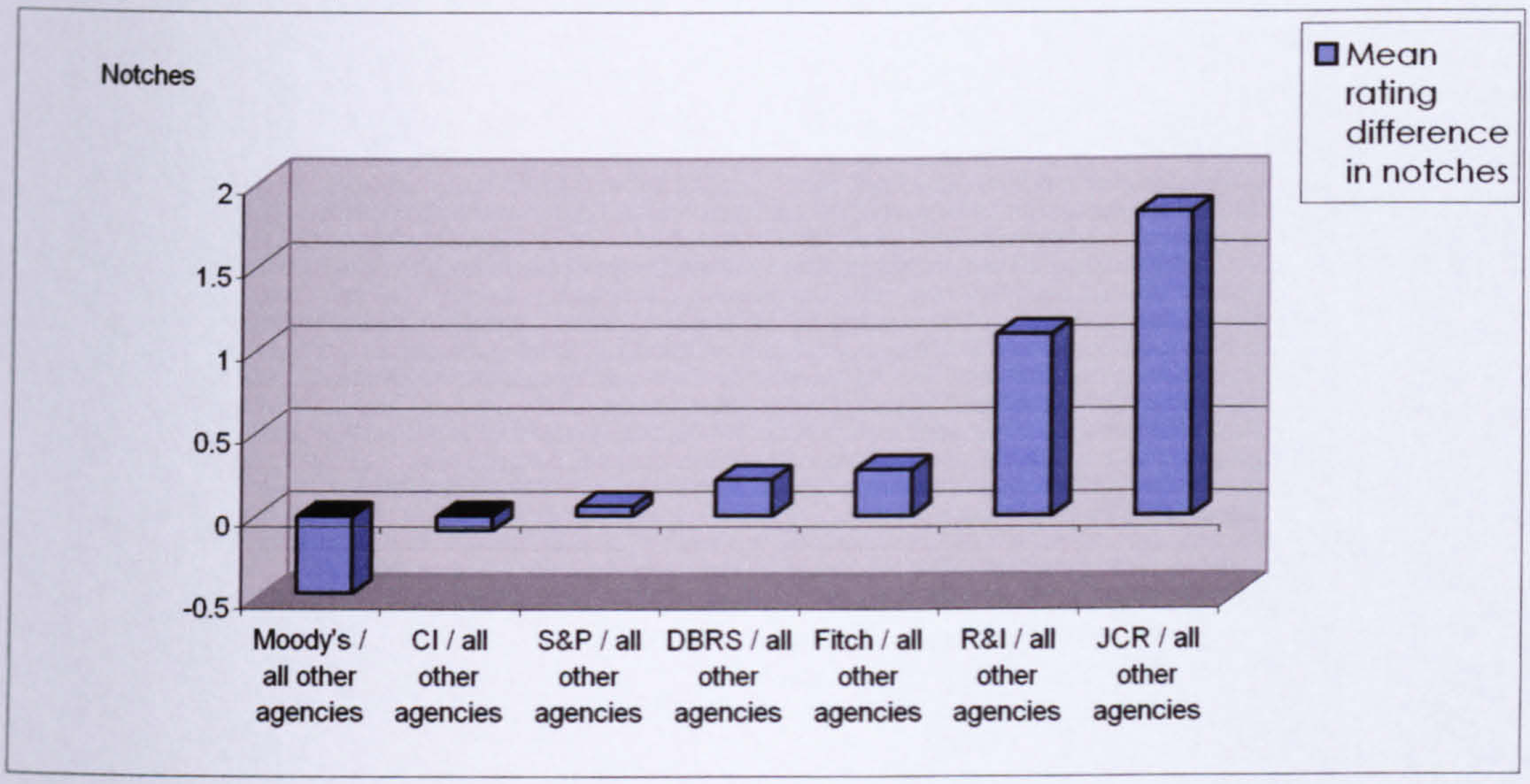
7.1 Differences between agency rating scales

Appendix 6 shows results for matched pairs for the live agencies in the data sample. These are Moody's, S&P, Fitch, DBRS, CI, JCR and R&I. The level of consensus and split ratings for all agency combinations are shown as well as a comparison of each agency with the combined data of all the other agencies.

7.1.2 Mean rating difference between agencies

The mean level of split ratings between agencies, in notches, is shown graphically in figure 7.1. The data for this graph is taken from Appendix 6, section D.

Figure 7.1: Mean rating difference between agencies (20-notch correspondence)



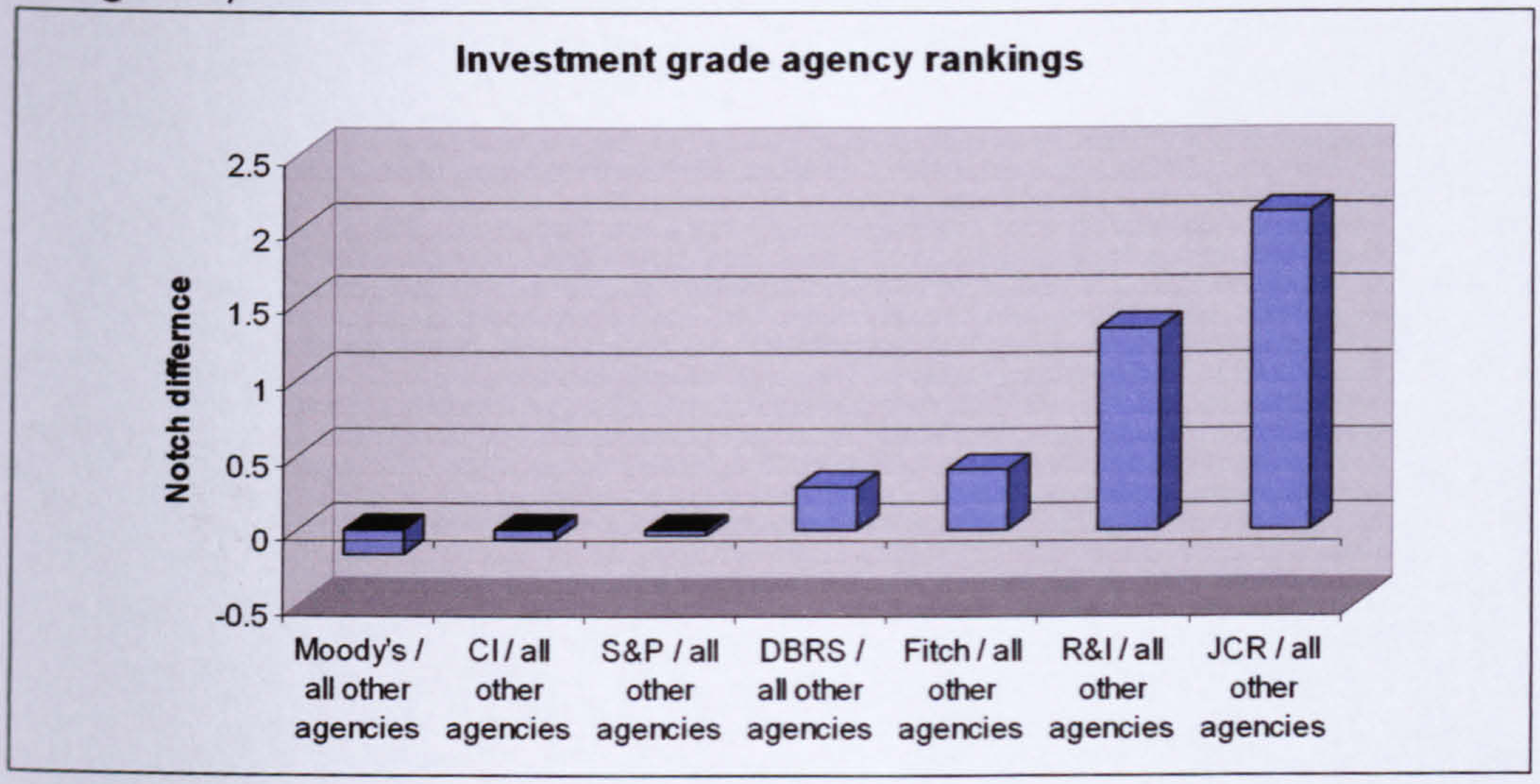
The mean differences are negative for Moody's and CI which indicates that their ratings, on average, are lower than those of other agencies by 0.5 and 0.1 of a notch respectively. For S&P the mean lies close to zero while the other four agencies have a positive mean with the highest being for JCR. As discussed in chapter six, the average rating from JCR is higher than for any of the other six agencies included in these results. It is interesting to note the ranking of the agencies. The results indicate that Moody's gives the toughest ratings and JCR the most lenient. DBRS and Fitch have very similar means and are in a position in the middle of the other agencies. The mean difference between the named agency and the other agencies with which ratings are matched is significantly different from zero at the 1% level in all cases except CI.

Significance tests can also be used to compare the results for each agency (i.e. comparing the blocks on the graph with each other, for example the mean of Moody's vs. all other agencies and CI vs. all other agencies). This shows that three agencies are significantly different from all the others at the 1% level. These are Moody's, R&I and JCR. CI and S&P are not significantly different from each other at the 1% level but are at the 5% level. DBRS and Fitch are not significantly different from each other at either level.

7.1.3 Changes in agency ranking due to issuer credit quality

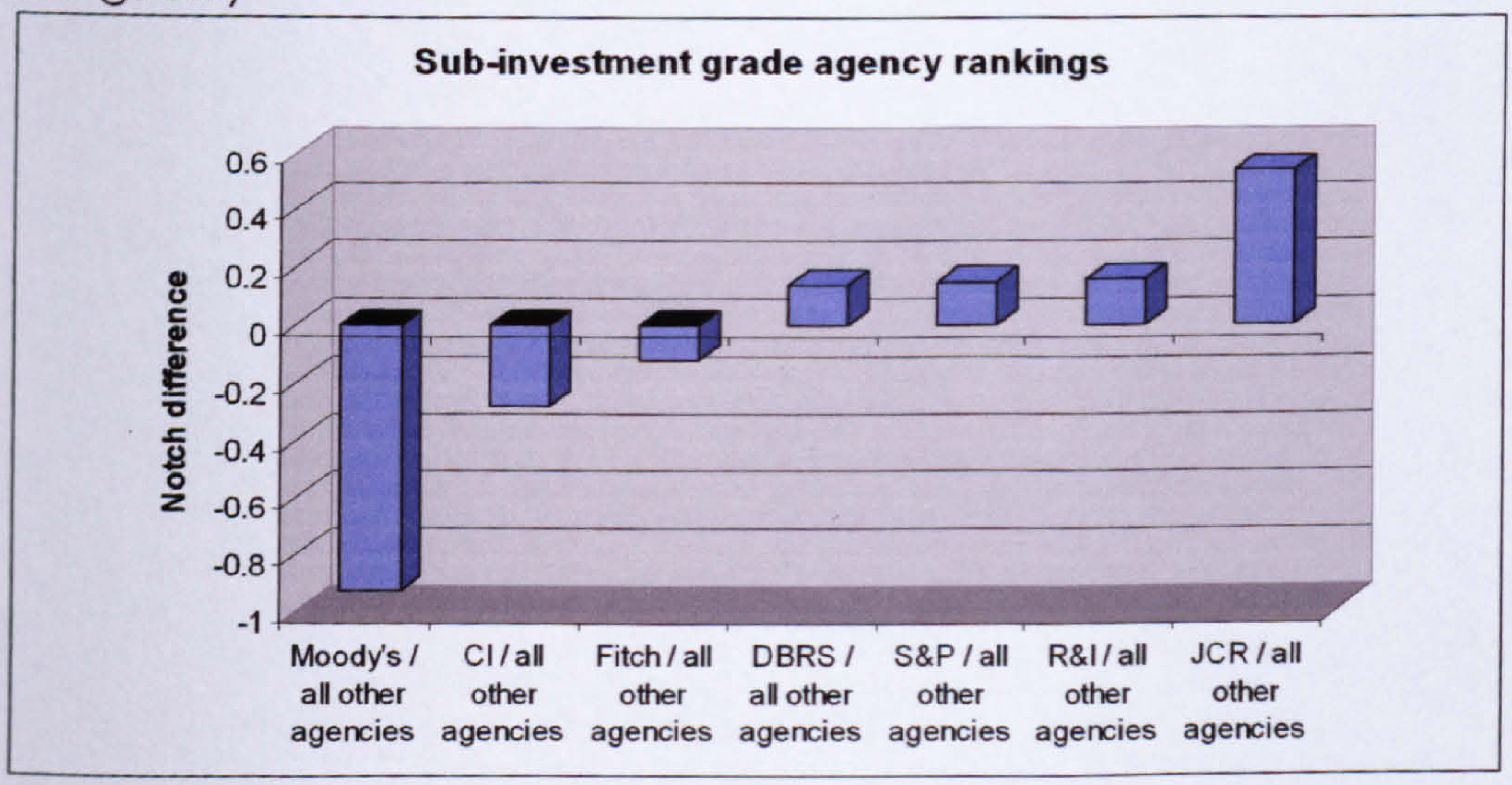
Figure 7.2 shows the ranking of agencies when only investment grade ratings are taking into account. The ranking is the same as figure 7.1 above except that S&P is now shown to be rating slightly lower than the other agencies.

Figure 7.2: Mean rating difference between agencies: investment grade ratings only



When only sub-investment grade ratings are taken into account there are some changes in the rankings observed in figures 7.1 and 7.2. Figure 7.3 shows that Fitch and S&P have changed places in the ranking so that, after Moody's and CI, Fitch is the least generous agency.

Figure 7.3: Mean rating difference between agencies: sub-investment grade ratings only

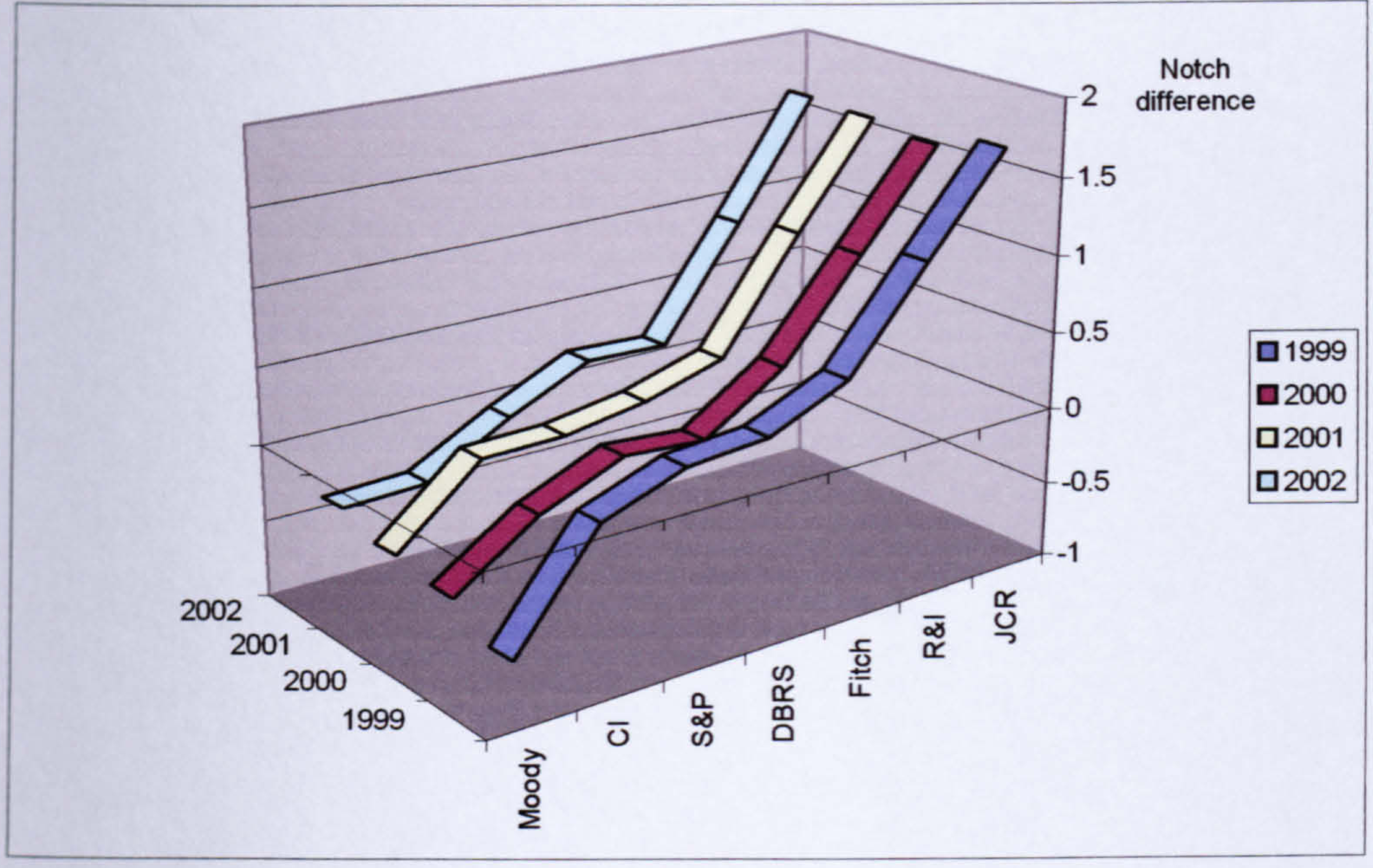


In place of Fitch, S&P is the most generous before R&I. These changes in the rankings of agencies, depending on the quality of the issuers under review, suggest that for some agencies the cut-off points between rating grades differ. For example Moody's is tougher on lower quality issuers while S&P is more generous, Fitch is considerably less generous with sub-investment grade issuers than investment grade. In contrast, for R&I and JCR the whole scale appears to be skewed upwards and is above the other agencies for all rating grades.

The mean difference between the named agency and the other agencies with which ratings are matched is significantly different from zero at the 1% level in all cases except S&P which is different at the 5% level and CI which is not significant. When the means of the different agency comparisons are compared with one another significance tests show that Moody's, CI, S&P, DBRS and Fitch are all significantly different from all other agencies at the 1% level but that R&I and JCR are not different from one another at the 1% or 5% level.

The analysis so far has been based on the whole FT-CRI database from 1999 to 2004. Figure 7.4 shows the mean rating difference between each of the six agencies for four 6 month periods ended 1999 through to 2002. Apart from slight changes in the position of DBRS the relative positions of the credit rating agencies is consistent over time. The mean difference between the named agency and the other agencies with which ratings are matched is significantly different from zero at the 1% level in all cases except DBRS and R&I which are not significant.

Figure 7.4: Mean rating difference between major agencies (20-notch correspondence over four different 6 month periods ending 31 Dec)

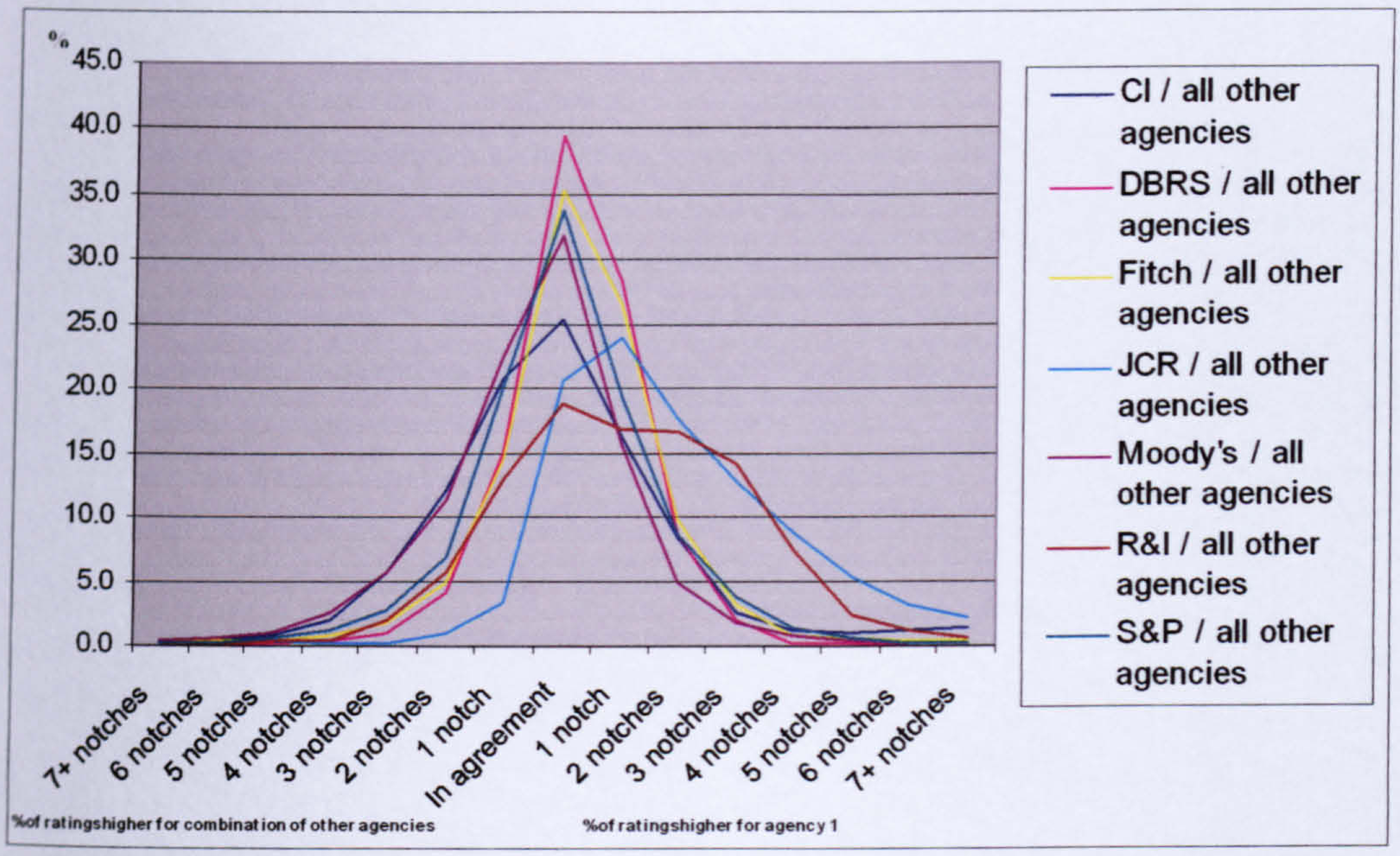


7.2 Comparison of the dispersion ratings by different agencies

The focus of the analyses above has been on the mean rating differences rather than on the level of split ratings. Another way of looking at the differences in rating scales and consensus between agencies is to plot the percentages of rating differences for the agencies. This combines an understanding of the mean as well as the relative dispersion of split ratings from different agencies.

Figure 7.5 plots data from section D of Appendix 6. The graph clearly shows the distribution of each agency. R&I and JCR are skewed to the right indicating that, on average, if there is a split rating the issuer is rated higher by those agencies. The line for JCR lies furthest to the right which is consistent with the graphs presented above. The navy blue line for CI lies furthest to the left. All agencies, apart from the Japanese ones, have similar levels of agreement and dispersion. The coloured lines broadly run in the order blue (CI), purple (Moody's), green (S&P), yellow (Fitch), pink (DBRS), brown (R&I) and light blue (JCR). This ranking is consistent with Figure 7.1.

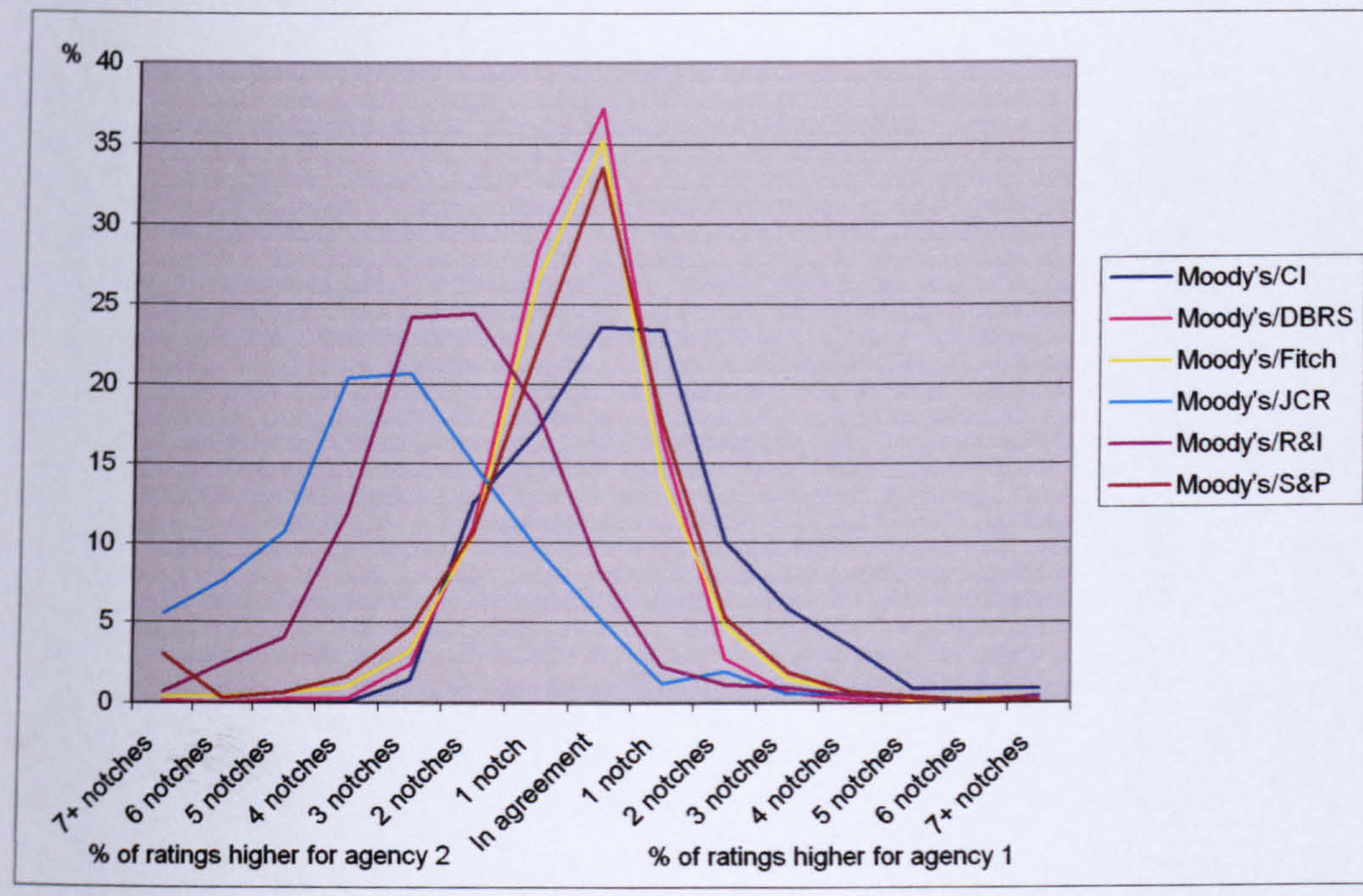
Figure 7.5: Relative ranking of major agencies (20-notch correspondence)



CI, R&I and JCR clearly show lower levels of agreement than other agencies. The distribution is not symmetrical due to the differences in rating scales and the distributions are more widely spread due to higher levels of disagreement.

A review of just one agency in comparison with the others reveals a consistent picture. Figure 7.6 plots data from section C of Appendix 6 and shows Moody's in comparison with each of the other six agencies used in this study. This time the results are presented as the ratings of the other agency in comparison to Moody's. The lines skewed to the left show that the ratings of the alternative agency are higher than those for Moody's. This is the case for R&I and JCR. The lines skewed to the right (CI) show that the ratings of the second agency are lower than those for Moody's.

Figure 7.6: Relative ranking of agencies in comparison to Moody's (11- notch correspondence)



It has been the aim of this section to clearly demonstrate that a ranking exists between the major rating agencies. This arises because the cut-off points between rating grades are systematically different and, in the cases of R&I and JCR, the whole rating scale is skewed upwards in comparison to other agencies.

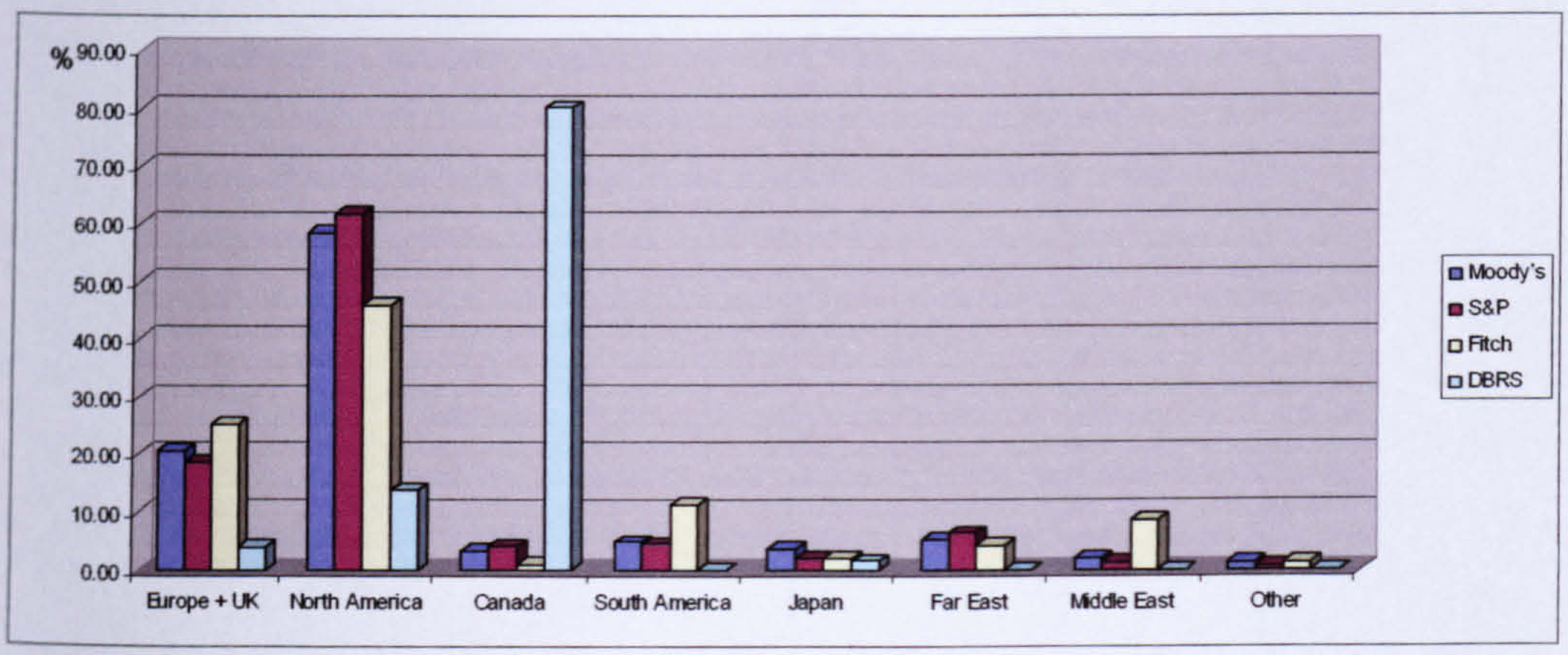
7.3 Agency characteristics

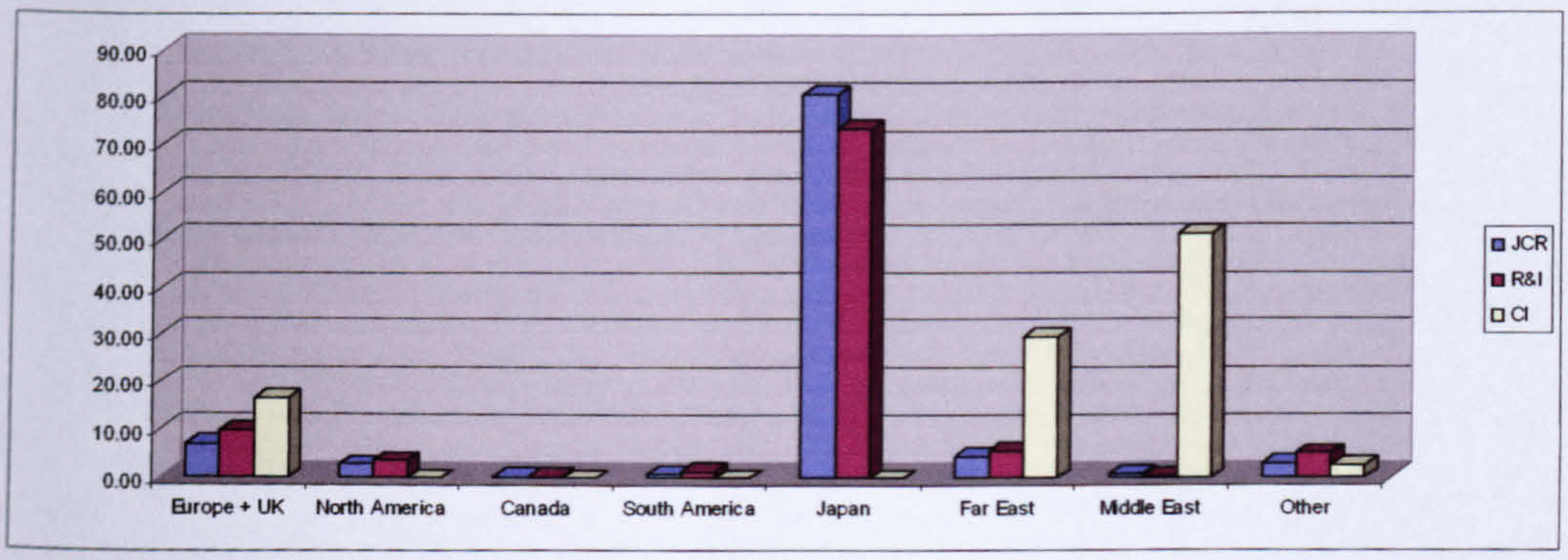
Previous studies have found that rating agencies are more generous on issuers from their own country and that there is more consensus between agencies from the same country. Using the data available in the FT-CRI this section will re-examine these findings and compare results with the earlier study.

7.3.1 Distribution of agency ratings between home and foreign issuers

The population of issuers rated by each agency is dominated by issuers from the agency's home country. Figure 7.7 shows the breakdown of each agencies' issues by country. For example DBRS is a Canadian agency and 79% of the issuers it rates are from Canada, the remaining 21% is split between the USA, Europe and Japan. On average 59% of issuers rated by Moody's and S&P are from the USA and 76% of issuers rated by the Japanese agencies are from Japan. The figure for US coverage by Fitch is a little lower at 45%. This is may be because this agency was formed from a merger with UK based IBCA so the percentage of UK and European issuers covered is higher than for Moody's and S&P.

Figure 7.7: Country distribution of issuers rated by different agencies





7.3.2 Agency consensus and issuers from the home country

Beattie and Searle (1992b) found that agencies are more generous to home country issuers than those from foreign countries. This suggests that when you compare matched pairs of ratings where the issuer is domestic to the agency to matched pairs where the issuer is foreign to the agency different levels of consensus and split ratings may arise.

Table 7.1: Comparison of average level of split ratings where issuer is from the agency's home country vs. issuer is from foreign countries (11 notch correspondence)

	vs. All other agencies Mean difference in notches		
	(1) All issuers	(2) Home country issuers	(3) Non-home country issuers
Moody's	< 0.23**	**< 0.15****	**< 0.33****
S&P	< 0.11**	**> 0.04****	**< 0.33****
Fitch	> 0.18**	> 0.2**	> 0.16**
DBRS	> 0.21**	**> 0.29****	**> 0.09****
CI	< 0.32**	**< 0.15****	**< 0.86****
R&I	> 0.97**	**> 0.81****	**> 1.28****
JCR	> 1.63**	**> 1.72****	**> 1.45****

\> Named agency rates higher than other agencies, on average
< Names agency rates lower than other agencies, on average
** Mean significantly different from zero at 1% level (two tailed test)
Red Means of home country issuers and non-home country issuers are significantly different from each other at the 1% level (two tailed test)

Table 7.1 shows the results of a comparison of split ratings between home country issuers and non-home country issuers. Split ratings for each of the live agencies were compared with all the other agencies. Columns 1, 2 and 3 show the mean difference in notches for all issuers, home country issuers and non-home country issuers respectively.

The data for Moody's shows that overall Moody's rates issuers less generously than the other agencies by 0.23 of a notch, on average. However when only issuers based in the US are considered Moody's is still less generous than other agencies but by 0.15 of a notch. The average difference for non-US issuers goes up to 0.33 of a notch. In other words, although Moody's still appears to rate less generously than other agencies, this effect is less for US issuers than for non-US issuers. The results for S&P are particularly interesting. Overall S&P is more generous than other agencies for US issuers but less generous for non-US issuers.

Where an agency is more generous than other agencies the interpretation of table 7.1 is a little different. Fitch is more generous than other agencies, on average, but this factor is greater for US issuers than for non-US issuers implying that Fitch rates more generously in the US than in other countries.

The results are consistent for all the agencies with the exception of R&I. For this agency the mean difference between ratings where a split occurs is 0.81 of a notch for Japanese issuers and 1.28 of a notch for non-Japanese issuers. This implies that this agency is less generous with the ratings of Japanese firms. This finding is interesting as previous research such as Shin and Moore (2003) has found that the differences between US and Japanese agencies are due to home-country bias. The finding for R&I in table 7.1 questions this conclusion.

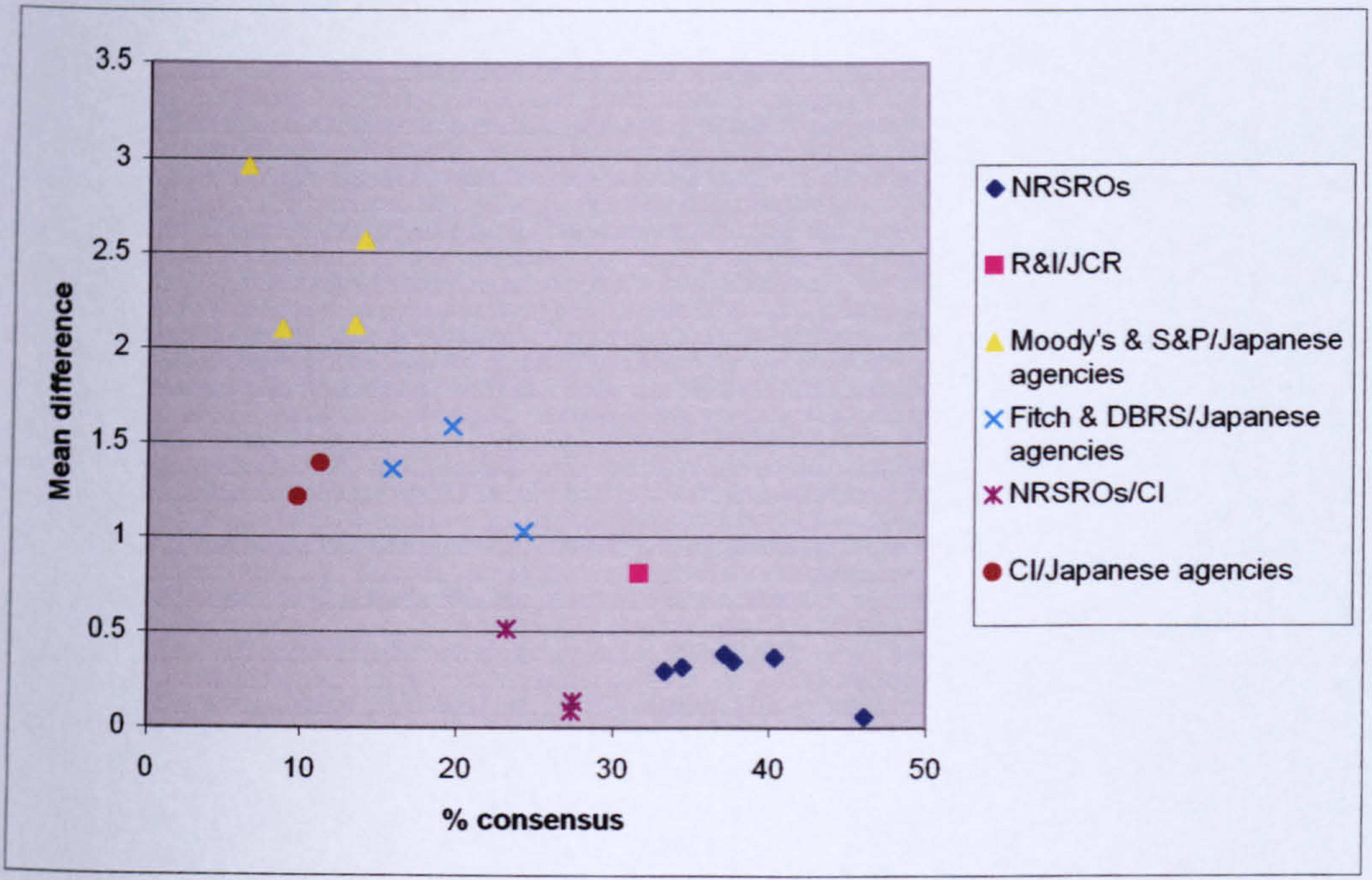
The mean difference between the ratings of the named agencies and the other agencies is significant at the 1% level for all observations. In addition the difference between the population of home country issuers and non-home country issuers is significantly different at the 1% level for all observations except Fitch ratings. This result may be due to the fact that the mix of Fitch issuers between the US and other countries is much more evenly distributed than for other agencies.

The conclusion drawn from table 7.1 is that all agencies do show home country bias except R&I which appears to be more generous to issuers from abroad.

7.3.3 Agency consensus and agencies from the same country

Figure 7.8 compares mean notch differences and levels of consensus for different matched pairs of agency ratings. Different colours represent agencies from different geographic areas. The highest level of consensus is observed between the NRSROs (navy blue) and the two Japanese agencies and the lowest between the US and Japanese agencies (yellow). Other clusters can be identified for Fitch and DBRS when compared to the Japanese agencies and CI when compared to other agencies. Figure 7.8 suggests that consensus is greater between agencies from the same country.

Figure 7.8: Consensus between agencies from the same country is greater than between agencies from different countries



In their study Beattie and Searle (1992b) used a sample of 25 rater pairs, 13 intra-country pairs and 12 inter-country pairs. The mean pairwise correlations for these sub-groupings were 0.91 and 0.754 respectively. Due to consolidation in the rating industry, this study uses 19 agency pairs with 7 intra-country pairs and 12 inter-country pairs. The mean pairwise correlations for these groupings are 0.931 and 0.852 respectively.

Beattie and Searle also found mean absolute differences of 0.94 and 1.25 for the two sub-groupings. The differences are in the expected direction but a t-test was not significant. The mean differences between the pairs in this study are 0.37 and 1.42 respectively, they are significantly different at the 1% level.

7.4 Summary

This chapter has shown that a ranking exists between the rating agencies meaning that some agencies appear to rate more generously than others. Previous research has not make it clear whether these differences arise due to systematic differences across the whole rating scale which cause the scale of one agency to be skewed above or below that of another or whether there are different cut off points between the grades.

This chapter has shown that for some agencies the whole scale is skewed upwards. JCR and R&I are consistently generous in their ratings across the whole rating scale. For other agencies the ranking does alter depending on the quality of the issuers under review. The ranking for sub-investment grades is significantly different to that for investment grade issuers. This suggests that there are differences around cut off points so that different agencies are relatively more or less generous depending on the quality of the issuers under review.

The chapter also confirms the findings of previous research in that the majority of rating agencies are more generous to issuers from their own country and relative consensus is greater between agencies from the same country than between agencies from different countries.

Industry and geographic characteristics

This chapter looks in detail at issuer and agency characteristics. Issuers are divided into different industries to see if there are systematic differences in average levels of consensus, mean split ratings and credit quality. Previous research has found that the country and industry characteristics of an issuer have an impact on the level of split ratings. This chapter adds to those studies with more recent data, a larger sample size, more detailed industry and country breakdowns and richer sub-investment grade data.

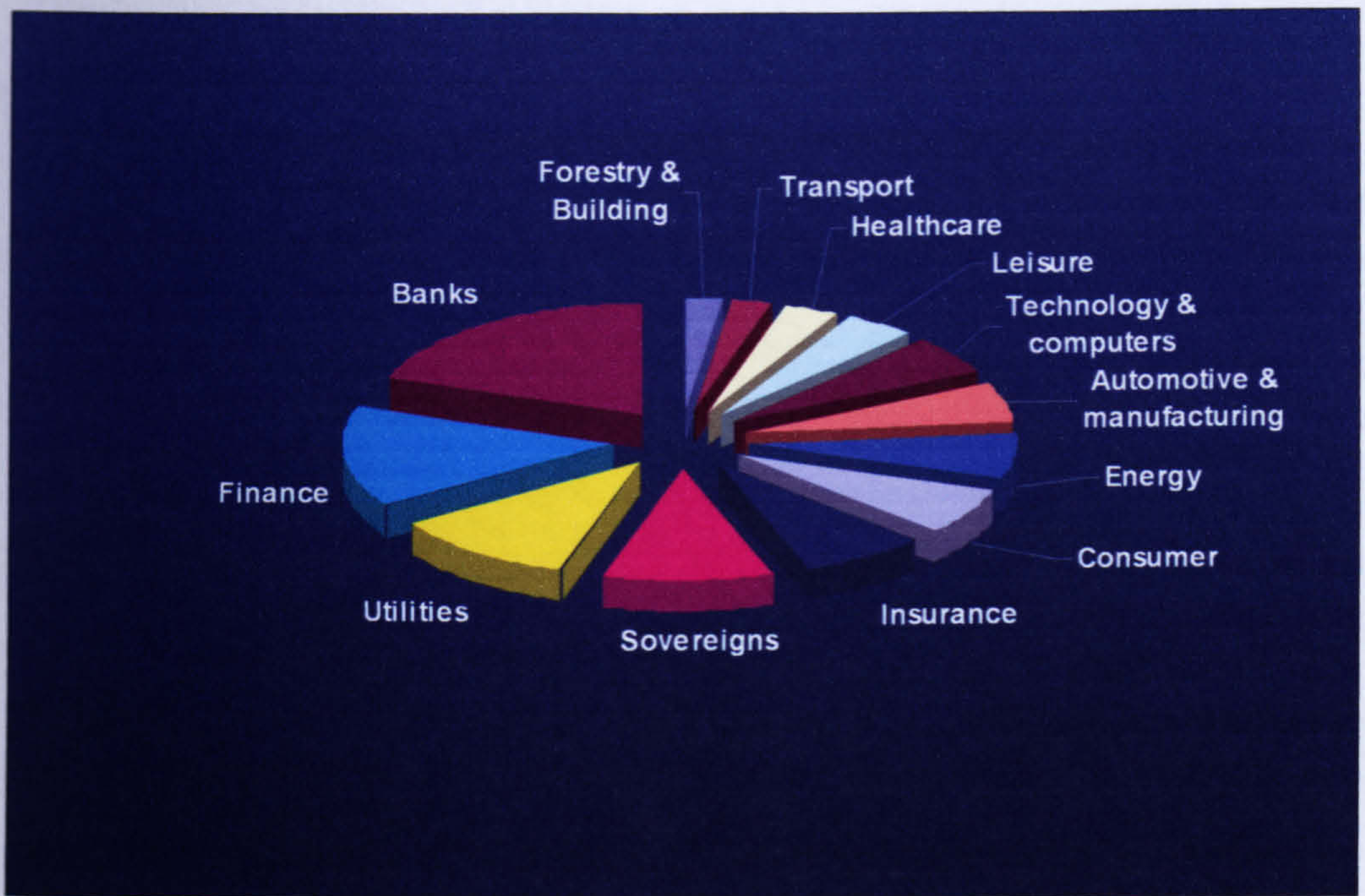
8.1 Industry characteristics

8.1.1 Breakdown of the data sample by industry

Many of the analyses in this study are based on the whole FT-CRI database but the data is dominated by the two largest agencies, Moody's and S&P[1] and also by two industries; Finance and Banking. Together these industries represent 34% of the total sample. Figure 8.1 shows the 13 different industry groupings that have been used, based on the 37 categories provided by the FT-CRI. The largest sample size is for banks with 12,196 matched pairs and, moving anti-clockwise around the pie chart, the smallest for forestry and building with 1,346 matched pairs.

[1] 78% of issuers included in the FT-CRI database are rated by Moody's or S&P.

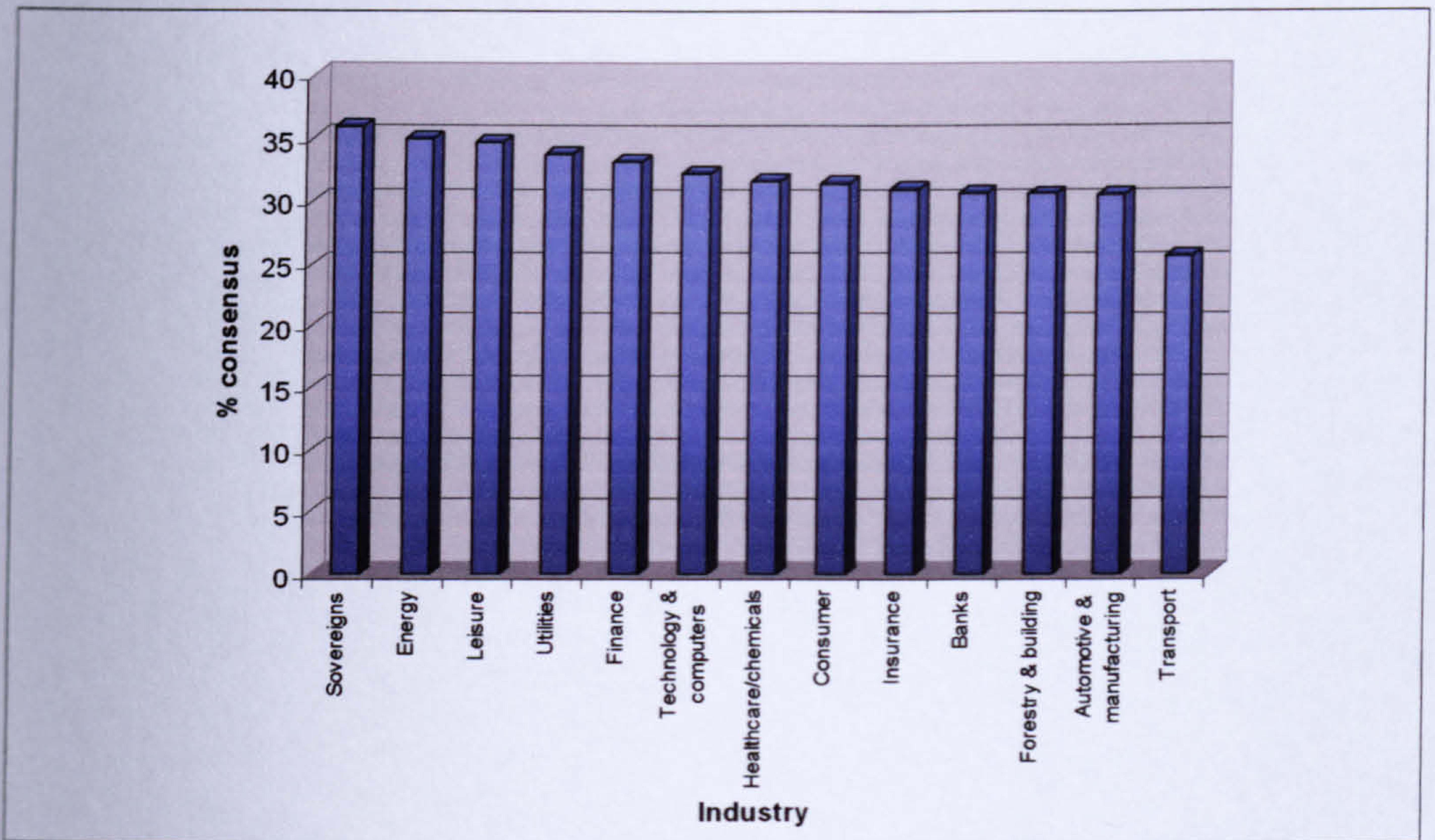
Figure 8.1: Breakdown of FT-CRI issuers by industry



8.1.2 Levels of consensus for different industries

Matched pairs for all agencies across all industries were analysed in chapter six. Table 6.1 on page 112 shows an analysis of the 51,342 matched pairs split between those that agree and a breakdown of the level of disagreement by notch. Figure 8.2 below is based on the same sample of 51,342 matched pairs for May 1999 to March 2004 but broken down between the 13 industry categories shown above. The percentage consensus is based on the 20-notch correspondence with the highest level of consensus shown on the left.

Figure 8.2: Comparison of % consensus for industry groups in FT-CRI



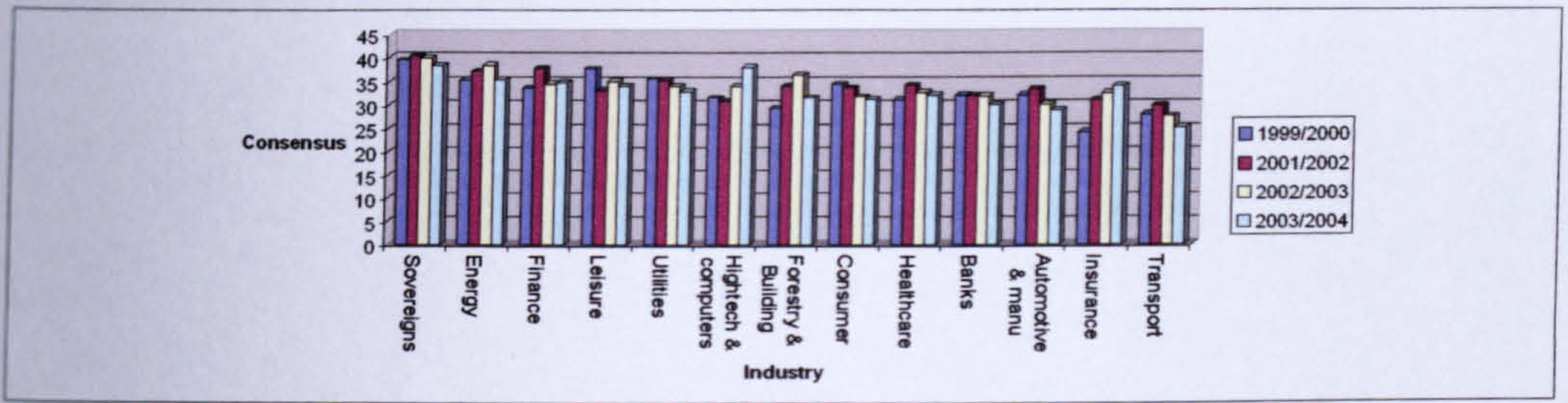
Sovereigns show the highest level of consensus (35.9%) and transport industry the lowest (25.6%). Banks have the fourth lowest level of consensus at 30.7%. In previous studies, banks have featured as the industry with the lowest level of consensus (Beattie and Searle 1992b, Cantor and Packer 1995 and Morgan 1997).

As researchers had much smaller data samples available to them 14 years ago they used wider industry categorisations. Beattie and Searle (1992) used 9 industry groups. Transport was a group in its own right but automotive and manufacturing and forestry and building were subsumed into larger groups. Transport did not appear to be an industry over which there was a high level of disagreement in 1990 but a full order of the differing levels of consensus is not published in that study.

8.1.3 Changes in rating agency consensus over time

Figure 8.3 shows the percentage consensus for four separate time periods between 1999 and 2004.

Figure 8.3: Comparison of level of consensus by industry over the four years of this study



The consensus between agencies rating issuers in certain industries, such as sovereigns, banks, utilities and healthcare have the lowest standard deviations and have been relatively stable over the four year period. Other industries show marked changes. For example, the consensus between agencies rating insurance companies has risen by 10% and technology by 7%. Consensus for forestry and building companies has fluctuated during the period. The consensus on the rating of transport companies appears to have fallen during the period, apart from 1999/2000 this has always been the industry with the lowest level of consensus.

8.1.4 Disagreement between agencies about bank ratings

Beattie and Searle (1992b) found a low level of agreement between ratings of banks and suggested that this is due to the regulated nature of banks meaning that regulators, rather than the market, dictate banking norms and this renders comparison between banks more difficult than other industries. Cantor and Packer (1995) reported the same finding and explained this by national differences in methodology and approach. Morgan (1997, 2002) suggests that the high level of split ratings over banks is caused by the opacity of bank assets, especially loans and trading assets, which are hard to observe and make it hard for agencies to judge the risk of banks.

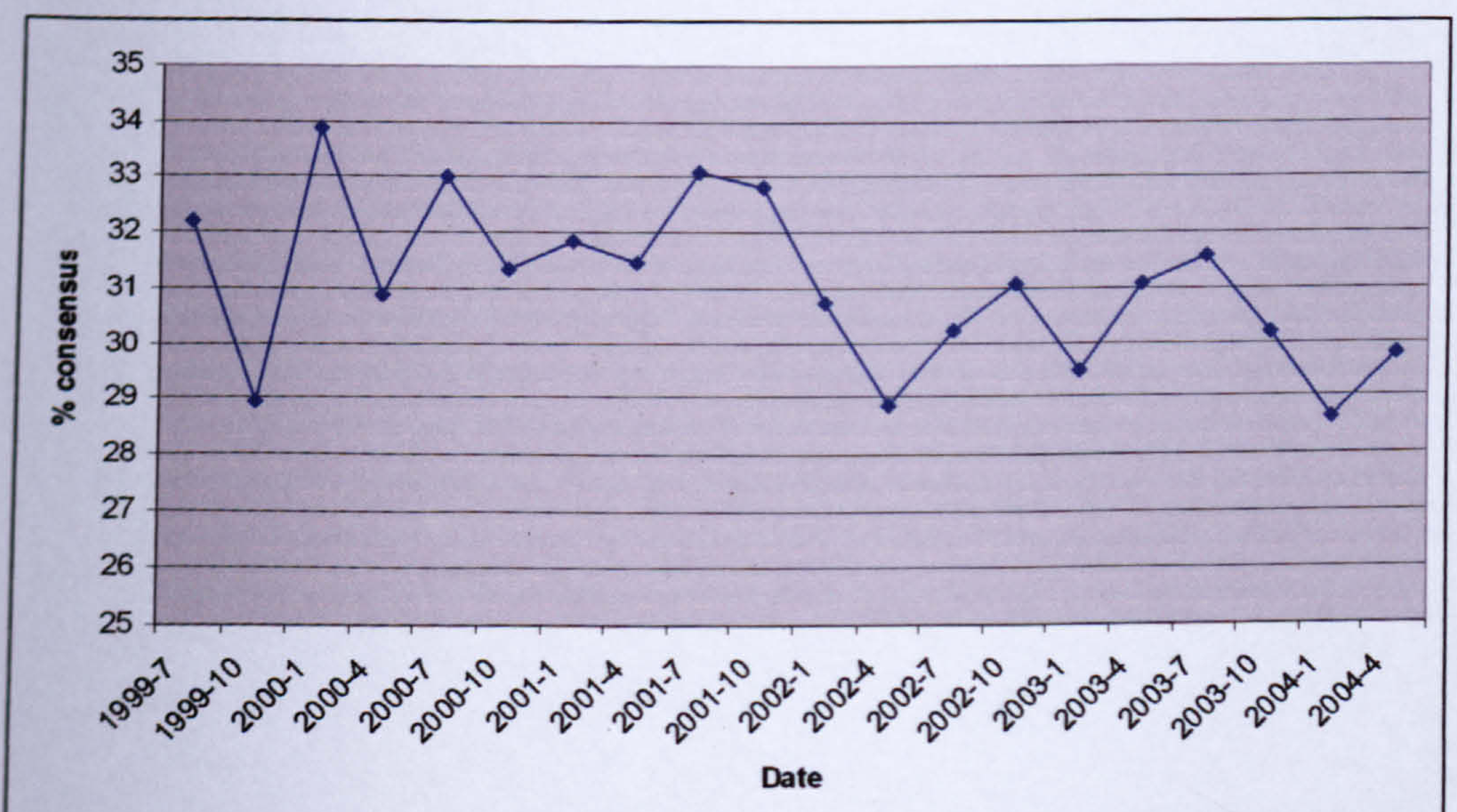
Beattie and Searle (1992b) stated that they found banks to have the lowest level of consensus but did not provide figures for the number or percentage of ratings that agreed and disagreed between agencies so a comparison of their findings is not possible. Cantor and Packer (1995) show the levels of bank consensus for each pair of agencies rather than on an overall basis, as is shown in this section, but the equivalent average consensus is 24% which is much lower than the level identified in this study.

Another reason why differences may arise between the ratings of banks is due to the fact that long term bank ratings are a combination of individual ratings and support ratings. Agencies may disagree with one another about the underlying risk characteristics of a bank due to the opacity of its assets but additionally they may disagree over the level of support that would be offered in the event that the bank ran into financial difficulties.

Although this study does show a relatively high level of disagreement over bank ratings, it is not clear that this is the industry over which there is the highest level of disagreement, as was the case in previous studies. To test whether there has been a change in the level of disagreement over banks since 1999, results for split ratings over banks for Moody's and S&P were compared over time.

The level of agreement between Moody's and S&P over banks has not altered greatly over the period of this study, if anything it has decreased slightly. Figure 8.4 shows an analysis of the agreement between Moody's and S&P over bank issuers in 3 monthly increments since May 1999. The trend does fluctuate but there is no observable increase in the level of agreement.

Figure 8.4: Level of agreement between Moody's and S&P over bank issuers between 1999 - 2004

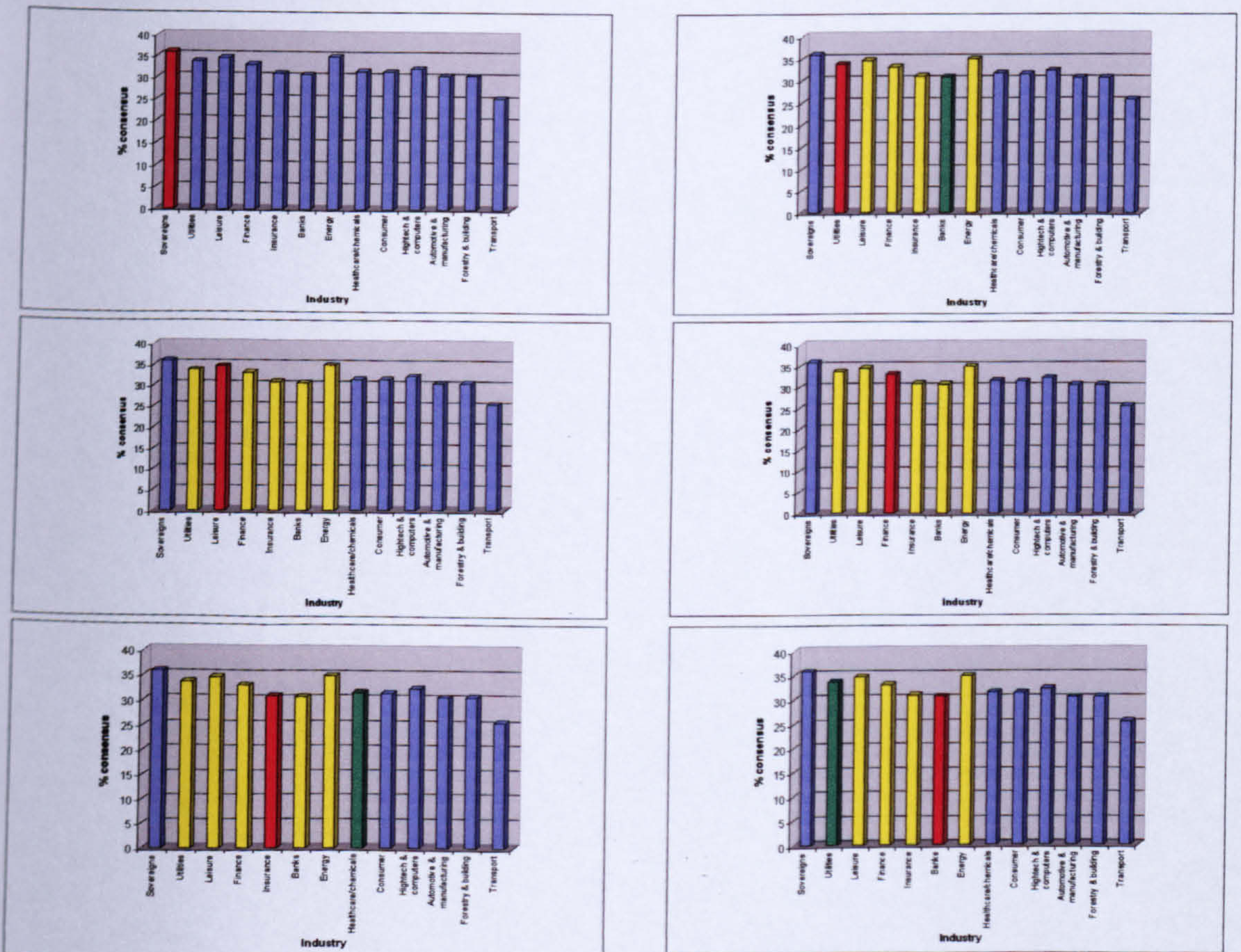


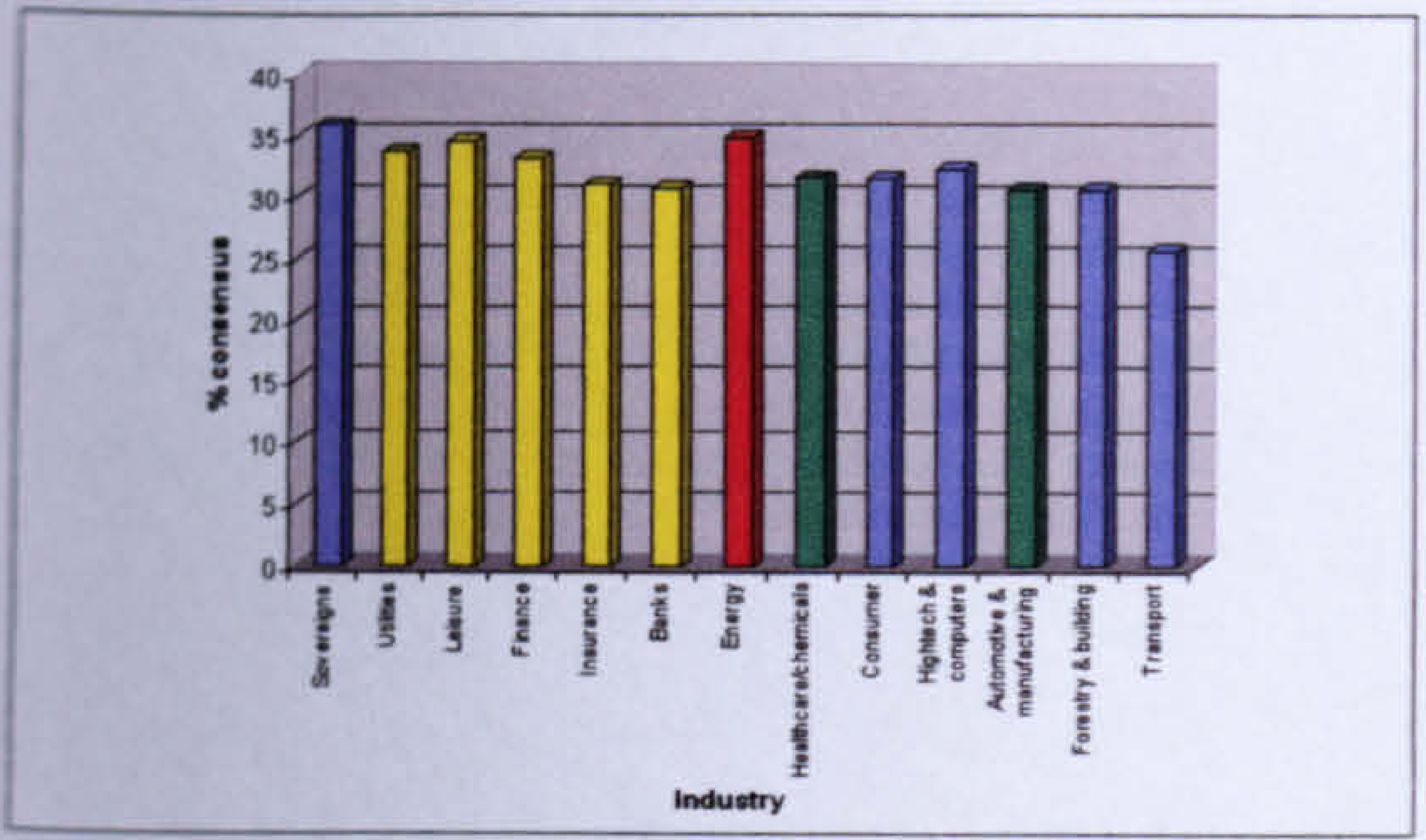
These findings do not entirely support the conclusions of previous studies which argued that banks have a higher incidence of split ratings than other industries due to the influence of regulation, accounting practices or difficultly in recording the value of assets. While banks do show a high level of split ratings this is no more than some other industries which do not have the same constraints of regulation, opacity of assets and the complication of determining a support rating.

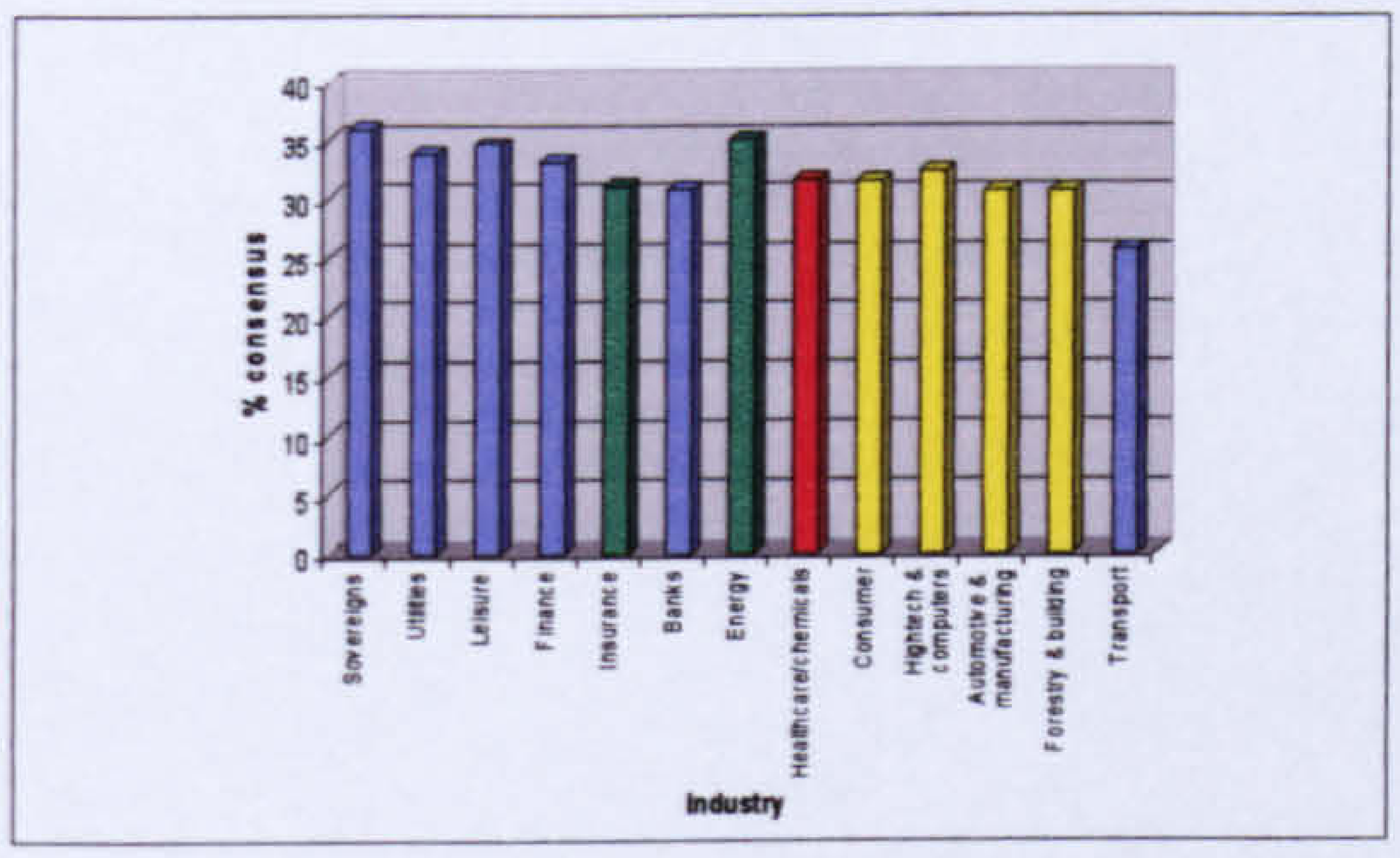
8.1.5 Industry groups established by significance testing

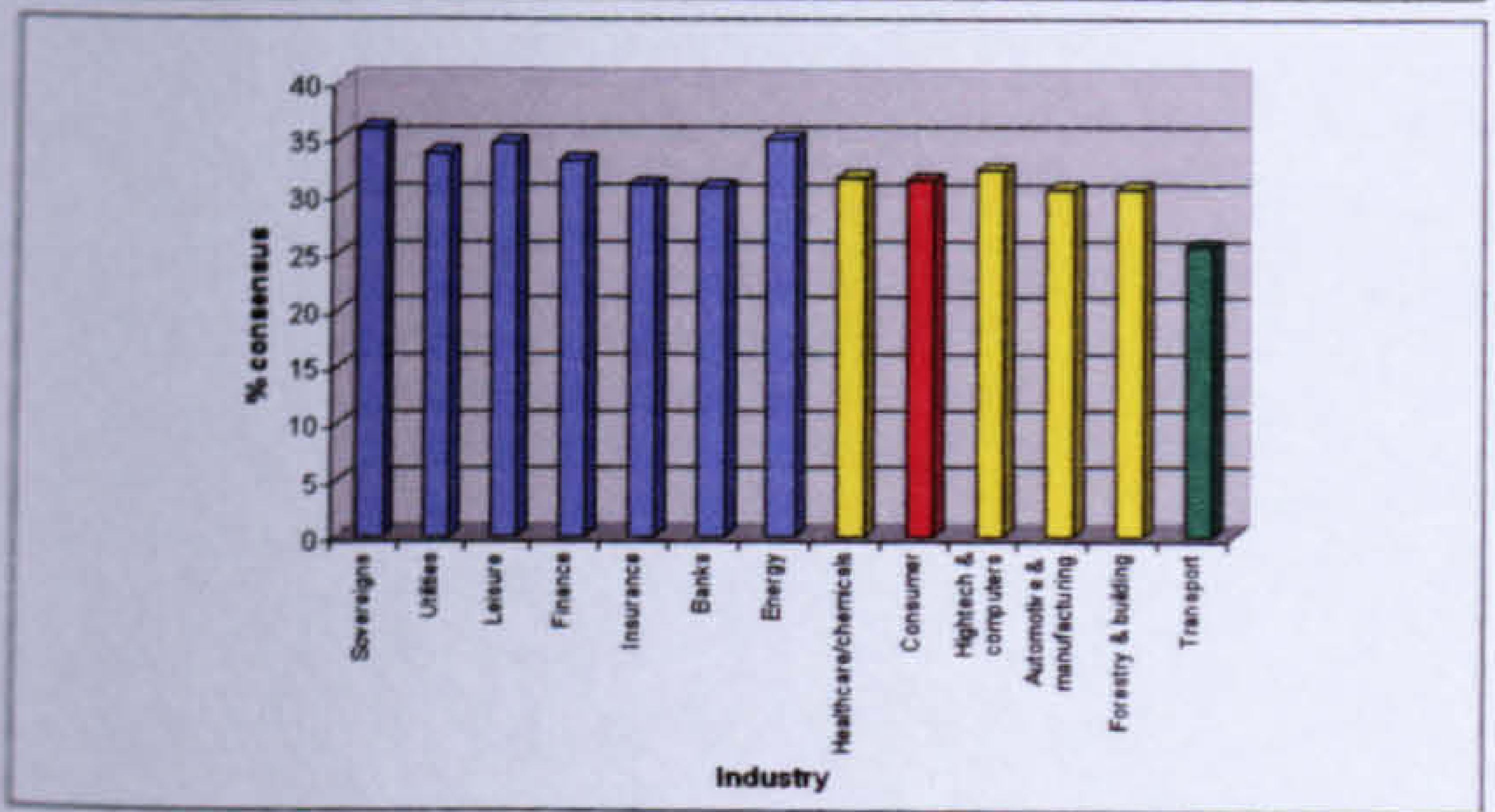
Figure 8.5 shows the levels of consensus for the different industries and the results of pairwise two tail significance tests. The red column on the graph shows which industry results are used for the comparison (the principle industry). Blue columns show that there are significant differences between the industry in red and those shown in blue at the 1% level, green columns that there are significant differences at the 5% level and yellow columns indicates that there are no significant differences between the industry means and the principle industry.

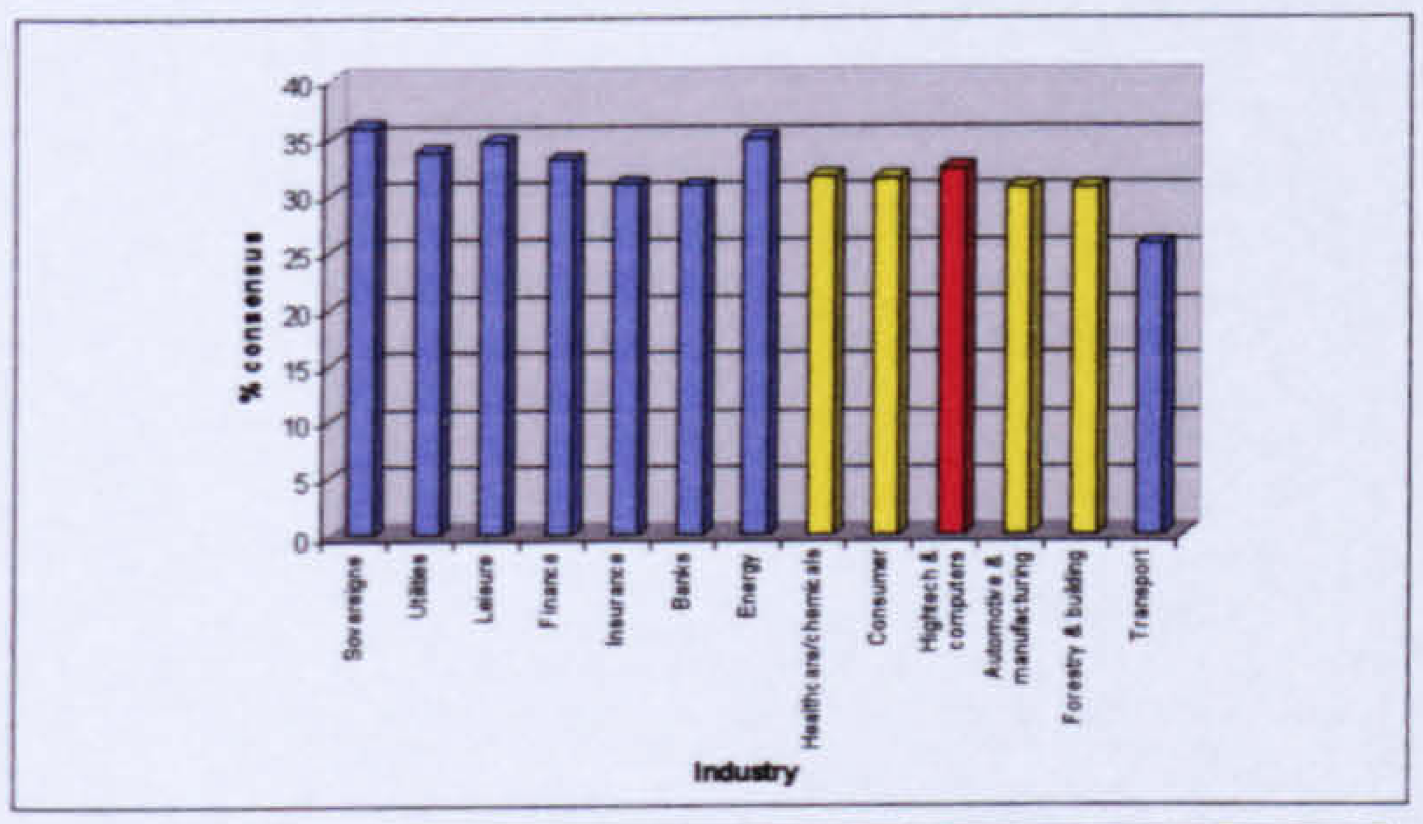
Figure 8.5: Results of significance tests for all industries

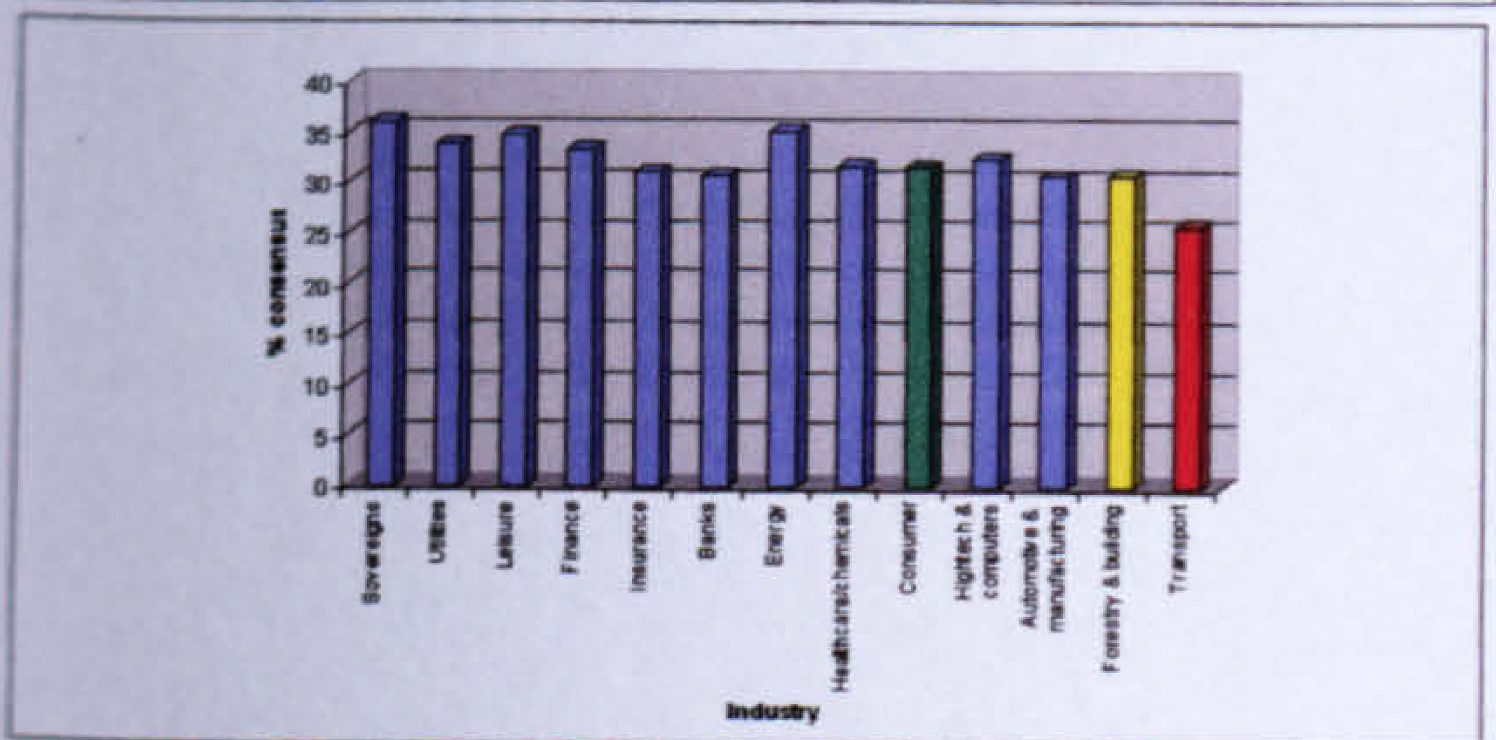


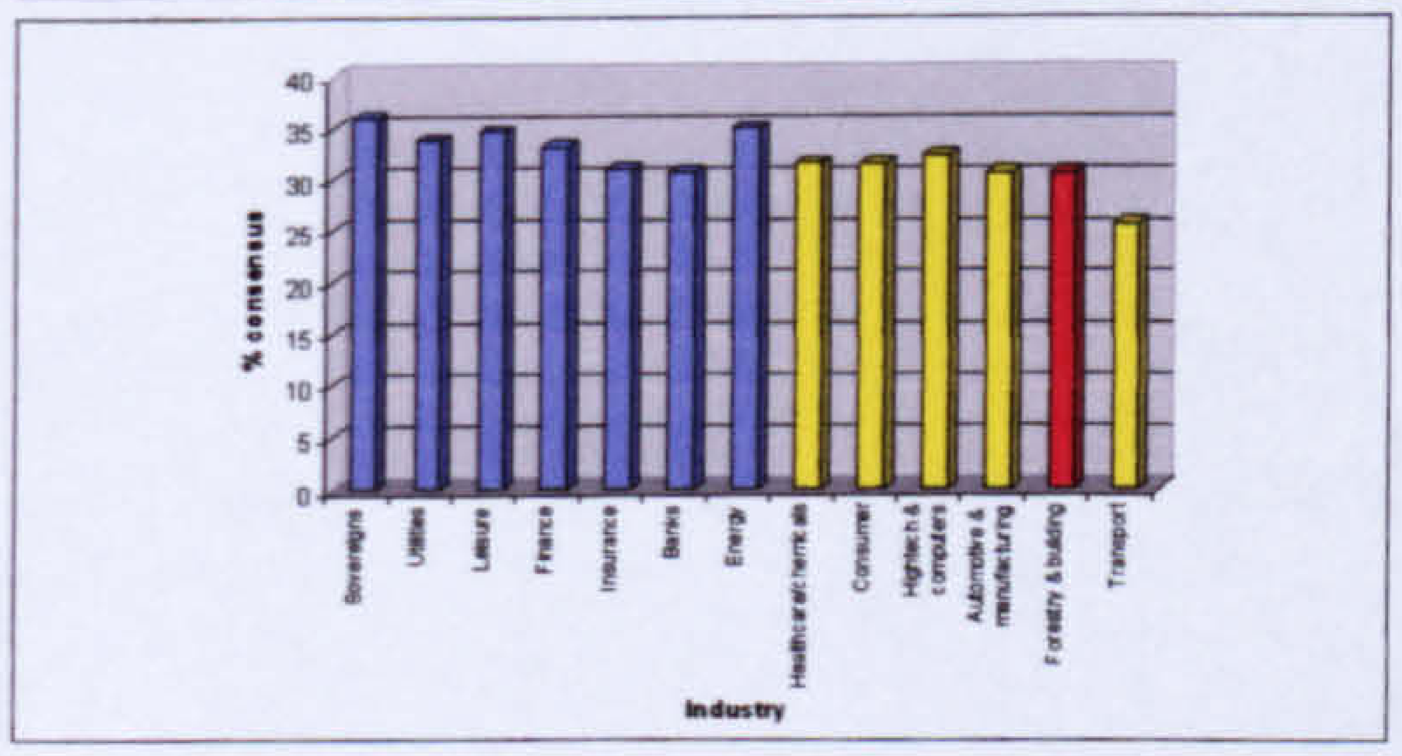


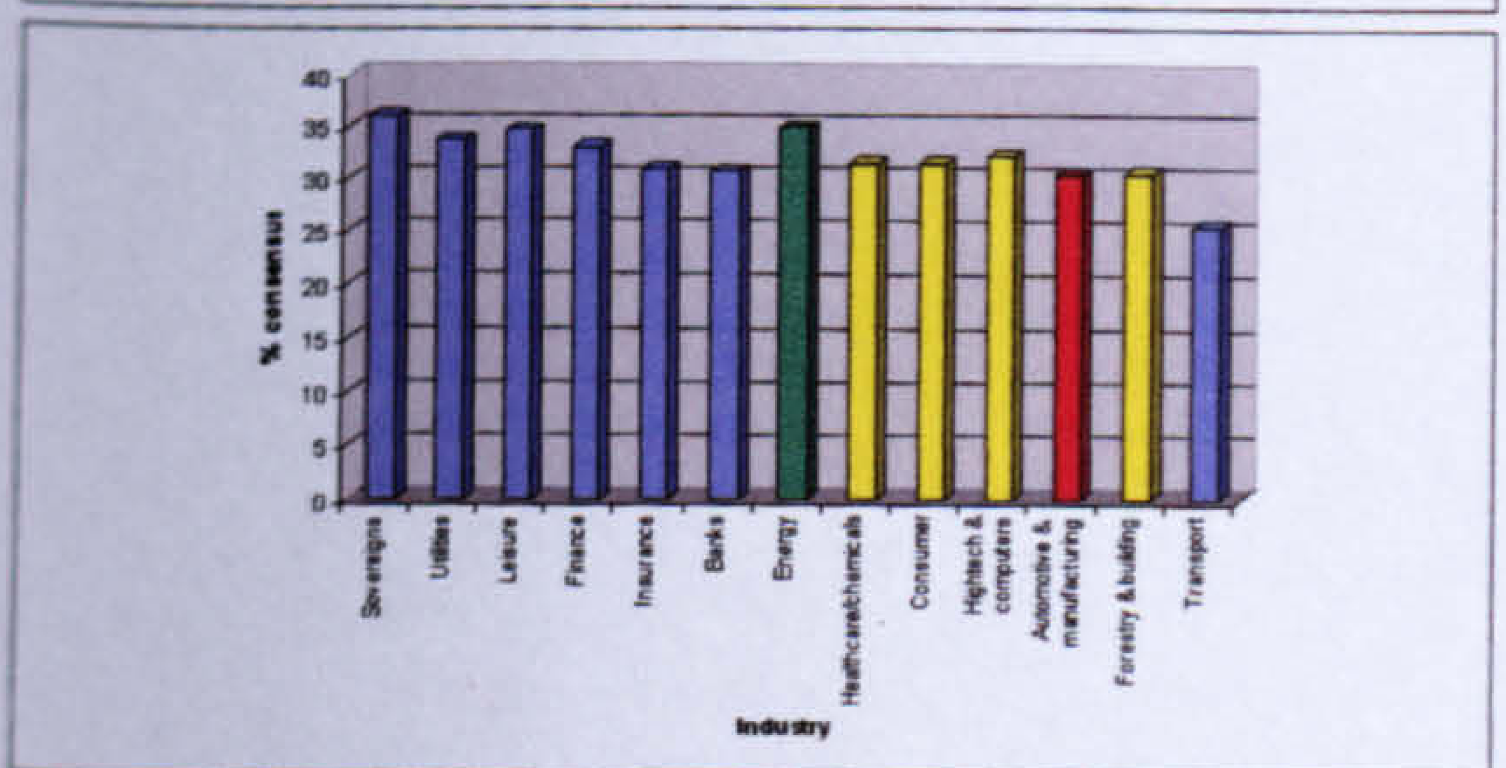












Sovereigns clearly stand alone as a group distinct from any other industry. There are significant differences between sovereigns and all other industry groups at the 1% level.

The next six graphs show that there are no significant differences (at the 1% level) between a group of six industries; utilities, leisure, finance, insurance, banks and energy. This is interesting as there is much examination of the banking industry in the literature, as discussed above, and the general conclusion is that there are differences between banking and other sectors. However in terms of significance, even in a sample of 51,342 matched pairs, there is no significant difference between banks and these five other industries. Beattie and Searle (1992b) found banks to be significantly different from the energy industry which is inconsistent with the findings of this chapter.

Beattie and Searle also found other significantly different industry groups which are consistent with the results of this thesis. Finance (which includes insurance) is significantly different from consumer goods and utilities are significantly different from consumer goods.

Figure 8.5 distinguishes a third industry group which is made up of the healthcare, consumer goods, technology, automotive and forestry industries. All these industries are significantly different from the banking/finance/utilities/energy/leisure group at the 1% level.

The mean level of split ratings in the transport industry is significantly different from all other groups at the 1% level except forestry and building. This industry consistently shows the lowest level of consensus when compared to the other industries.

8.1.6 What causes a higher level of consensus in some industries?

The graphs in figure 8.5 show that industries in the FT-CRI can be broken into three groups. The industries within these groups do not have significantly different levels of split ratings. The group with the highest level of consensus is sovereigns, the middle group consists of financial institutions (insurance, banking and finance) as well as energy, utilities and leisure. The group with the lowest level of consensus is the manufacturing group which consists of technology, consumer goods, healthcare, forestry and building, automotive and manufacturing and transport.

The emergence of these groups is not consistent with previous studies with respect to the level of split ratings over banks. This study finds that manufacturing industries have lower levels of consensus despite the fact that their accounts are generally easier to interpret than banks, insurance companies and other financial institutions. Contrary to the findings of Morgan 1997 and 2002 this suggests that the opacity, or otherwise, of accounting information is not the primary cause of split ratings.

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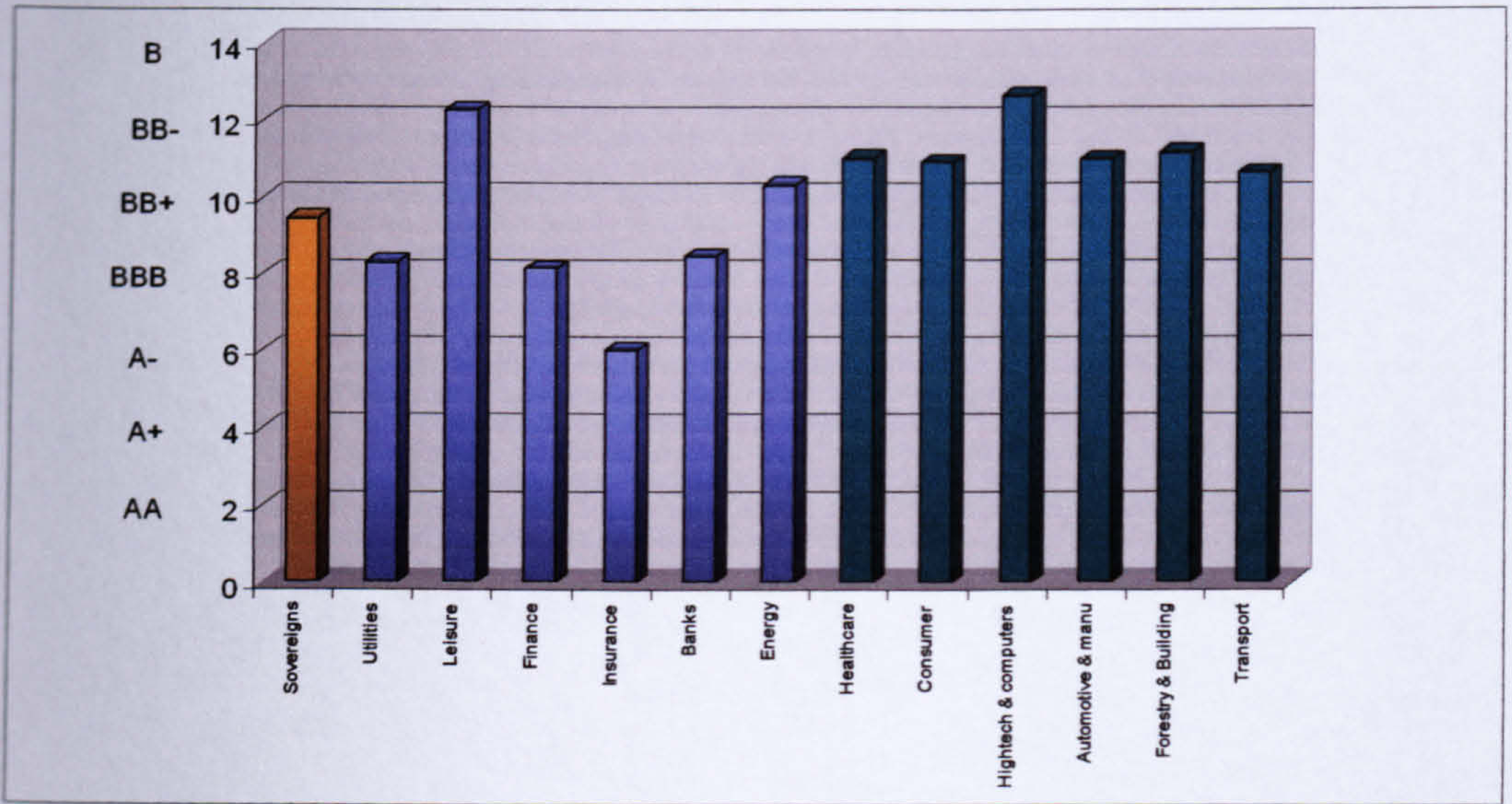
The average level of credit ratings within each group may explain the differences in split ratings. Cantor and Packer (1995) find that for sub-investment grade bonds the regularity and scale of split ratings increases. This finding is supported in chapter six. Figure 8.6 shows the rating distribution for the industry groups discussed above.

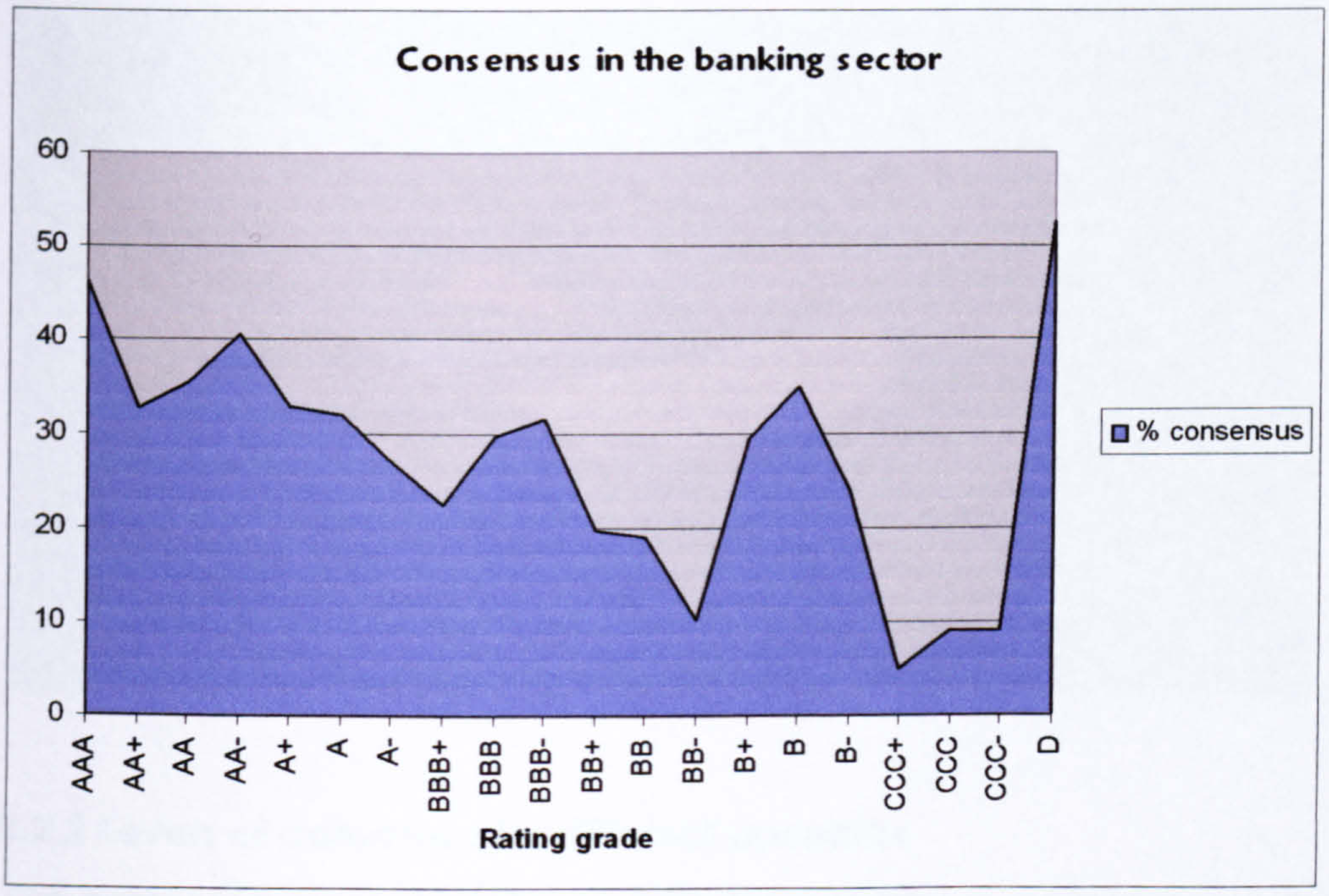
Figure 8.6: Average rating level for each industry group



These results are averaged from the results of the live agencies (Moody's, S&P, Fitch, DRBS, CI, JCR and R&I). Figure 8.6 shows that the consumer group (shown in green) appears to have a lower average credit rating than the banking and finance group. The average credit rating for the consumer group is BB which is sub-investment grade. The average rating for the finance, utilities, leisure and energy group is BBB- which is an investment grade rating. Sovereigns are a separate industry group with an average rating of BBB-. The differences between the means of these three groups are significant at the 1% level. This suggests that the reason for the difference in the level of split ratings between sovereigns and other industries is due to the average credit quality of the particular industry group.

Figure 8.7 shows that for the banking industry, as the credit quality falls so does the level of consensus between agencies. Peaks at the letter grade B may be caused by the fact that the smaller credit rating agencies do not use the full range of letter grades for sub-investment grade ratings so there will be a higher level of agreement at B than at B+ or B-.

Figure 8.7: Changes in consensus at different ratings grades



This section has considered the relationship between split ratings and issuers from different industries. It has shown that there are three broad groups of industries which have significantly different levels of split ratings. This has been linked to the average credit quality to show that the level of split ratings increases (consensus decreases) as credit quality falls.

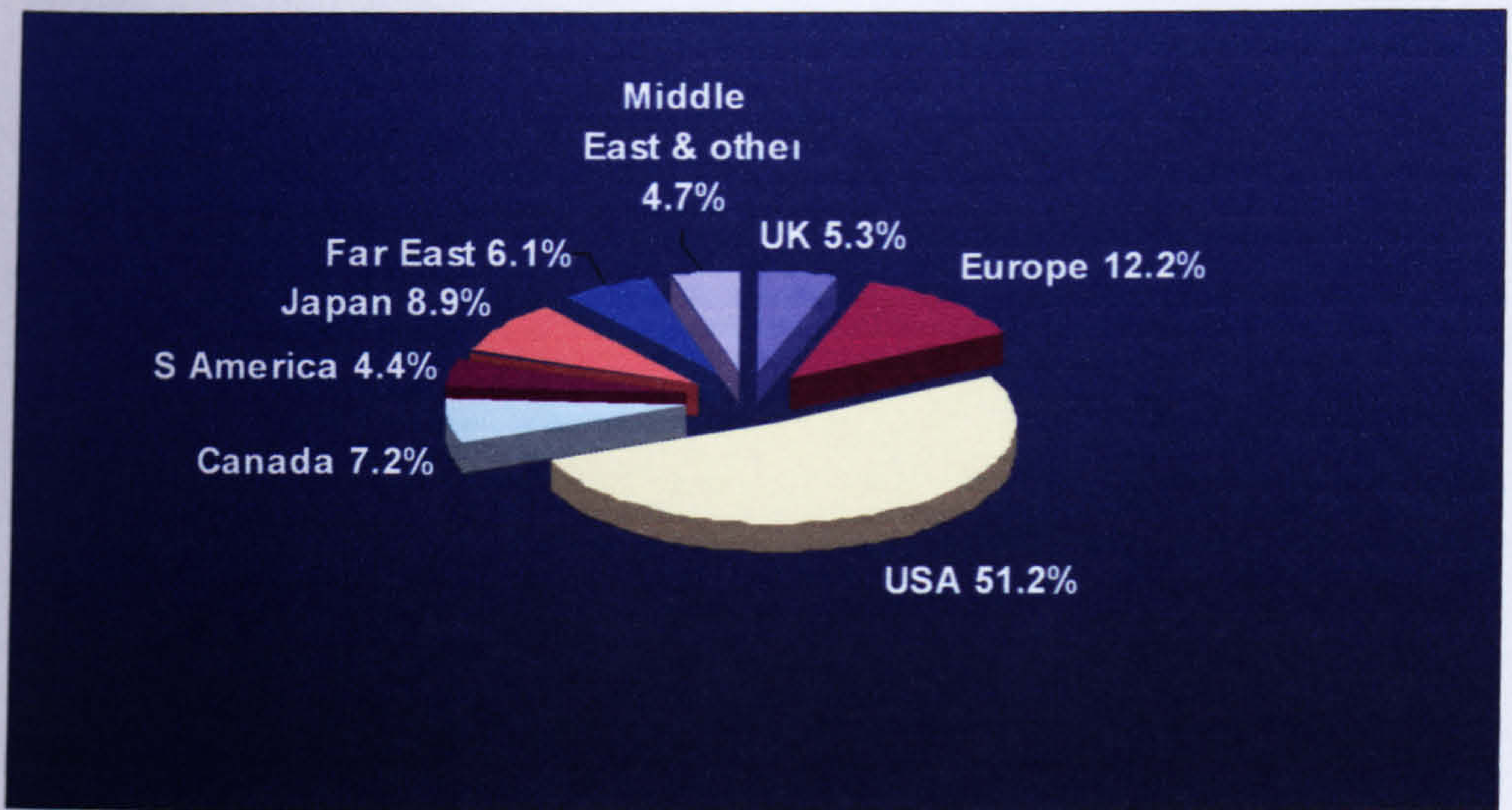
8.2 Country characteristics

8.2.1 Breakdown of the data sample by country

Analysis of the country in which the issuer is based also shows significant differences in the level of split ratings between agencies.

51.2% of the matched pairs identified in the database relate to issuers from the USA. This is not surprising as the three largest agencies, Moody's, S&P and Fitch are all based in the US. Of the 51,342 matched pairs identified across the whole database, 45% relate to either Moody's or S&P ratings. Out of Moody's and S&P ratings, 65% relate to issuers based in the USA. Europe is the next largest region, 12% of matched pairs from the whole sample relate to European issuers. The distribution of issuers by country is shown in figure 8.8.

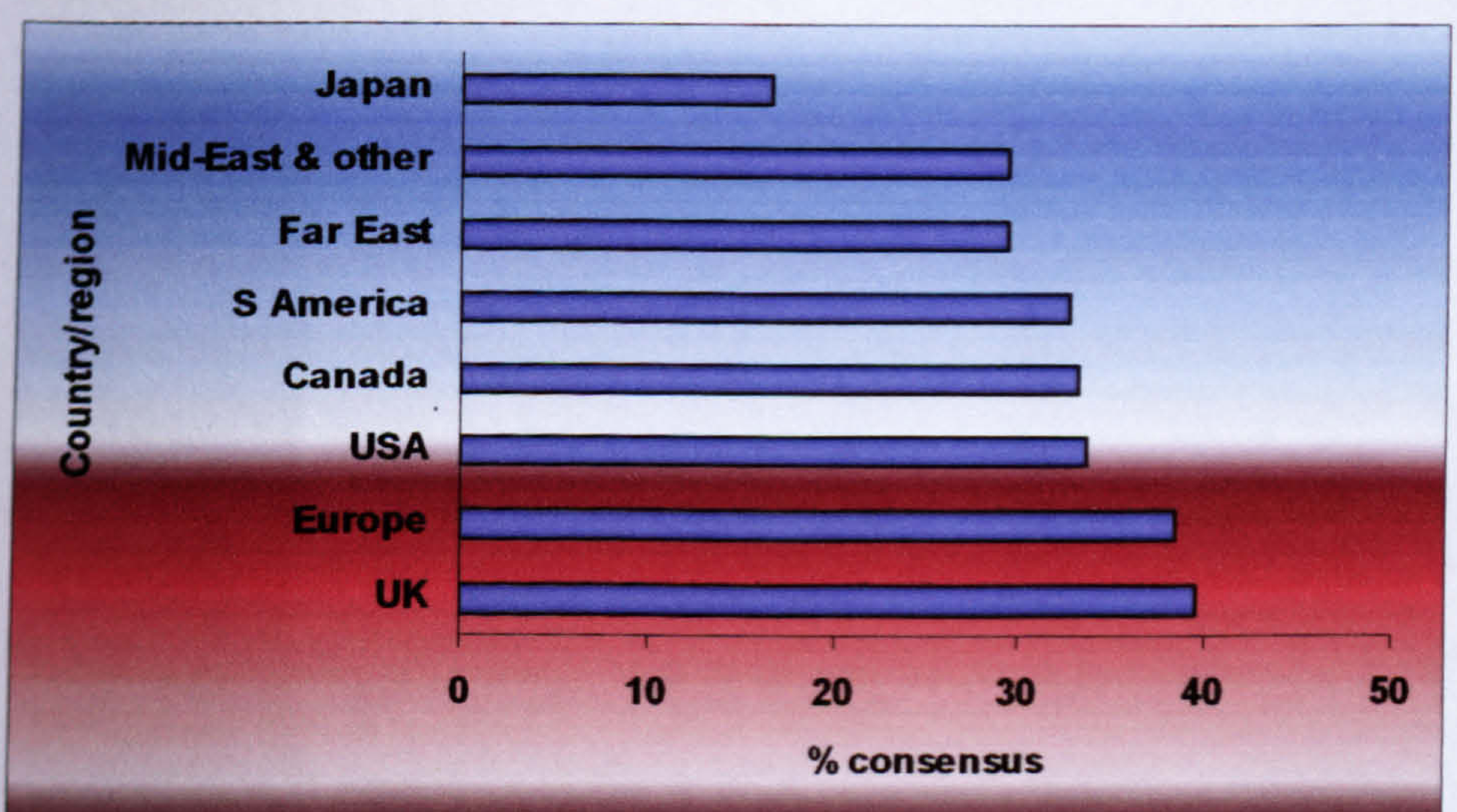
Figure 8.8: Analysis of FT-CRI issuers by country



8.2.2 Levels of consensus for different countries

The consensus in ratings between different countries is measured in exactly the same way as for industries. The matched pairs for all agencies are pooled and split according to the country of the issuer. The relative percentage consensus of the different regions are show in figure 8.9.

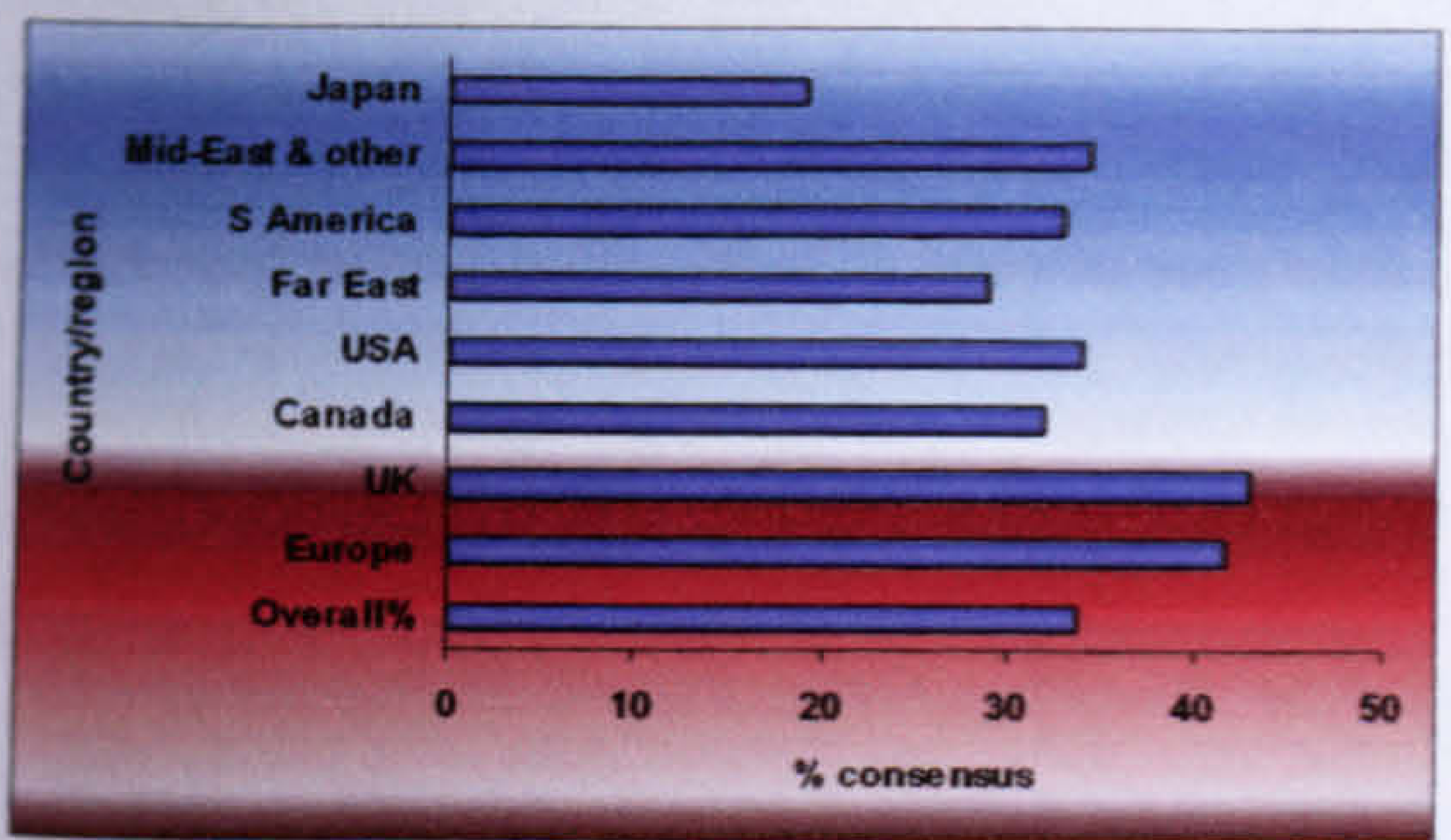
Figure 8.9: Percentage consensus by country for the whole database 1999 - 2004



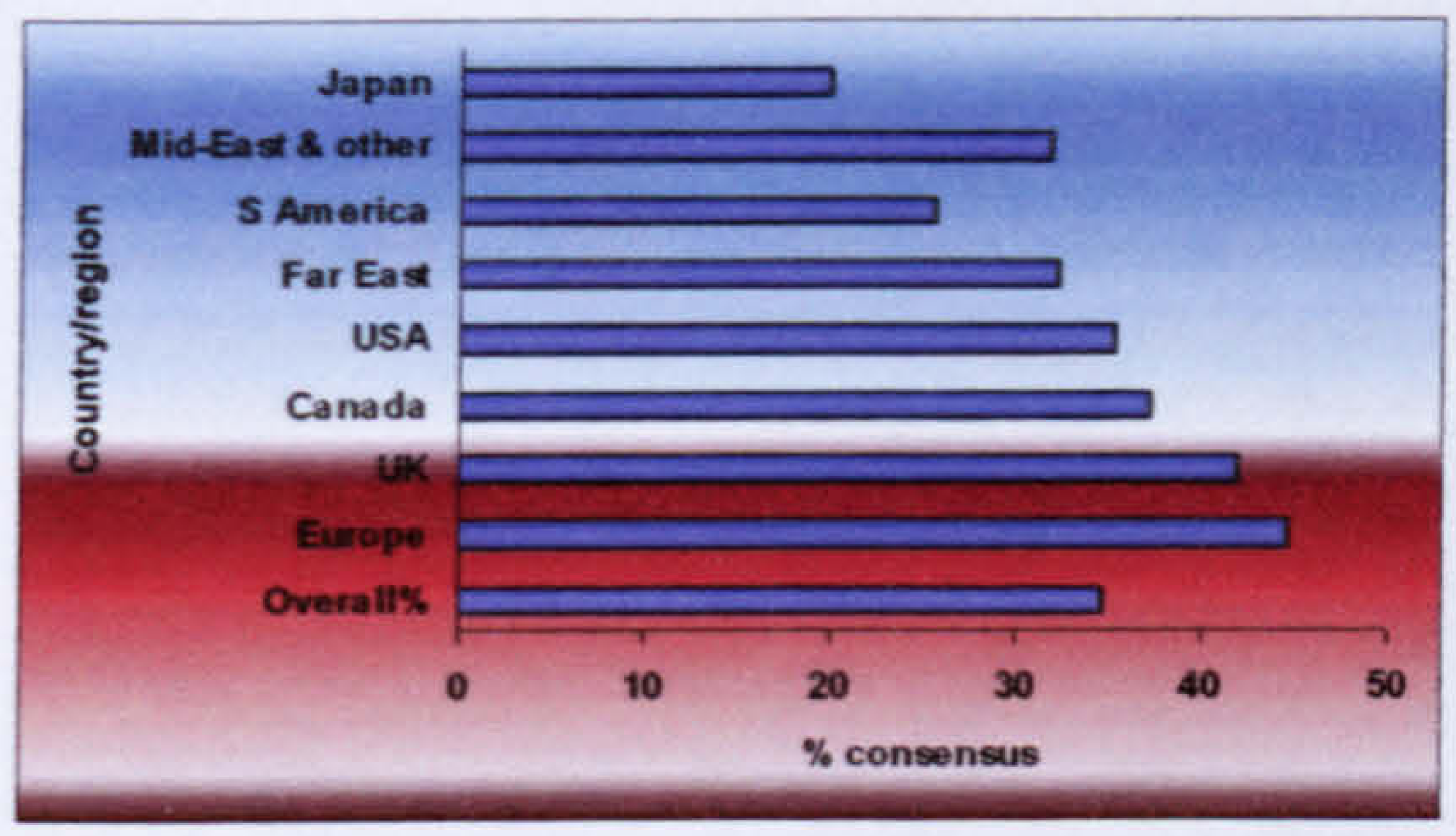
The UK and Europe have the highest level of consensus at 39.5% and 38% respectively and Japan has the lowest at 17%. The results for Japan will be influenced by the high level of disagreement between the Japanese and US rating agencies which has already been discussed.

Analysis of the level of consensus over time shows that the relative order of countries with the most and least consensus has changed little during the four years considered in this study.

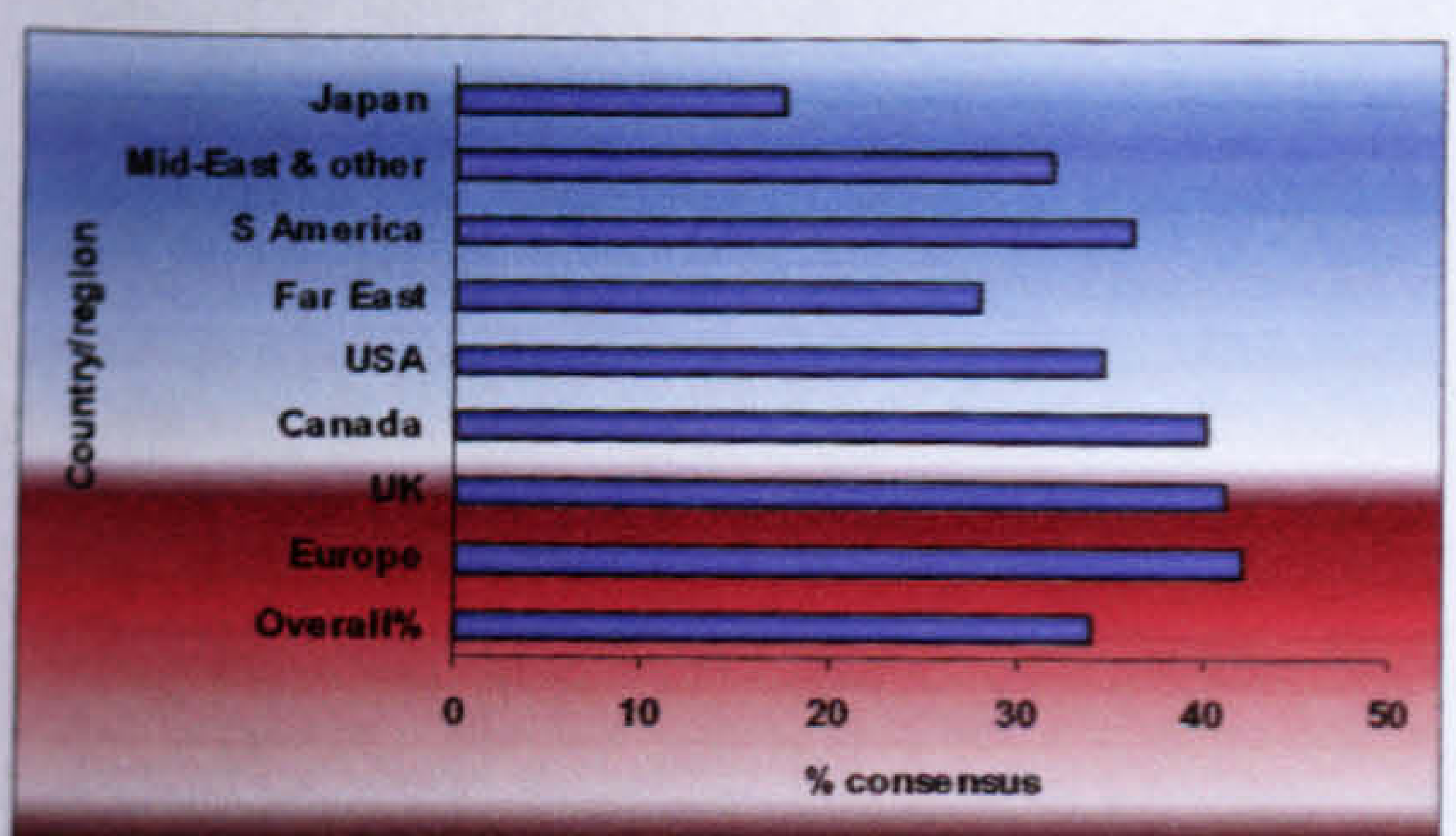
Figure 8.10: Percentage consensus by country over the period of the database



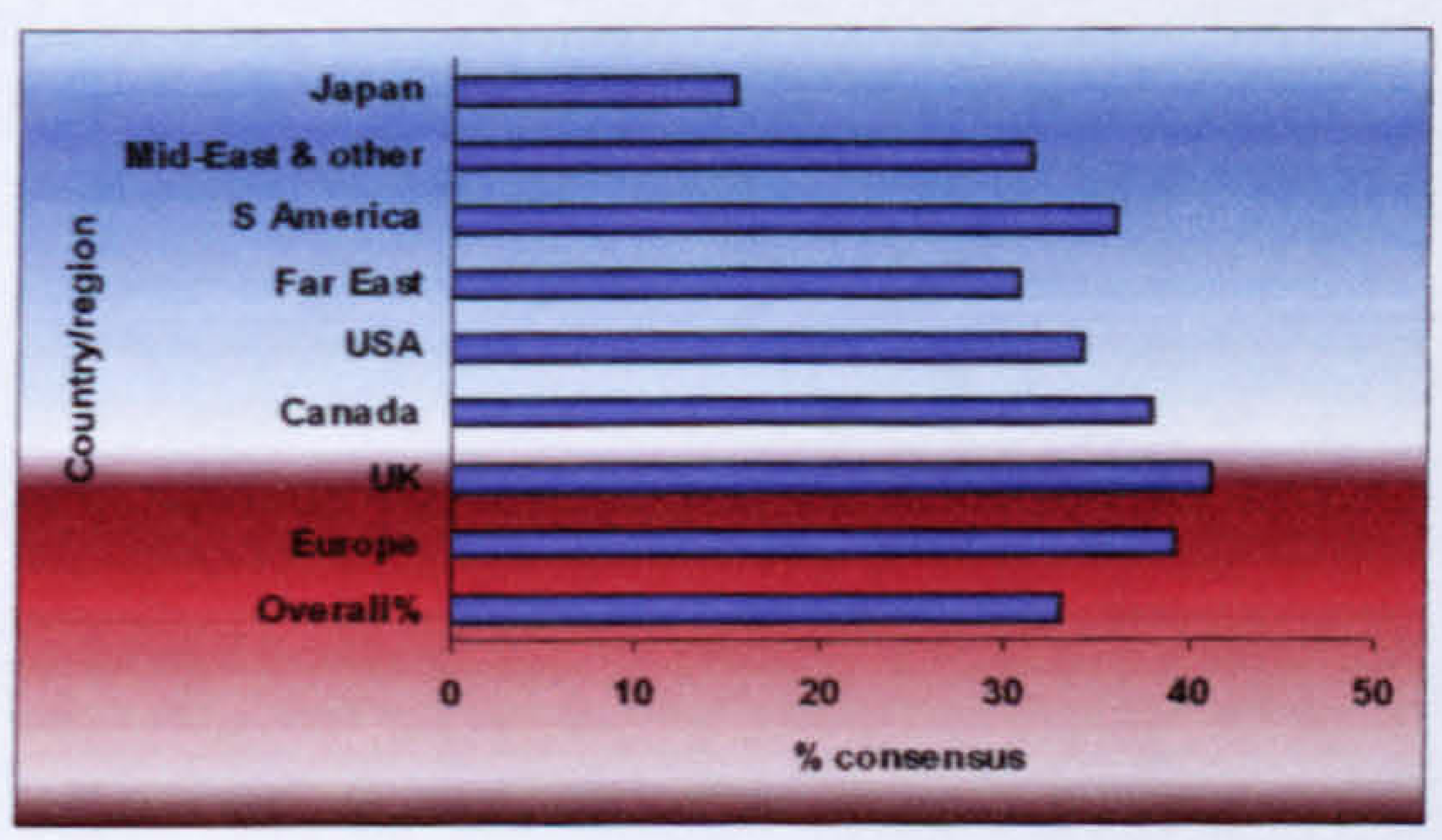
2000



2001



2002



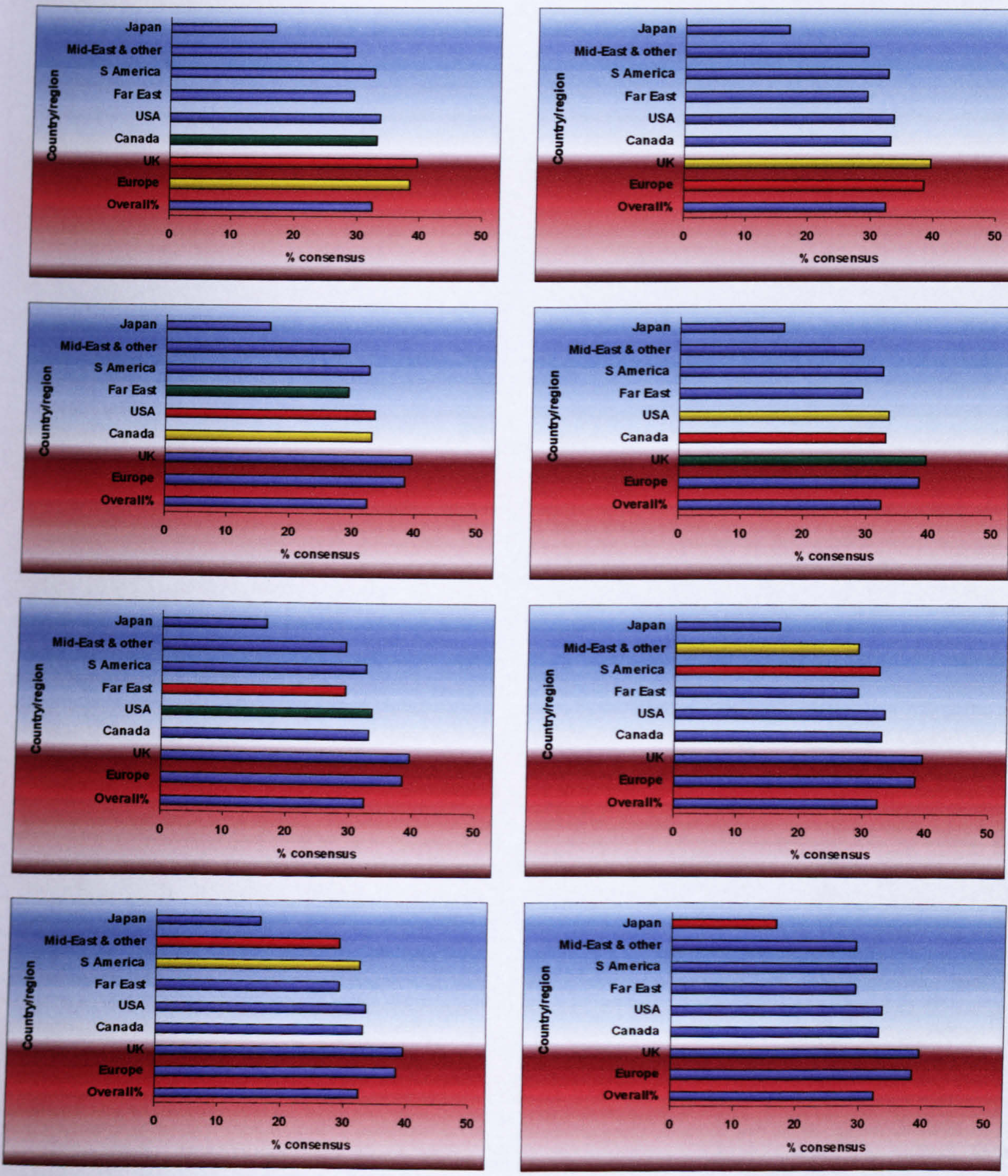
2003

UK and Europe show the highest levels of consensus (these two countries trade positions in 2001 and 2002). Agencies show the lowest level of agreement over Japanese issuers.

8.2.3 Country groups established by significance testing

As with the industry groups, significance testing reveals groups of countries which are different from one another. In Figure 8.11, the red bar shows which country is used for the comparison (the principle country), blue bars show a significant difference between the principle country and the other country at the 1% level and green bars show a significant difference at the 5% level. Whereas, yellow bars show no significant difference.

Figure 8.11: Results of significance tests for all countries



Significance testing shows that 5 different groups emerge. UK and Europe are not significantly different from each other. USA and Canada are not different from each other. The Far East is not significantly different from the USA and Canada at the 5% level. South America and the Middle East (this country group includes other countries that do not fall into any other group) are not different from one another. Japan is a separate group that is significantly different from all other groups (this result is significant at the 1% level).

8.2.4 Split ratings based on country groupings

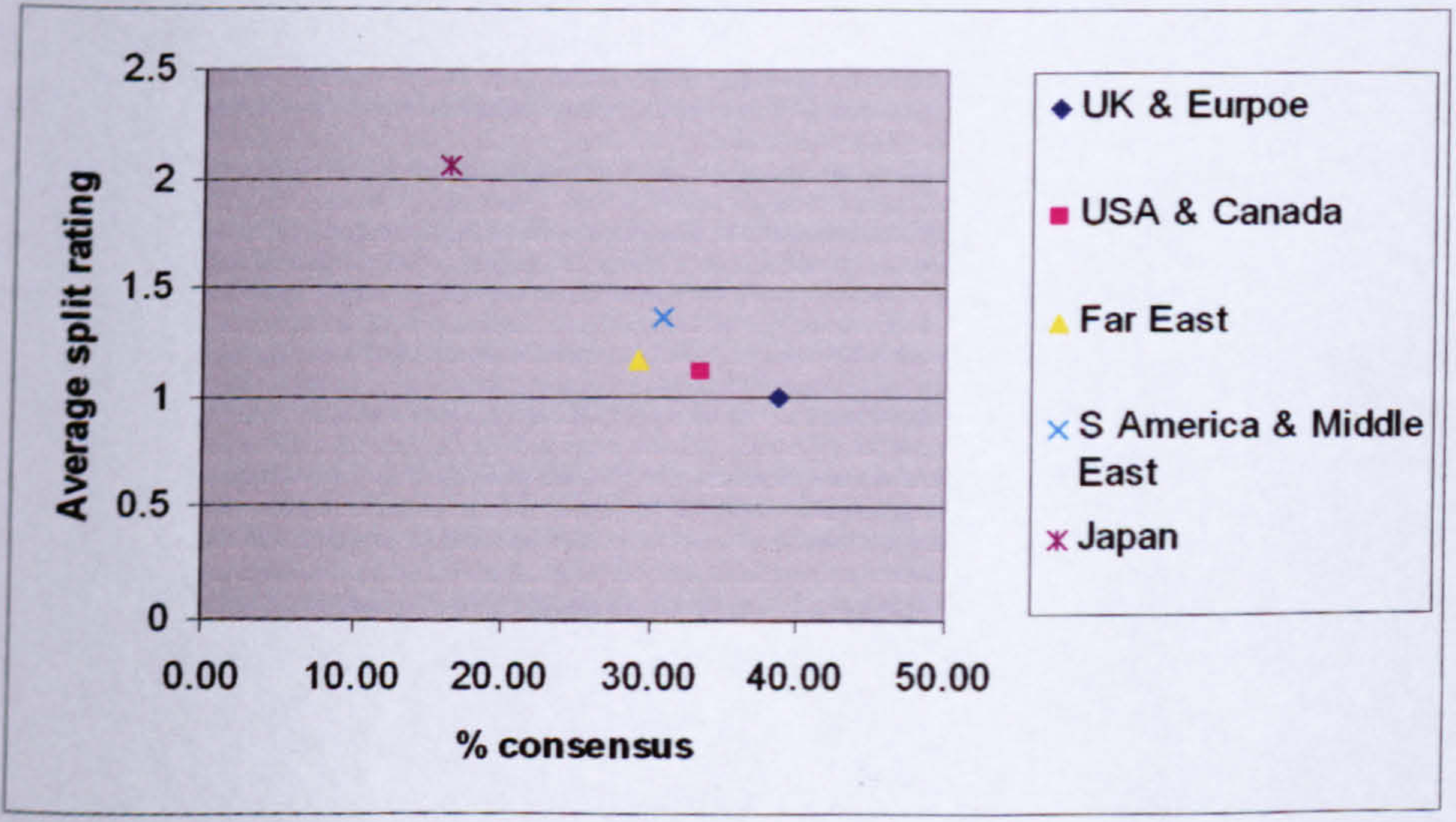
The consensus, means, standard deviations and counts of matched pairs were recalculated on the basis of the country groupings identified above.

Table 8.1: Percentage consensus & mean split ratings for country groups

	Consensus	Average split rating	Std.Dev.	Number of matched pairs
UK and Europe	38.7	1.00**	1.20	10,969
USA and Canada	33.5	1.12**	1.23	36,544
Far East	29.2	1.17**	1.13	3,791
S America and Middle East	30.9	1.37**	1.54	5,705
Japan	16.6	2.06**	1.68	5,537
USA, Canada & Far East	33.1	1.12**	1.23	40,335

** Mean significantly different from zero at 1% level (two tailed test)

Figure 8.12: Comparison of mean split rating and consensus between issuers from the five geographic regions identified



The results for UK and Europe are consistent with figure 8.9, it is expected that they have the highest level of consensus and the lowest mean difference between split ratings. The star representing Japan has a much lower percentage consensus and the mean split rating is greater than 2 notches. The mean of each region is significantly different from all the others at the 1% level except for the USA, Canada and the Far East.

These results are calculated using the whole database from 1999 – 2004. If the results are broken down and reviewed again for each year of the database the findings remain consistent. UK and Europe are significantly different from all other regions in all periods at the 1% level. USA and Canada show no significant difference from the Far East at the 1% level in 2001 and 2003. There is no significant difference at the 5% level in 2002. There is a significant difference at the 1% level in 1999/2000.

The Middle East and South America show differences from all other regions in all periods except for the Far East in 1999/2000. Japan shows significant differences at the 1% level to all other regions in all periods.

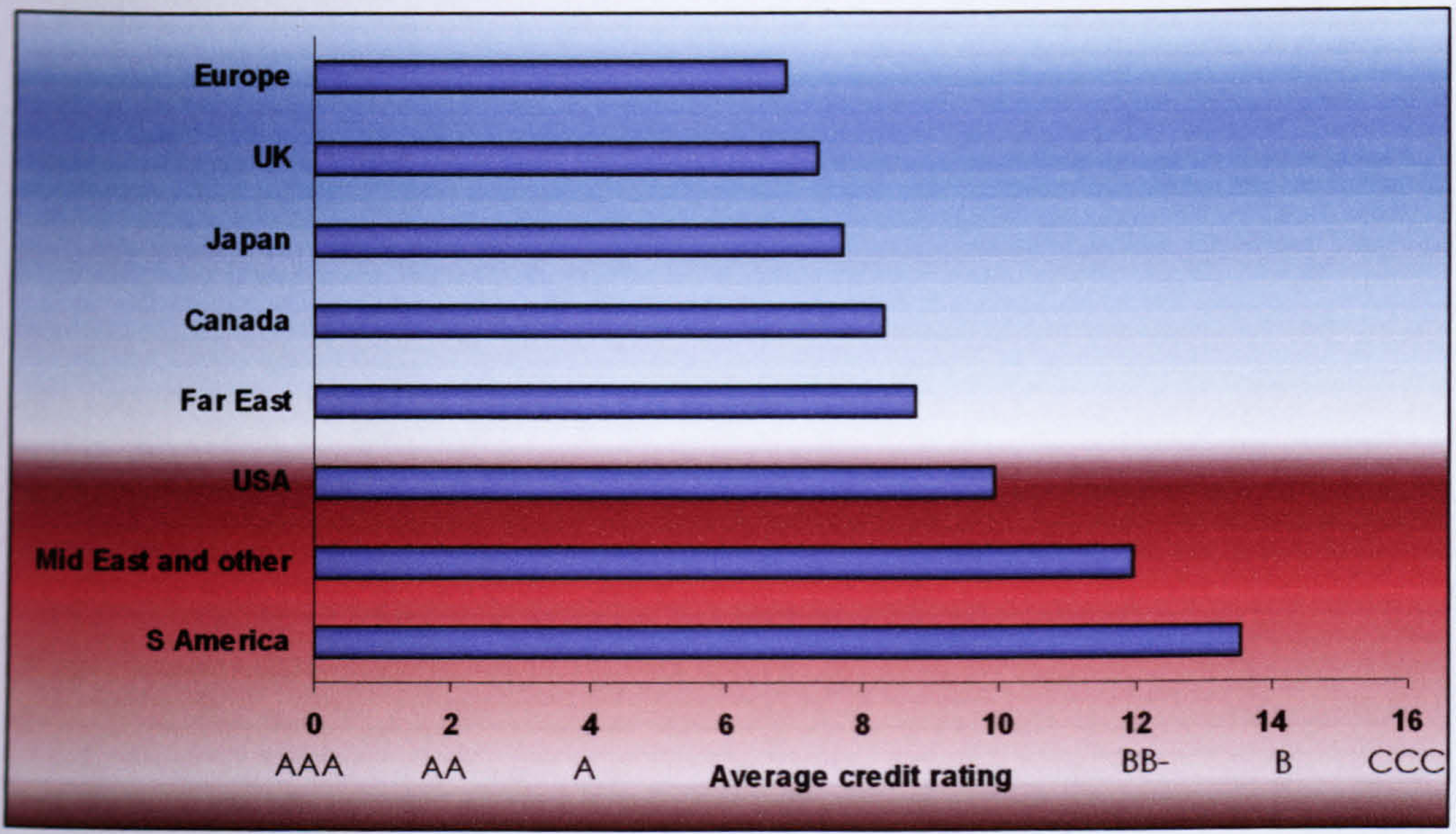
8.2.5 Quality distribution of issuers in different countries

This chapter has presented evidence to suggest that industry groups with a higher average credit rating have a higher level of consensus and those with a lower average credit rating have a lower level of consensus. Country groupings are analysed in the same way below.

It has already been shown, in this study as well as others, that Japanese agencies rate, on average, 1.5 to 2.5 notches higher than other agencies. As most Japanese issuers are rated by either R&I or JCR you would expect the average credit rating of Japanese issuers to be higher than for other regions because of the influence of generous ratings.

There are more US issuers with credit ratings than any other region. In all regions the largest companies who are most active in the bond market will be rated by the major credit ratings agencies. In the USA a larger cross section of issuers have credit ratings because all SEC registered corporate bonds have a rating from Moody's and S&P. Because the US rating coverage is higher than in other regions the average credit rating for the USA may be biased downwards in comparison with other countries and have a higher proportion of sub-investment grade debt.

Figure 8.13: Average credit rating by country



The results show that the highest average credit ratings are for Europe and the UK, the average rating for both countries is BBB+. Figure 8.9 also shows that these regions have the highest level of consensus between agencies. This finding supports the hypothesis that there is less disagreement over higher quality issuers.

As expected, the results for Japan show that there is a high average credit rating in comparison to other countries, the average rating is BBB. The USA, Canada and the Far East have a similar level of average credit ratings at BBB-, BBB and BBB- respectively. The average rating for the USA is likely to be lower because a large number of sub-investment grade issuers are rated in the US by Moody's and S&P and equivalent ratings are not included for other countries in this sample. The average credit ratings for South America and the Middle East are lower than for any other region. These are B and BB- respectively.

8.3 Summary

Now that the major industrial nations are reaching agreement over Basel II, external credit ratings are becoming increasing important as part of the bank regulatory process. The last two chapters have established that there is a high level of disagreement over credit ratings, even by the major players in the industry. This chapter has looked in more detail at the reasons why some of these disagreements arise.

The industry and domicile of the issuer does influence the likelihood that there will be split rating between agencies. There is also more disagreement over lower quality issuers.

Three statistically significant industry groups appear from this research. Sovereigns, Finance/Energy/Leisure group (including Banks, Finance, Insurance, Energy, Utilities and Leisure) and a Consumer group (including Manufacturing, Transport, Healthcare, Hi-tech and Forestry). There are no significant differences between individual industries apart from Sovereigns and transport. In contrast to previous research this study does not find the highest level of split ratings to be for banks.

Five significantly different regional groups are identified: UK & Europe, USA & Canada, Far East, South America & Middle East and Japan. The highest level of consensus exists for UK and Europe, this region also has the highest average level of credit ratings. Japan shows the lowest level of consensus which is consistent with the findings of earlier chapters.

Do split ratings have an impact on Basel II risk assessments?

The previous three chapters have looked in detail at split ratings and shown differences between overall rating levels and between particular pair of agencies. There appears to be a ranking of the agencies from the most to the least generous due to differences in rating scales. Agencies rate issuers from their home country more favourably then foreign issues and the ratings of agencies from the same country show a higher level of consensus than those from different countries. There is generally a lower level of consensus between manufacturing-type companies than between sovereigns and finance, utility and energy-type companies which appears to be due to the lower average credit quality of manufacturing entities in the data sample used.

These observed differences in the credit ratings assigned by different agencies become much more important when Basel II is adopted into European law. Depending on the extent to which regulators use Annex 2 of Basel II to smooth out differences between agencies, the different rating scales of the agencies could influence the risk weighted capital of a bank. The implication of split ratings on Basel II is examined and quantified in this chapter to assess whether the problem is significant.

9.1 Overall level of inter-rater agreement: Basel II risk weights

Credit ratings in the FT-CRI database have been mapped to the Basel II risk weights as specified in the Capital Accord. A Basel II correspondence was designed and is described in chapter five (see page 97). Table 9.1 shows that the overall level of agreement between the live agencies, (Moody's, S&P, Fitch, DBRS, CI, JCR and R&I) is 76.5% using the Basel II correspondence but this varies between sector with banks showing less agreement than corporates or sovereigns. Where split ratings occur they most frequently give rise to a 50% difference in risk weight, except for banks where the difference is most frequently 30%. Clear guidelines exist within Basel II to determine the treatment of split ratings and generally the highest risk weighting should be used in the case of a split, these details are outlined in full in chapter three.

Table 9.1: Summary of split ratings and consensus between agencies when applying Basel II risk weights

Split rating of:	All issues %	Corporates %	Banks %	Sovereigns %
130%	0.02	0.03	0	0
100%	0.13	0.13	0.19	0
80%	0.52	0.51	0.7	0.26
50%	14.51	15.86	9.14	14.51
30%	6.3	5.36	11.15	4.14
20%	2.04	0	11.22	0
In agreement%	**76.47**	**78.11**	**67.58**	**81.09**
Sample size	54,316	39,381	9,890	5,045

9.2 Mapping external credit ratings to risk assessments under the Standardised approach

Each of the live agencies included in the database used for this thesis would almost certainly qualify for recognition by local supervisors for the purposes of the Standardised approach of Basel II. A study in chapter three reviewed relative agency probabilities of default and shows how supervisors would consider relative agency scales. Annex 2 only provides guidelines so it is unclear how agencies would treat the differences between Moody's and JCR, for example.

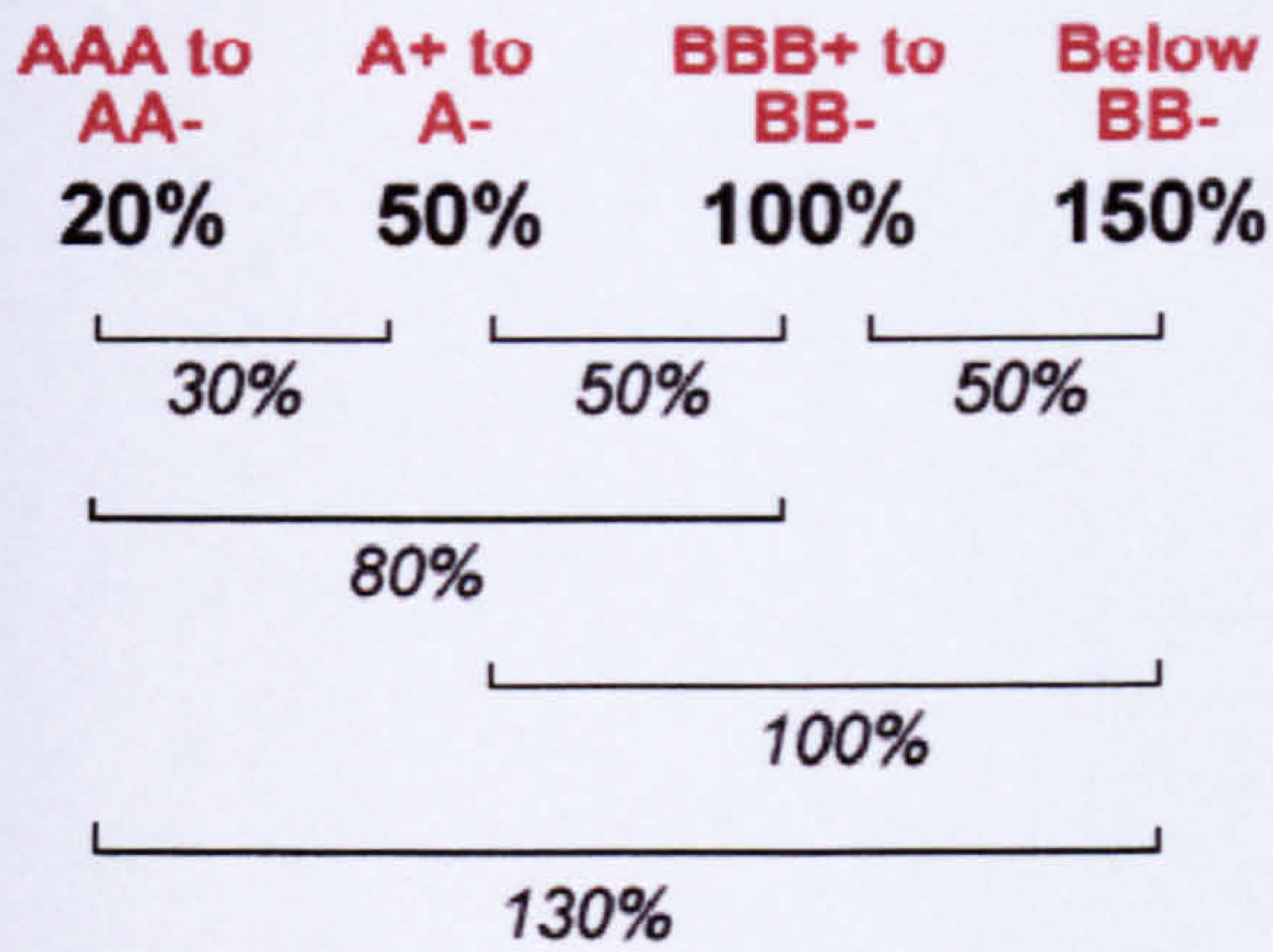
In the example given in chapter three, R&I's most recent 3 year cumulative default rates are within the trigger levels for all but the B grade assessments so it is likely that some, if not all, supervisors will map R&I's rating scale directly to the risk assessment in Basel II. For example, an AA grade allocated by JCR may be mapped to an AA risk assessment under the standardised approach of Basel II and the risk weight would be determined accordingly. An AA from Moody's would also map to an AA risk assessment and the same risk weight would be allocated. However, it is clear from a detailed analysis of the matched pairs available for the agencies that there are consistent differences in the rankings that will inevitably impact the capital adequacy requirements determined from use of these credit ratings.

9.2.1 Corporate claims

The risk weights for corporate claims are determined as follows:

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BB-	Below BB-	Unrated
Risk Weight	20%	50%	100%	150%	100%

The split ratings for corporate claims are determined according to this scale:



These bands are fairly wide compared to the 11 notch correspondence that has been used for many of the studies in this thesis. The largest number of split ratings will be between the risk weight bands 20% to 50%, 50% to 100% and 100% to 150% as these represent split ratings of anything from one to four notches. Table 9.1 above shows that less than 1% of the population has a split rating of 80% or more. A 50% difference in risk weight is caused by a split rating between A+/A- and BBB+/BB- as well as BBB+/BB- and Below BB-. Consequently there are a large number of split ratings showing a difference of 50% between risk weights. A discussion of these bandings is important in relation to Figure 9.1.

Figure 9.1: Differences in risk weights between matched pairs of agencies – corporate claims

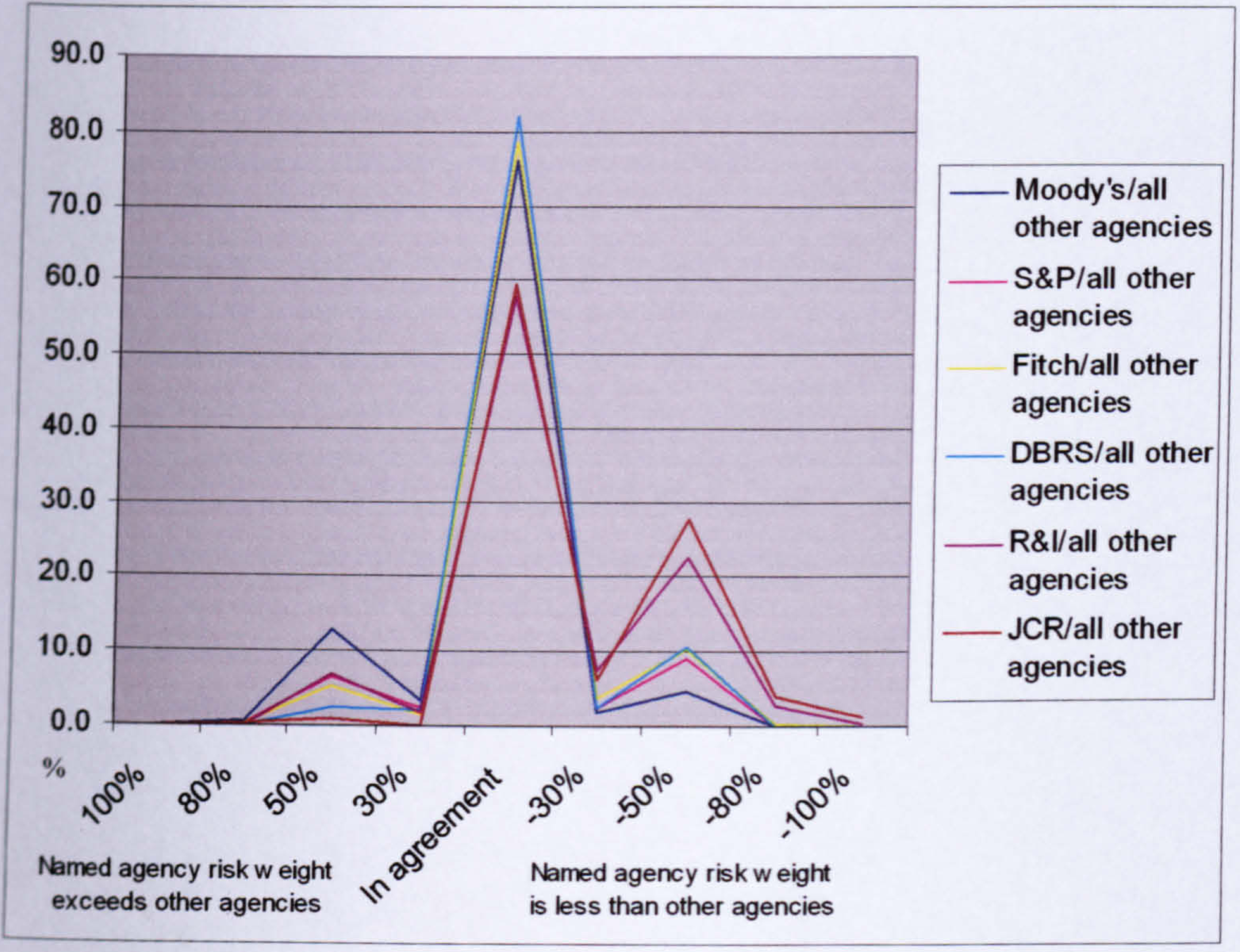


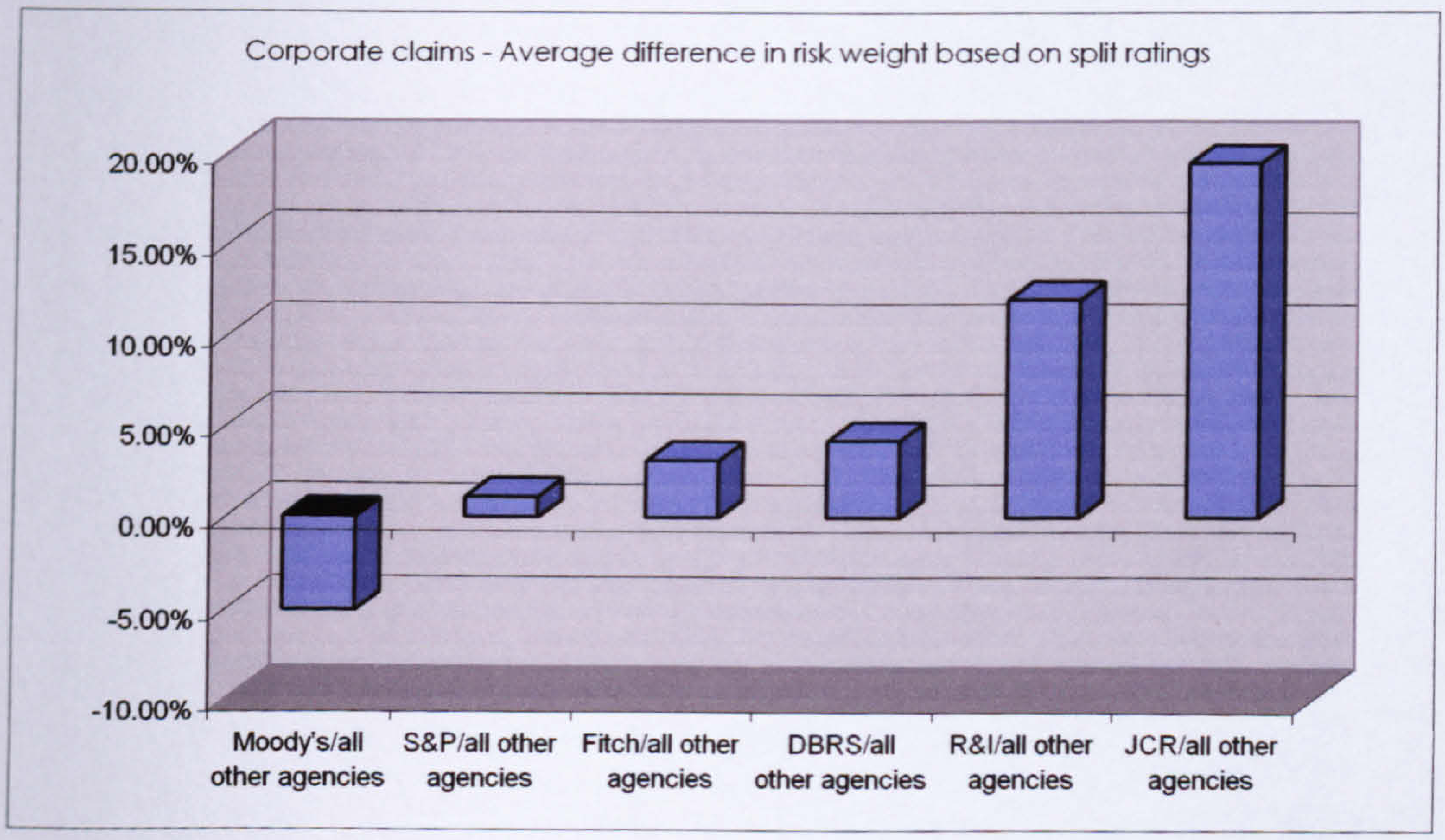
Figure 9.1 plots the percentage of matched pairs that are in agreement and the percentage and size of split ratings in terms of Basel II risk weights. The level of consensus shown by these 6 individual agencies[1] is consistent with an overall level of agreement of 78%, as shows in table 9.1. As discussed above there are more differences of 50% than any other split rating and this can be seen on the graph. Higher percentages of split ratings to the right of the graph indicate that the named agency on the key has a higher credit rating than the other agencies. For example, the purple and brown lines on the right of the graph show that R&I and JCR have a high level of split ratings at the 50% level in comparison with the other agencies. The purple and brown lines on the left of the graph show a very low level of split ratings where R&I or JCR have the higher risk assessment than other agencies. This finding is entirely consistent with earlier chapters of this thesis. As you would expect the plot for Moody's, in dark blue, shows a higher incidence of split ratings where Moody's has the lower risk assessment and a low number of splits where Moody's has the higher

[1] CI does not rate corporate claims

risk assessment. Again, this finding is entirely consistent with expectations. S&P, Fitch and DBRS appear to have fairly symmetrical distributions.

Figure 9.2 shows the mean differences in split ratings between each of the major agencies and ratings from all other agencies. For corporate claims this graph shows that the ranking of claims is similar to that shown in chapter seven using the 20 notch correspondence. This ranking is almost consistent with figure 7.1 on page124 except that Fitch appears less generous than DBRS for corporate risk assessments. On average the rating of Moody's would be attributed a risk weighting of 6.5% more than the other agencies and JCR a risk weighting of 18% less.

Figure 9.2: Mean difference in ratings between major agencies under Basel II



The quality distribution of the ratings in the FT-CRI database for the live agencies matched to Basel II risk weights are as follows:

Table 9.2: Quality distribution of ratings in Basel II corporate 'buckets'

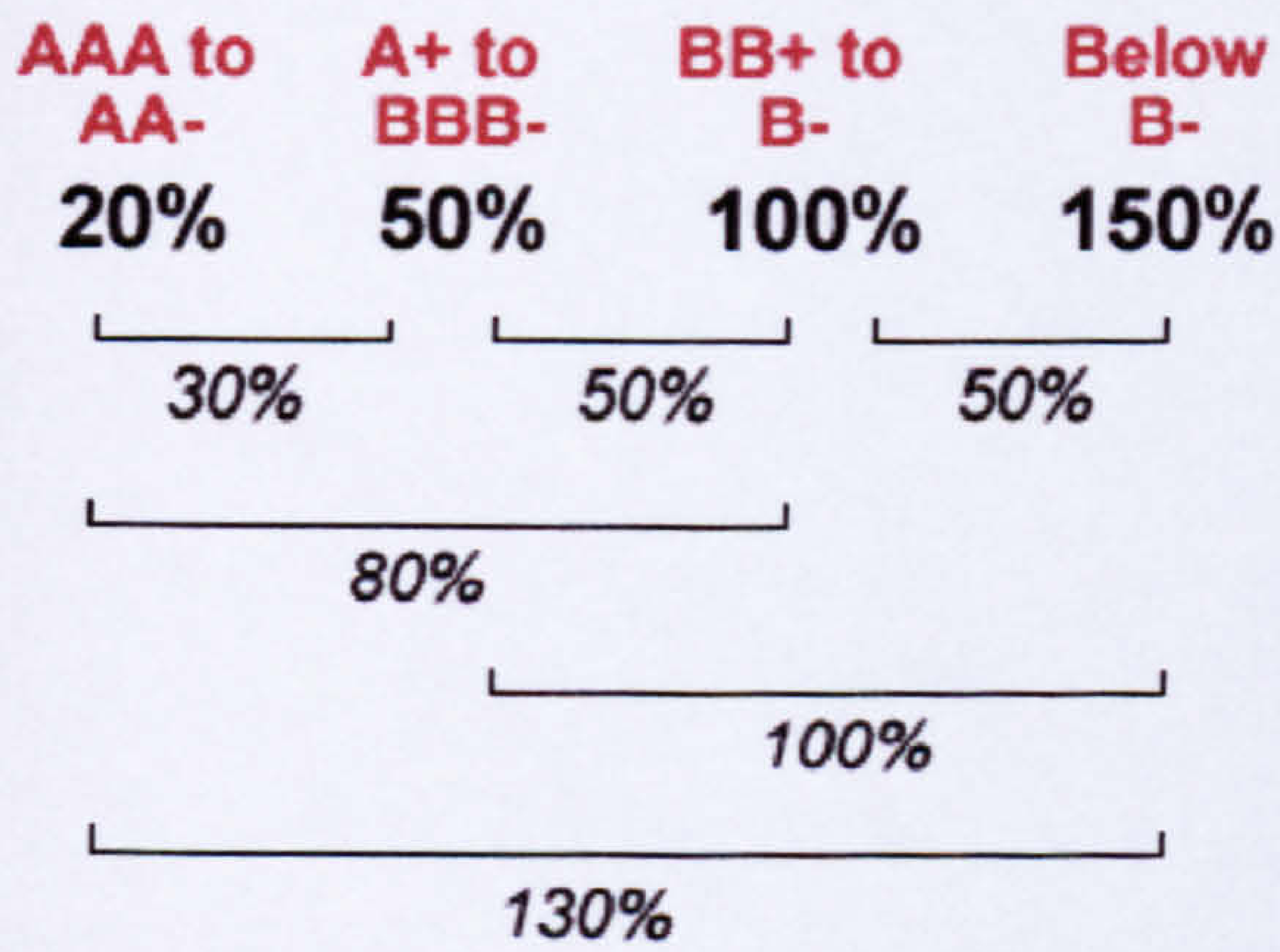
Band of rating grades	**Risk weight**	**% of distribution in each category**
AAA to AA-	20%	14.5%
A+ to A-	50%	25.9%
BBB+ to BB-	100%	37.0%
Below BB-	150%	22.6%

The lowest percentage of ratings are included in the highest quality band. This explains the dip shown at the 30% difference and increase for 50% difference shown in Figure 9.1.

In summary, the findings for corporate claims using the Basel II risk weights are consistent with those presented in the earlier part of this chapter. There appears to be an ordered ranking of agencies which suggests that the choice of agency could have an influence on capital requirements under the standardised approach.

9.2.2 Bank Claims

Risk weights for banks are discussed in chapter three. For this thesis option 2 for claims on banks has been used[2]. This option includes lower risk weights for short term claims but the FT-CRI is an issuer database and the age of a claim is issue specific. Therefore all claims have been treated as having a maturity of more than three months.



The 50% risk weight band is much wider for bank claims that corporates and the higher weights are allocated to lower credit ratings.

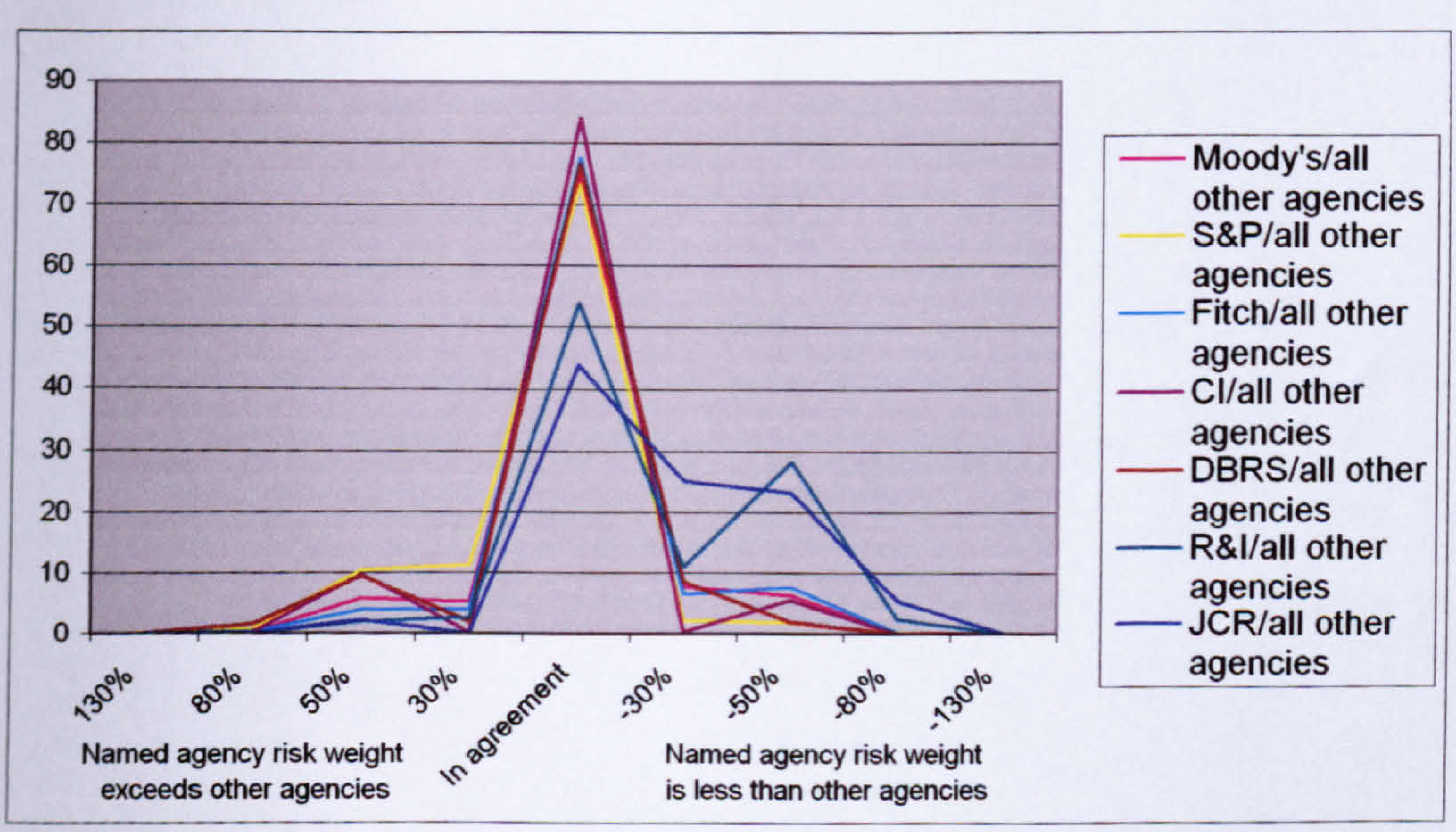
[2] See chapter three, page 45.

Table 9.3: Quality distribution of ratings in Basel II bank 'buckets'

Band of rating grades	Risk weight	% of distribution in each category
AAA to AA-	20%	23%
A+ to BBB-	50%	30%
BB+ to B-	100%	43.2%
Below B-	150%	3.8%

The quality distribution in the FT-CRI database is more evenly spread for banks than corporates and few banks have a rating below B- compared to sub-investment grade corporates. Given this distribution the majority of split ratings would be expected to fall into the 30% and 50% band.

Figure 9.3: Differences in risk weights between matched pairs of agencies – bank claims

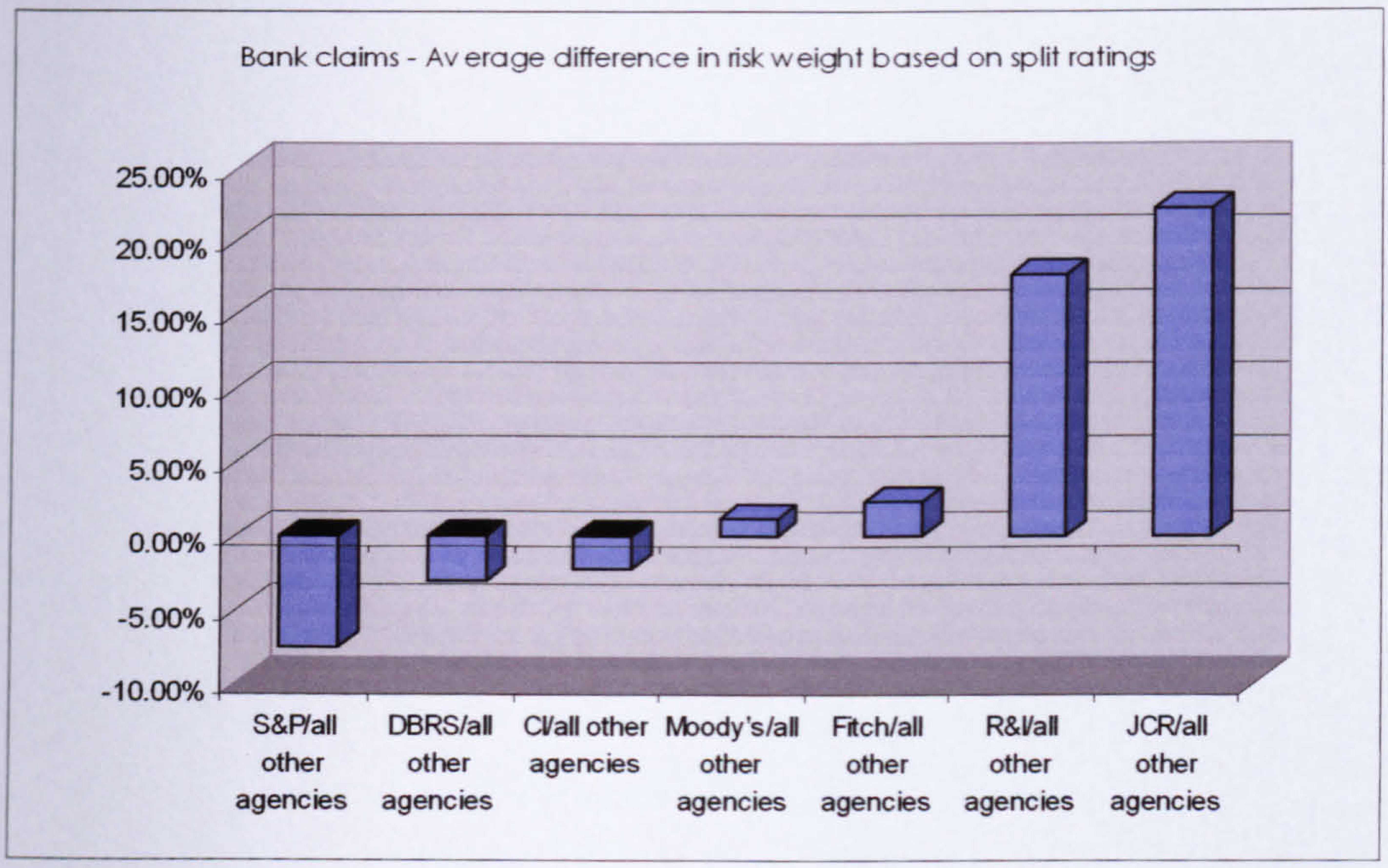


The average level of agreement is slightly lower for banks at 67%. The blue lines shows that JCR is markedly more generous than other agencies. The line for R&I is also higher on the right than on the left which means that lower risk weights would also be attributed to R&I ratings.

The yellow line for S&P shows that this agency is less generous for banks than other agencies. DBRS also shows a high level of split ratings where it is the least generous agency and there are a high level of split ratings at the 50% level.

Figure 9.4 shows analysis of Basel II risk weights for banks. For the first time, there is a significant departure from the ranking of the agencies that is shown above and in chapter seven.

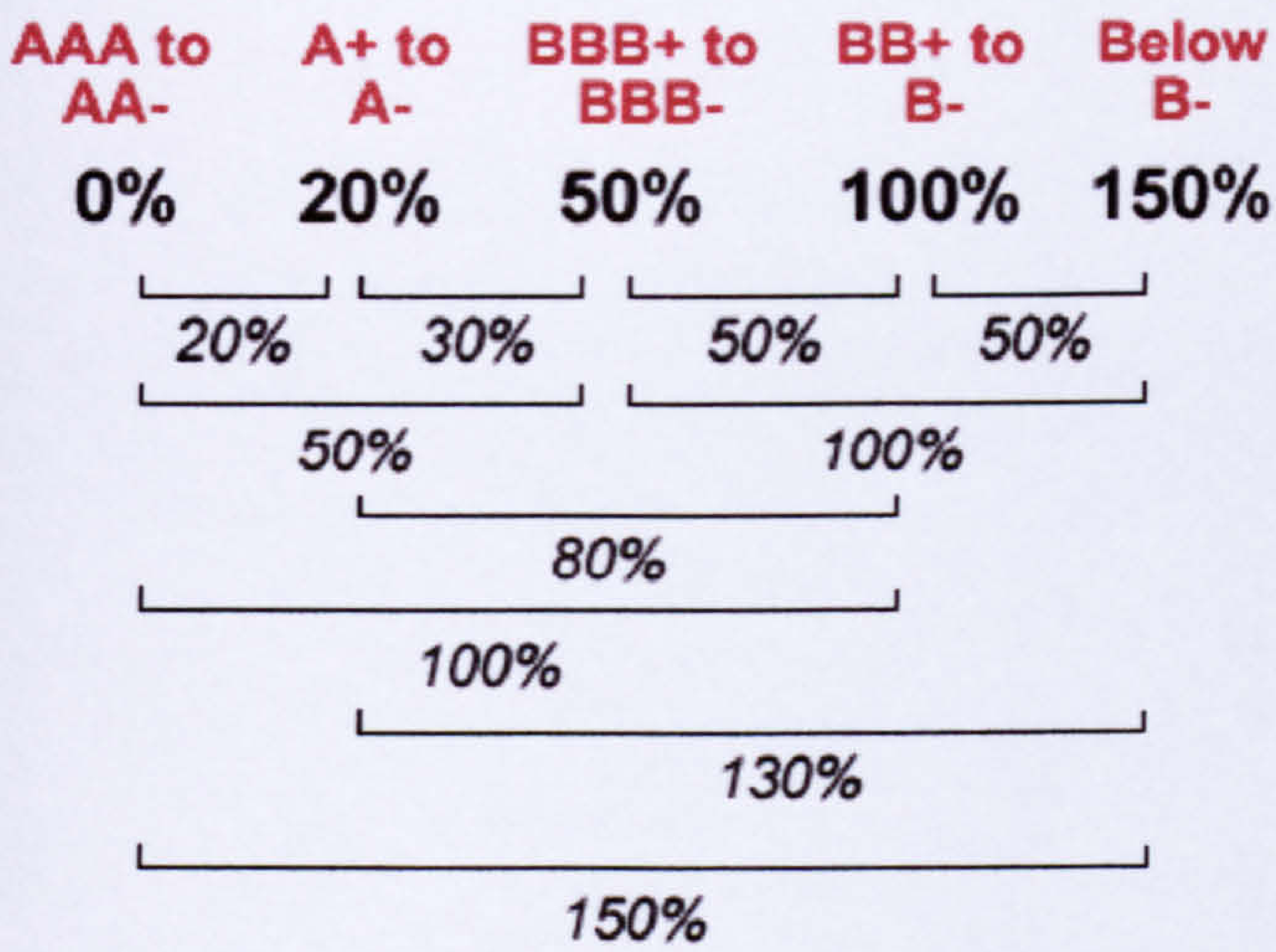
Figure 9.4: Mean difference in ratings between major agencies under Basel II - bank claims



For bank claims, S&P now appears to be the agency that gives the lowest ratings, followed by DBRS, CI then Moody's and Fitch. The Japanese agencies still hold their place as the most generous agencies for banks as well as corporate claims.

9.2.3 Sovereign claims

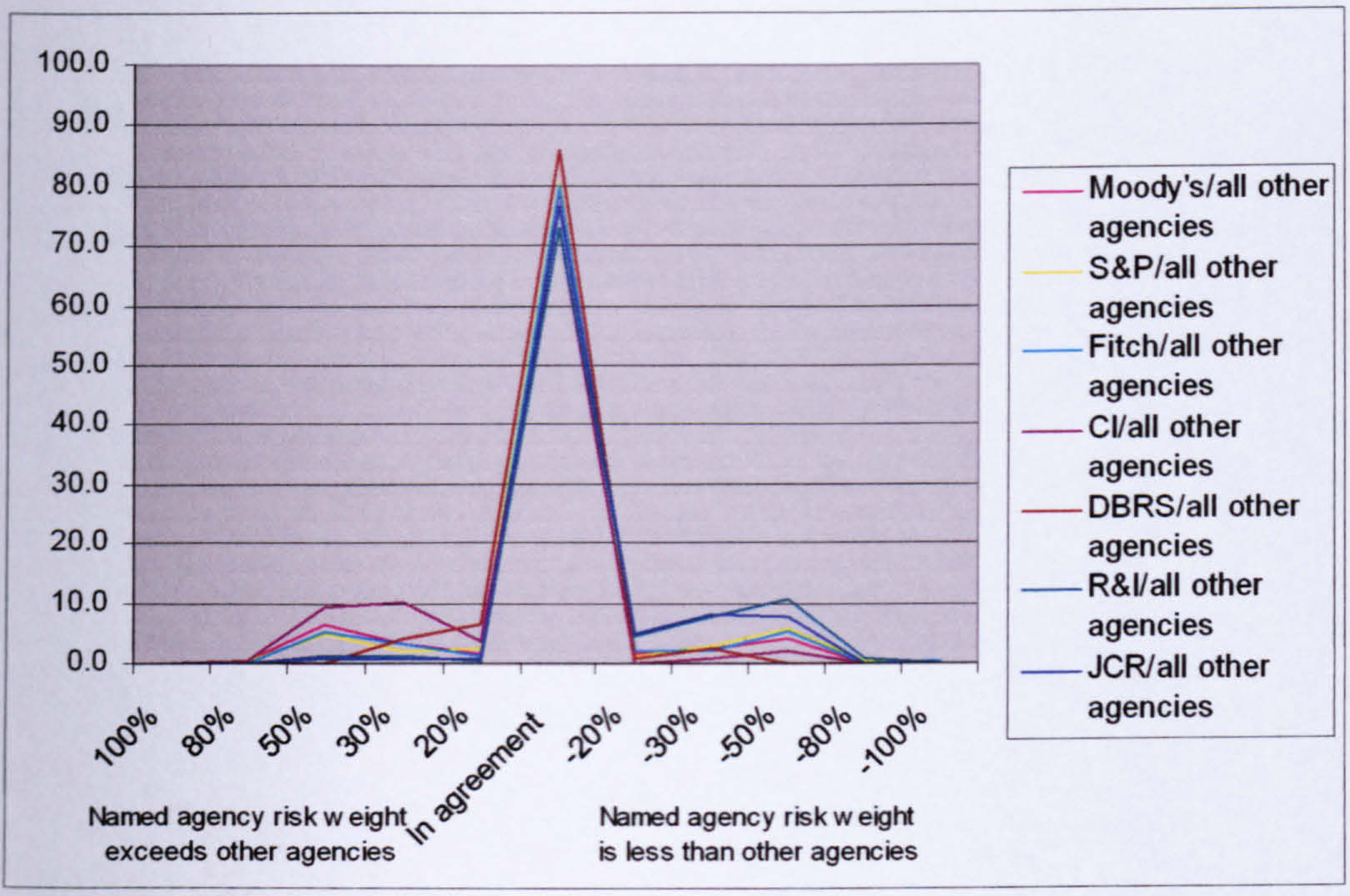
Calculating split ratings for sovereigns is more complex than for corporates or banks. There are 5 different risk weightings available which increases the number of differences between risk weights that are possible when there are split ratings.



There are five percentage differences between risk weightings that can arise; 20%, 30%, 50%, 80%, 100% and 130%.

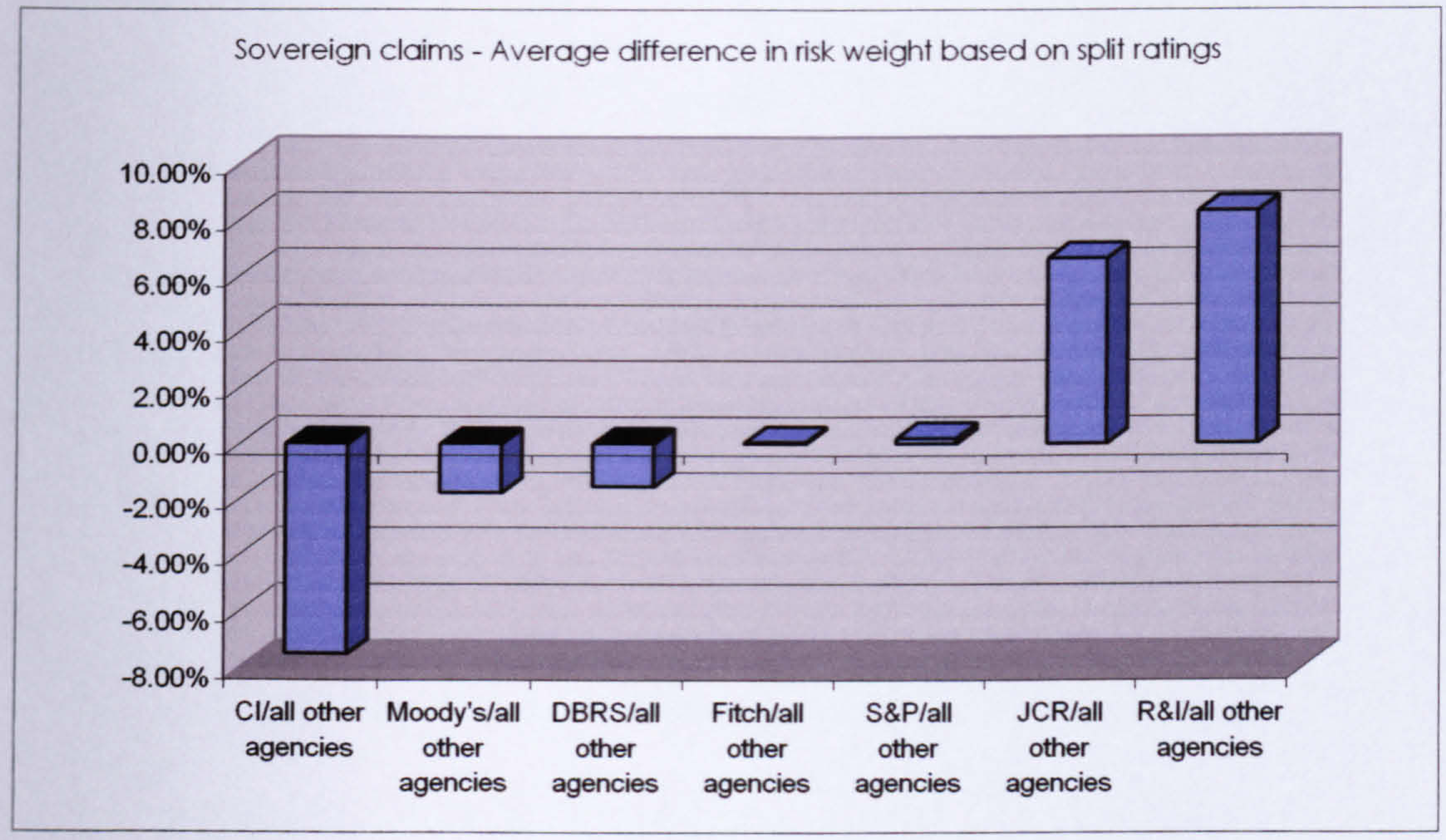
The level of consensus for sovereign claims is higher than for corporates and banks at 81%. Figure 9.5 shows that JCR and R&I are more generous if there is a split rating and Moody's and CI are less generous. The purple line on the left of the graph shows that 20% of all ratings by CI have risk weights that are either 30% or 50% higher than those from other agencies.

Figure 9.5: Differences in risk weights between matched pairs of agencies – sovereign claims



The average difference in risk weight based on split ratings for sovereign claims largely returns to the familiar pattern of agency rankings. S&P is again the agency that appears to deviate from its position in the corporate agency rankings. Another interesting finding is that JCR and R&I swap their well established places for sovereign claims. CI appears to be very much tougher on sovereign claims than any other agency.

Figure 9.6: Mean difference in ratings between major agencies under Basel II - sovereign claims



9.3 Does is matter which agency is used to determine Basel II Standardised risk weights?

The purpose of this section is to ask whether the split ratings identified actually make a significant difference to the level of Basle II risk weights and whether this would matter to banks. Clearly the importance of the split ratings identified in this thesis is entirely dependant on the mapping process chosen by each supervisor in individual countries. The next section is based on the assumption that for the seven agencies under review (Moody's, S&P, Fitch, DBRS, CI, R&I and JCR) their present rating scales would be used to map to risk assessments without adjustment. There is no obligation under Basel II for a bank to use more than one approved rating agency for external assessments if it does not wish to.

9.3.1 Most and least generous agencies for Basel II

The first analysis of most and least generous agencies for the purposes of Basel II risk weights compares issuers rated by two agencies. For example, table 9.4 shows that for all issuers rated by both Moody's and S&P the average risk assessment is lower for Moody's than S&P. In this case Moody's ratings are slightly more generous than S&P

and the difference is statistically significant at the 1% level. The difference is 2.2% in terms of risk weights.

Table 9.4: Most and least generous agencies for the purpose of Basel II risk weights

Agency 1	Agency 2: Moodys	S&P	Fitch	CI	DBRS	R&I	JCR
Moodys	-	< **	>	<	<	> **	> **
S&P		-	> **	>	>	> **	> **
Fitch			-	>	<	> **	> **
CI				-	No data	>	>
DBRS					-	>	> *
R&I						-	> **
JCR							-

> Agency 1 has higher risk weights that agency 2 (agencies with higher risk weights are less generous with their credit ratings)

< Agency 1 has lower risk weights that agency 2 (agencies with lower risk weights are more generous with their credit ratings)

** agency means are different from each other at the 1% level

* agency means are different from each other at the 5% level

The table clearly shows that using credit assessments from R&I and JCR will give rise to lower risk assessments. This is entirely consistent with earlier findings of this study. For Moody's, S&P and Fitch differences between the US agencies and Japanese agency risk weightings are statistically significant at the 1% level. Moody's, S&P, Fitch, CI and DBRS do not show consistent significant differences between each other. The relationship between Fitch and the other agencies is as expected but some of the results for DBRS are not in the expected direction but are not statistically significant. Most of the levels of risk weights between S&P and the other agencies are as expected apart from Moody's. Given the ranking of agencies identified in this study Moody's would have been expected to give higher risk weights than S&P.

Given the findings presented in table 9.4 it appears that R&I and JCR should be rescaled before the rating assessments are mapped to risk assessments to make the ratings more equivalent to the other agencies. For Moody's, S&P, Fitch, DBRS and CI it seems appropriate that their ratings could be mapped directly to the risk assessments as in Basel II.

9.3.2 Which US agency is it most beneficial to use for risk weight assessments?

The population of issuers rated by Moody's, S&P and Fitch is far greater than for any other agency. This means that, in reality, banks may need to use the ratings of one of the major agencies for the Standardised approach. The next section considers the difference in risk assessments between Moody's, S&P and Fitch to answer the question as to whether there are any advantages in using the ratings of one agency rather than another.

Table 9.4 shows that there are significant differences between two of the three agencies. S&P's ratings gave a significantly higher risk assessment than Moody's or Fitch's ratings. Comparisons for each pair of agencies were broken down into the following groups to see if any significant differences arose. Significant differences in the risk weights assigned to different agencies would suggest that there is an advantage in using one agency over another for issuers in a particular industry group or located in a particular region.

- Consumer group made up from healthcare, consumer goods, technology, automotive, building and transport
- Finance and Utilities group made up from utilities, energy, banks, insurance, finance and leisure
- Sovereigns

And into country groups:

- UK and Europe
- USA and Canada
- Far East
- Japan

These industry and country groups were determined from results of studies in chapter eight.

The average risk weight, standard deviation and number of observations were calculated for all combinations of agencies between Moody's, S&P and Fitch for each industry and country. There were no significant differences between any of these pairings. As the results were not significant they have not been replicated here. This finding suggests that the choice of US rating agency will not make a significant difference to the allocation of Basel II risk weights under the Standardised approach.

9.4 Summary

Throughout this study of split ratings a statistically significant ranking of rating agencies has been found to exist. Based on these findings the question was asked as to whether significant differences also arose between the risk assessments determined from different agencies under the Basel II rules for the standardised approach. Such systematic differences could lead to selection of particular rating agencies for the purposes of achieving the most favourable risk assessments.

This chapter has shown that, apart from the Japanese agencies, no such systematic differences exist when Basel II risk weights are applied to the rating grades of Moody's, S&P, Fitch, DBRS and CI. These findings apply across industry and country sectors. Significant differences do arise between the Japanese agencies and all other agencies. This suggests that supervisors should exercise their options under Annex 2 of Basel 2 to realign the rating scales of the Japanese agencies downwards to bring them into line with those of other regions.

Predicting bank bond ratings from financial data

There have been a large number of studies over the last 40 years attempting to build models that accurately predict agency bond ratings. These models take on additional importance with the implementation of Basel II and the advantages, in terms of minimum capital requirements, that will be offered by adopting Internal ratings-based (IRB) Foundation Approach or IRB Advanced Approach. These methods both require banks to be able to calculate the probability of default on assets so they need to have internal credit rating models in place to the satisfaction of regulators.

Chapter four of this thesis has already reviewed the previous studies performed in the area of credit rating prediction and highlighted the wide range of different methodologies that have been used. These studies show that financial variables can be used to estimate between 55% - 70% of corporate bonds accurately. Chapter four also discussed the selection of independent variables for bank analysis.

The majority of the literature uses samples from industrial enterprises rather than banks. This thesis extends previous studies by focusing on banks and reviews both individual ratings and long term credit ratings. The data sample consists of 8,901 worldwide banks, for which accounting data was available, matched to credit ratings from Financial Times Credit Ratings International. Details of these databases and the process of matching these two different datasets is discussed in chapter five. Appendix 4 shows the standardised template into which accounting data from many different countries was mapped. The full list of countries for which bank financial information was available is included in Appendix 3. The final list of financial ratios and variables used as independent variables is shown in Appendix 5.

10.1 Methodology

In this section, the main modeling technique used to develop the bank rating models is described. For binary classification problems like bankruptcy prediction, ordinary least squares (Altman, 1968) and logistic regression (Ohlson, 1980) are key techniques to build a discriminant function between two classes: e.g. class 1 (defaults) and class 2 (non-defaults).

Logistic regression is typically preferred because: its model formulation is specific to a binary classification problem (defaults/non-defaults); it is known to exhibit better generalization behaviour than least squares regression, as is observed empirically (Baesens, 2003; Lim et al., 2000; Van Gestel et al., 2004); and it is theoretically proven to be more robust to deviations from multivariate Gaussian distributed classes (Efron, 1975).

The ordinal logistic regression (OLR) model (Johnson and Albert, 1999; McCullagh, 1980; McCullagh and Nelder, 1989) is an extension of the binary logistic regression model for ordinal multi-class categorization problems, like e.g., class 1 (very good), class 2 (good), class 3 (medium), class 4 (bad) and class 5 (very bad). Hence, it is obvious that ordinal logistic regression is an interesting technique to model bank credit ratings.

In the cumulative ordinal logistic regression formulation, the cumulative probability of the rating *y* is given by:

$$P(y \leq i) = \frac{1}{1 + \exp(-\theta_i + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)} \qquad i = 1, \ldots, m,$$

with the vector $x = [x_1, x_2, \ldots, x_n]^T$ of *n* explanatory variables $x_1, x_2, \ldots, x_n$ and the corresponding coefficient vector $\beta = [\beta_1, \beta_2, \ldots, \beta_n]^T$. Because $P(y \leq m) = 1$, the parameter θ_m is equal to ∞. The latent variable z is the linear combination of the explanatory variables $x_i, (i = 1, \ldots, n)$:

$$z = -\beta_1 x_1 - \beta_2 x_2 - \ldots - \beta_n x_n = -\beta^T x,$$

and summarizes the financial information of the risk entity. Essentially, the cumulative probability $P(y \leq i)$ is linked to the latent variable (plus a category dependent constant θ_i) via the logistic link function. Given the cumulative probabilities $P(y \leq i)$, with $i = 1, \ldots, m$, one obtains the probabilities $P(y = i)$ as follows:

$$P(y=1)=P(y\leq 1)$$
$$P(y=i)=P(y\leq i)-P(y\leq i-1)$$
$$P(y=m)=1-P(y\leq m-1).$$

Given a training data set $D=\{x_i,y_i\}_{i=1}^{N}$ of N data points, the parameters $\theta_1,\theta_2,...,\theta_m$ and $\beta_1,\beta_2,...,\beta_n$ are estimated using a maximum likelihood procedure to minimize the negative log likelihood (NLL):

$$(\hat{\theta}_1,\hat{\theta}_2,...,\hat{\theta}_m;\hat{\beta}_1,\hat{\beta}_2,...,\hat{\beta}_n)=\arg\min NNL(\theta,\beta)=-\sum_{i=1}^{N}\log(P(y=y_i)),$$

With $\theta_m=\infty$ and $y_i\in\{1,...,m\}$.The maximum likelihood estimate is obtained via iteratively re-weighted least squares using Levenberg-Marquardt optimization.

As a result of the optimization, not only the optimal parameters are obtained, but also the standard errors (square roots of the diagonal elements of the inverse Hessian) and the corresponding p-values (z-test, Friedl and Tilg, 1994). The model deviance is equal to twice the negative log likelihood in the optimum and can be used for model comparison, e.g., using an appropriate information criterion (Agresti, 2002).

10.2 Results

The ordinal logistic regression results are shown in tables 10.1 to 10.11. A variety of different models were estimated and the results are organised as follows:

Table 10.1 compares the results of models using financial ratios to estimate: Moody's long term ratings (Moody's LTR), Moody's BFSR (BSFR) and BFSR using financial ratios and Moody's long term ratings (BFSR with LTR). The same comparison is made for Fitch ratings; Fitch long term ratings (Fitch LTR), Fitch individual ratings (Fitch Individual) and Fitch Individual ratings estimated using financial ratios and Fitch long term ratings (Fitch individual with LTR).

Table 10.2 compares results from 10 different rating agencies, 7 live and 3 dead agencies.

Tables 10.3 to 10.5 compare the results for Moody's, S&P and Fitch when the rated banks are split into country regions.

Tables 10.7 to 10.9 show results for Moody's, S&P and Fitch when the banks are split into size bandings based on the banks' total assets.

The final set of tables, 10.10 to 10.12, compare the results for Moody's, S&P and Fitch when the banks are split between bank holding companies, subsidiaries and thrifts.

Two measures of performance are used to summarise the explanatory power of the models. The significance of the model based on the chi-square wald, chi-square score, log likelihood is shown for each model. The classification accuracy of the model is also tested using a holdout sample of one third of the total data sample. For each model the results are shown at the zero notch (complete agreement), one notch (agreement to within one category etc.), two notch and three notch levels. These results refer to the holdout sample in all cases. An explanation of the categories of ratings used for this study is given in chapter five, page 99.

10.2.1 Modeling individual bank ratings and long term ratings

Table 10.1 shows a comparison of results for models based on long term ratings and BFSRs or individual ratings for Moody's and Fitch respectively. Models estimated from BSFRs, or Fitch individual ratings, have a higher classification accuracy at zero notch and one notch than either model based on long term ratings. For Moody's, the model with the best zero notch (64.6%) and one notch (98.3%) classification accuracy is estimated when long term ratings are included as one of the independent variables. This finding is consistent with Poon, Firth and Fung (1999) as they also found that a model of BFSRs estimated on financial ratios does not perform as well as a model including Moody's long term ratings. Zero notch classification accuracy for Moody's long term ratings and the BFSR model are 47.4% and 51.6% respectively.

For Fitch, the model with the best zero notch (68.5%) and one notch (93%) classification accuracy is also for individual ratings. However, unlike Moody's the

Table 10.1: Comparison of results from individual and long term rating models for Moody's and Fitch

	Variable	Moody's Long term ratings	BFSR	BFSR with Moody's LTR	Fitch Long term ratings	Fitch Individual ratings	Fitch Invid with Fitch LTR
LTR	Long term rating			<.0001			<.0001
R5	Return on equity: Net income/Shareholder's funds				0.0003	<.0001	
R10	Return on assets: Net income/Total assets				<.0001	<.0001	0.0014
R30	Tax expense/Total assets		0.0002		<.0001	0.0009	0.011
R70	Interest expense/Total assets	<.0001	0.0162	0.0043	<.0001		
R100	Efficiency ratio: Non-int expense/Total revenue	<.0001	<.0001			<.0001	
R110	Interest expense/Interest bearning liabilities						
R120	Shareholder's funds/interest bearning liabilities						
R125	Net interest income/Total revenue	0.0356			<.0001		
R130	Non-interest income/Total revenue		0.0202	0.0042	<.0001		0.0017
R150	Loan loss provisions/Total revenue	<.0001					
R160	Net income/Total revenue	0.0003		<.0001			
R180	Shareholders' funds/Total liabilites						
R185	Loans (net)/Total assets					<.0001	
R195	Total deposits/Total liabilities	<.0001	0.0034				
R215	Loan loss reserves/Loans (gross)	<.0001	<.0001	0.0037		0.001	0.0131
R290	Total revenue						0.0013
R295	Net interest income	<.0001					
R300	Operating profit after loan loss provisions				<.0001		
R310	Loan loss provisions		0.0011		0.015		
R320	Net income		0.0001	<.0001		0.0002	<.0001
R325	Loans						<.0001
R330	Total assets						
R335	Earning assets				<.0001		
R350	Shareholder's funds		0.0001				
R355	Common equity	<.0001	<.0001	<.0001	0.0267	0.0001	0.002
	No of observations						
	Training sample	1457	1457	1457	1054	1054	1054
	Holdout sample	735	735	735	546	546	546
	Significance of the model						
	Chi-square wald/p-value	246.3538/<.0001	213.1892\<.0001	486.1404\<.0001	261.2113\<.0001	143.9179\<.0001	324.1501\<.0001
	Score/p-value	226.208/<.0001	205.0715\<.0001	509.8578\<.0001	251.183\<.0001	136.9554\<.0001	307.0886\<.0001
	Log Likelihood/p-value	277.9568/<.0001	261.4374\<.0001	731.4019\<.0001	298.2052\<.0001	159.5172\<.0001	398.5447\<.0001
	Degrees of freedom	9	10	7	10	8	10
	Classification accuracy (holdout sample)						
	0 notch	47.35	51.56	64.63	42.31	68.5	67.58
	1 notch	88.57	96.05	98.23	90.29	93.04	93.59
	2 notch	99.18	100	100	99.27	99.63	100
	3 notch	100	100	100	100	100	100

model of individual ratings without long term ratings as one of the independent variables performs slightly better than the model including long term ratings. The model for Fitch long term ratings performs poorly with 42.3% classification at zero notch and 90.2% at one notch.

These findings are not consistent with the Moody's models. Whereas the classification accuracy of the Moody's BFSR model improved with the addition of long term ratings, the classification model of Fitch individual ratings is worse when long term ratings are included (although long term ratings are a highly significant input to the model). The classification of Fitch long term ratings is markedly worse than Fitch individual ratings. The Fitch results support the hypothesis that financial ratios can be used to model individual ratings as these are primarily driven by bank-specific factors. Models are less successful in correctly classifying long term ratings because financial ratios are not significant determinants of support ratings which are likely to be determined by macro-economic variables. The chi-square values were highly significant in all models.

Table 10.1 shows the ratios that were selected in the stepwise model building process. There are very few ratios that are common to the long term rating models for Moody's and Fitch. Only interest expense/total assets, net interest income/total assets and common equity are common to both models. For individual rating models there are more similarities. BFSR and Fitch individual rating models have the ratios tax expense/total assets, noninterest expense/total revenue, loan loss reserves/loans, net income and common equity common to both models. The models of individual ratings which include long term ratings as one of the independent variables also share loan loss reserves/loans, net income and common equity with the addition of noninterest income/total revenue. Long term ratings are highly significant for both models which would be expected as the individual rating is a component of the long term rating.

Many banks use external ratings as part of the process of determining internal ratings, either as a reference point or as an input to the model. This study finds that long term ratings can be an effective input when modeling unsupported ratings, even though the long term rating does include a support element.

Table 10.2: Comparison of results from 10 different rating agencies

	Variable	Moody's	S&P	Fitch	DCRS	Captial Intelligence	JRI	JCR	CBRS	Duff & Phels	Thomson Bank Watch
		Live agencies							Dead agencies		
LTR	Long term rating										
R5	Return on equity: Net income/Shareholder's funds		0.0247	<.0001			0.0255				
R10	Return on assets: Net income/Total assets										
R30	Tax expense/Total assets						<.0001			0.002	
R70	Interest expense/Total assets			<.0001						0.0022	<.0001
R100	Efficiency ratio: Non-int expense/Total revenue	<.0001	<.0001				0.0361	<.0001			
R110	Interest expense/Interest bearning liabilities									0.0399	
R120	Shareholder's funds/interest bearning liabilities		0.0048			0.0003					
R125	Net interest income/Total revenue	0.001	<.0001	<.0001			0.03		0.0083		
R130	Non-interest income/Total revenue			<.0001							
R150	Loan loss provisions/Total revenue	0.0003									<.0001
R160	Net income/Total revenue			0.0032							
R180	Shareholders' funds/Total liabilites		0.0006								
R185	Loans (net)/Total assets	<.0001	0.0181	0.0001	0.0102						
R195	Total deposits/Total liabilities	0.017		0.0121				0.0298			0.0003
R215	Loan loss reserves/Loans (gross)	<.0001	<.0001			0.0091					0.0173
R290	Total revenue	0.038				0.0002					
R295	Net interest income										
R300	Operating profit after loan loss provisions	0.0122		0.0133						<.0001	
R310	Loan loss provisions		0.0118	0.0001	0.0072					0.0074	
R320	Net income			0.0358	<.0001						
R325	Loans	<.0001	<.0001								
R330	Total assets		0.0003								
R335	Earning assets	<.0001									<.0001
R350	Shareholder's funds	<.0001	<.0001	<.0001							
R355	Common equity	<.0001	<.0001	<.0001		0.0042					<.0001
	No of observations										
	Training sample	2103	1771	1733	276	268	318	218	69	263	752
	Holdout sample	1062	785	103	147	113	166	125	32	121	349
	Significance of the model										
	Chi-square wald/p-value	305.6266/<.0001	234.6596/<.0001	364.5838/<.0001	22.1562/<.0001	28.693/<.0001	49.4563/<.0001	59.22/<.0001	6.9695/0.0083	51.9325/<.0001	144.3614/<.0001
	Score/p-value	286.384/<.0001	235.7514/<.0001	335.3775/<.0001	32.7733/<.0001	29.8752/<.0001	52.3084/<.0001	66.5925/<.0001	7.5725/0.0059	65.6601/<.0001	136.0815/<.0001
	Log Likelihood/p-value	348.064/<.0001	284.9788/<.0001	432.8481/<.0001	50.6008/<.0001	41.9719/<.0001	60.8315/<.0001	79.3469/<.0001	7.8781/0.005	85.06/<.0001	165.4753/<.0001
	Degrees of freedom	12	12	12	3	4	4	2	1	5	6
	Classification accuracy (holdout sample)										
	0 notch	45.29	45.61	44.39	70.75	52.21	54.22	67.2	65.63	42.15	61.03
	1 notch	88.51	94.14	90.85	93.88	83.19	98.8	100	100	90.08	86.53
	2 notch	99.06	100	99.54	100	100	99 4	100	100	99.17	95.13
	3 notch	100	100	100	100	100	100	100	100	100	100

10.2.2 Comparison of bank bond rating models for different agencies

Table 10.2 shows the results of long term rating models estimated for 10 different rating agencies. The classification accuracy for the holdout samples at the zero notch level ranges from 42.15% for Duff and Phelps to 70.75% for DCRS. The classification accuracy to one notch ranges from 83% for Capital Intelligence to 100% for JCR and CBRS. The Japanese agency, JCR shows a classification accuracy of 67% (zero notch difference) and 100% (one notch). The worst performing models for the live agencies are Moody's, S&P and Fitch. The chi-square results are highly significant for all of the models.

Different independent variables are significant for different agency models. Table 10.2 shows that there are similarities in the variables selected by the stepwise logistic regression for Moody's, S&P and Fitch. The variables common equity, shareholders' funds, loans/total assets and net interest income/total revenue are highly significant for all three agencies. A number of other variables are highly significant (at the 1% level) for two out of three of these agencies; non-interest expense/total revenue, loan loss reserve/loans and loans and significant (at the 5% level); net income/shareholders' funds, total deposits/total liabilities, operating profit after loan loss provisions and loan loss provisions.

There is a high classification accuracy for the holdout sample for DBRS of 70.75%. The logistic regression model generated a relatively simple model for this agency showing the variables loan loss provisions and net income to be highly significant and loans/total assets to be significant.

The Japanese agencies are the only agencies for which only ratios are chosen in the stepwise selection process and none of the absolute values. Japanese agencies generally rate higher than the other agencies in the study so there are many more ratings grouped in the first and second of the four categories of dependent variables.

10.2.3 Comparison of bank bond rating models for different regions

The models for long term ratings of Moody's, S&P and Fitch classified less than half of the holdout sample correctly (on average 45.1% of the holdout sample was correctly classified at the zero notch level). To understand if there are certain

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Table 10.3: Comparison of results for Moody's when rated banks are split into country regions

	Variable	Moody's whole model	Moody's USA	Moody's Europe	Moody's All Asia Pacific	Moody's Japan	Moody's Asia Pacific (excl Japan)	Moody's South America & other
LTR	Long term rating							
R5	Return on equity: Net income/Shareholder's funds			0.0039	<.0001			
R10	Return on assets: Net income/Total assets							
R30	Tax expense/Total assets							
R70	Interest expense/Total assets				0.0006			
R100	Efficiency ratio: Non-int expense/Total revenue	<.0001				<.0001		
R110	Interest expense/Interest bearning liabilities				<.0001		0.0005	
R120	Shareholder's funds/interest bearning liabilities							
R125	Net interest income/Total revenue	0.001		<.0001				
R130	Non-interest income/Total revenue							
R150	Loan loss provisions/Total revenue	0.0003						
R160	Net income/Total revenue							
R180	Shareholders' funds/Total liabilites							
R185	Loans (net)/Total assets	<.0001				<.0001		
R195	Total deposits/Total liabilities	0.017		0.0025				0.0019
R215	Loan loss reserves/Loans (gross)	<.0001	0.003	0.0045	0.0001		<.0001	
R290	Total revenue	0.038		0.0135				<.0001
R295	Net interest income				<.0001	<.0001		
R300	Operating profit after loan loss provisions	0.0122						
R310	Loan loss provisions			<.0001				
R320	Net income			0.0001			0.0032	
R325	Loans	<.0001	<.0001	<.0001				
R330	Total assets							
R335	Earning assets	<.0001						0.0105
R350	Shareholder's funds	<.0001	<.0001				0.0289	0.0001
R355	Common equity	<.0001	0.0029		0.0306	<.0001	0.0014	
	No of observations							
	Training sample	2103	912	687	367	203	164	136
	Holdout sample	1062	455	355	193	114	79	60
	Significance of the model							
	Chi-square wald/p-value	305.6266**	58.7838**	111.5358**	78.1655**	41.5335**	59.7725**	44.5670**
	Score/p-value	286.384**	61.2429**	111.3271**	78.3142**	41.5861**	61.1002**	47.1114**
	Log Likelihood/p-value	348.064**	75.7108**	127.3819**	116.7237**	52.2427**	94.163**	58.4906**
	Degrees of freedom	12	4	8	6	4	5	4
	Classification accuracy (holdout sample)							
	0 notch	45.29	47.25	63.38	39.9	56.14	51.9	51.67
	1 notch	88.51	90.11	96.62	91.19	95.61	82.28	76.67
	2 notch	99.06	99.78	99.72	100	100	98.73	96.67
	3 notch	100	100	100	100	100	100	100

Table 10.4: Comparison of results for S&P when rated banks are split into country regions

	Variable	S&P whole model	S&P USA	S&P Europe	S&P All Asia Pacific	S&P Japan	S&P Asia Pacific (excl Japan)	S&P South America & other
LTR	Long term rating							
R5	Return on equity: Net income/Shareholder's funds	0.0247						
R10	Return on assets: Net income/Total assets							0.006
R30	Tax expense/Total assets		0.0018					0.0054
R70	Interest expense/Total assets							<.0001
R100	Efficiency ratio: Non-int expense/Total revenue	<.0001	0.0063	0.0003		0.0002		
R110	Interest expense/Interest bearning liabilities				<.0001			
R120	Shareholder's funds/interest bearning liabilities	0.0048						
R125	Net interest income/Total revenue	<.0001		<.000	0.0065	0.0206		
R130	Non-interest income/Total revenue							
R150	Loan loss provisions/Total revenue							
R160	Net income/Total revenue				<.0001			
R180	Shareholders' funds/Total liabilites	0.0006						
R185	Loans (net)/Total assets	0.0181						0.0033
R195	Total deposits/Total liabilities					0.0005	0.0006	
R215	Loan loss reserves/Loans (gross)	<.0001	<.0001	0.0005	<.0001		<.0001	
R290	Total revenue							
R295	Net interest income				0.0354			
R300	Operating profit after loan loss provisions							
R310	Loan loss provisions	0.0118		0.0144		0.0104		
R320	Net income		0.0015				<.0001	
R325	Loans	<.0001	<.0001			0.0001		
R330	Total assets	0.0003						
R335	Earning assets		0.005					
R350	Shareholder's funds	<.0001	<.0001	<.0001				
R355	Common equity	<.0001	<.0001				<.0001	
	No of observations							
	Training sample	1771	565	546	235	92	143	91
	Holdout sample	785	294	265	100	45	55	41
	Significance of the model							
	Chi-square wald/p-value	234.6596**	83.901**	100.092**	68.5765**	18.5832**	50.2674**	29.0087**
	Score/p-value	235.7514**	99.7404**	104.7145**	69.7216**	27.8524**	54.6279**	31.9208**
	Log Likelihood/p-value	284.9788**	128.1411**	113.6113**	95.0207**	42.5315**	94.9045**	42.0035**
	Degrees of freedom	12	8	5	5	5	4	4
	Classification accuracy (holdout sample)							
	0 notch	45.61	50.34	56.23	43.00	64.71	44.12	39.02
	1 notch	94.14	97.96	97.36	94.00	100	85.29	56.1
	2 notch	100	100	100	99.00	100	98.53	70.73
	3 notch	100	100	100	100.00	100	100	100

Table 10.3: Comparison of results for Fitch when rated banks are split into country regions

	Variable	Fitch whole model	Fitch USA	Fitch Europe	Fitch All Asia Pacific	Fitch Japan	Fitch Asia Pacific (excl Japan)	Fitch South America & other
LTR	Long term rating							
R5	Return on equity: Net income/Shareholder's funds	<.0001					0.0063	
R10	Return on assets: Net income/Total assets				<.0001			
R30	Tax expense/Total assets							
R70	Interest expense/Total assets	<.0001			0.0006	0.0003		
R100	Efficiency ratio: Non-int expense/Total revenue		0.0164					
R110	Interest expense/Interest bearning liabilities				<.0001			0.0001
R120	Shareholder's funds/interest bearning liabilities							
R125	Net interest income/Total revenue	<.0001	<.0001	<.0001				<.0001
R130	Non-interest income/Total revenue	<.0001		<.0001				0.0004
R150	Loan loss provisions/Total revenue			0.0006		0.0043		
R160	Net income/Total revenue	0.0032					0.0045	
R180	Shareholders' funds/Total liabilites				0.0014			
R185	Loans (net)/Total assets	0.0001						
R195	Total deposits/Total liabilities	0.0121					<.0001	
R215	Loan loss reserves/Loans (gross)			<.0001	0.0007		0.0002	
R290	Total revenue			<.0001				
R295	Net interest income							0.0056
R300	Operating profit after loan loss provisions	0.0133						
R310	Loan loss provisions	0.0001					0.0477	
R320	Net income	0.0358		0.0007			0.0062	
R325	Loans				<.0001			
R330	Total assets							
R335	Earning assets							
R350	Shareholder's funds	<.0001	<.0001					
R355	Common equity	<.0001						
	No of observations							
	Training sample	1733	875	573	169	82	87	116
	Holdout sample	103	398	306	104	54	50	66
	Significance of the model							
	Chi-square wald/p-value	364.5838**	60.6013**	132.6301**	50.7956**	16.7114**	38.6432**	21.9805**
	Score/p-value	335.3775**	57.4861**	141.0825**	47.0542**	18.8074**	49.4762**	28.8751**
	Log Likelihood/p-value	432.8481**	62.0137**	163.5736**	70.7379**	20.4256**	81.8622**	31.1825**
	Degrees of freedom	12	3	6	6	2	6	4
	Classification accuracy (holdout sample)							
	0 notch	44.39	40.7	64.71	52.88	62.96	48.0	62.12
	1 notch	90.85	93.22	95.42	91.35	96.3	88.0	83.33
	2 notch	99.54	100	99.67	99.04	98.15	96.0	89.39
	3 notch	100	100	100	100	100	100.0	100

regions for which bank bond rating models perform better than others the sample was split into 5 regions; North America, Europe, Asia Pacific (excluding Japan), Japan and South America and other (the constituent countries are shown in Appendix 3).

Tables 10.3 to 10.5 show that for all three rating agencies the model for the USA is one of the most poorly performing models (in terms of correct classification of the holdout sample). The data for the USA is further analysed in the sections below to try explain this result. For all agencies, Europe is either the best or second best performing model. Tables 10.3 to 10.5 show consistently high levels of correct classification at zero and one notch levels for European models. Correct zero notch classification accuracy for Moody's, S&P and Fitch respectively in Europe where 63%, 56% and 65% respectively which compares favourably with the 41.5% average for the USA.

Models for the Asia Pacific region have been estimated both including and excluding Japan. The results for the whole of Asia Pacific show poor results, especially for Moody's and S&P samples. When the sample is split between Japan and other Asia Pacific banks the classification accuracy increases substantially for Japan and increases in some cases for the rest of the region. This suggests that the characteristics and accounting practices of Japanese banks are different to other banks in the Asia Pacific region and should be modelled separately. The conflicting results for Asia Pacific excluding Japan may be due to the mix of different countries with varying accounting and banking practices included in the sample (see Appendix 3 for constituent countries).

The most interesting finding from this breakdown of the sample by region is that individual country models appear to outperform the model estimated from the whole sample. For S&P each of the regional models gives a higher classification accuracy than the full model, for Fitch this is true with the exception of the USA and for S&P with the exception of Asia Pacific. This result suggests that banks should be modelling internal credit ratings on a country basis rather than using a global model.

For some regions there are certain ratios or variables that are used in the regional model estimated for all three agencies. The models for Japan show a high level of consensus but the agencies do not appear to use the same inputs to determine the ratings. None of the ratios selected by the stepwise process for the models for South America and other regions agree. This could be due to small sample sizes or disparate countries included in this data.

A summary of different variables selected by the stepwise process of different models is shown in table 10.6.

Table 10.6 : Ratios and variables used in regional models estimated for all three US agencies

	Used in all 3 regional models for Moody's, S&P & Fitch	Used in 2 out of 3 of the models
USA	Shareholder's funds	Noninterest expense/total revenue Loan loss reserves/loans Log loans Common equity
Europe	Net interest income/total revenue Loan loss reserves/loans	Log revenue Net income Loan loss provisions
All Asia Pacific	Interest expenses/interest bearing liabilities Loan loss reserves/loans	Interest expenses/total assets
Japan	No variables	Noninterest expense/total revenue
Asia Pacific (excl Japan)	Loan loss reserves/loans Net income	Total deposits/total liabilities Shareholder's funds
Other	No variables	No variables

10.2.4 Comparison of bank bond rating models for banks of different size and type

The estimation of bank rating models by region raises the question as to why the models for the USA are performing relatively poorly. To try to answer this question the USA data samples were broken down by size of bank (using total assets as a proxy for size) and by type of bank. Fitch Ratings provided the USA bank accounting data in a number of different templates such as holding companies, subsidiaries, investment banks and thrifts so it was possible to split the USA sample of banks into different types.

10.2.4.1 Comparison by size

The data sample was split into three sections; total assets of less than £4bn, total assets of greater than £4bn and less than £35bn and total assets of greater than £35bn.

Tables 10.7 to 10.9 show the results of these models for the three major agencies. The classification accuracy of the models for all agencies declines with bank size. For the largest banks, classification of the holdout sample at the zero notch level is higher than the whole USA sample (by 25%, 10.5% and 16% for Moody's, S&P and Fitch respectively) but for the smallest banks the classification accuracy is lower than the whole sample (by 10%, 8% and 2% respectively).

An analysis of the different variables selected by the stepwise process of each of the models gives some interesting results. The ratings of large banks appear to be determined by the proportion of total liabilities to total deposits, the absolute value of operating profit after loan loss provisions and the value of loans. Total liabilities to total deposits and the absolute value of operating profit after loan loss provisions are variables not selected by any of the other models in this comparison.

In the estimation of medium sized bank ratings the items non-interest expense to total revenue and loans appear most frequently. For small banks the predominant variable is total assets. This is selected by all three models for small banks and is the only variable in the models for Moody's and Fitch.

Table 10.7: Comparison of results for Moody's when rated banks are split into size bandings based on total assets

	Variable	Moody's	Moody's USA	USA banks rating by Moody's with TA > £35bn	USA banks rating by Moody's with TA > £4bn <£35bn	USA banks rating by Moody's with TA < £4bn
LTR	Long term rating					
R5	Return on equity: Net income/Shareholder's funds					
R10	Return on assets: Net income/Total assets					
R30	Tax expense/Total assets					
R70	Interest expense/Total assets				0.0155	
R100	Efficiency ratio: Non-int expense/Total revenue	<.0001				
R110	Interest expense/Interest bearning liabilities					
R120	Shareholder's funds/interest bearning liabilities					
R125	Net interest income/Total revenue	0.001				
R130	Non-interest income/Total revenue					
R150	Loan loss provisions/Total revenue	0.0003				
R160	Net income/Total revenue					
R180	Shareholders' funds/Total liabilites					
R185	Loans (net)/Total assets	<.0001				
R195	Total deposits/Total liabilities	0.017		0.0495	0.0087	
R215	Loan loss reserves/Loans (gross)	<.0001	0.003			
R290	Total revenue	0.038				
R295	Net interest income					
R300	Operating profit after loan loss provisions	0.0122		0.0026		
R310	Loan loss provisions				0.0239	
R320	Net income			0.0237		
R325	Loans	<.0001	<.0001	0.0001	0.035	
R330	Total assets					0.0137
R335	Earning assets	<.0001				
R350	Shareholder's funds	<.0001	<.0001			
R355	Common equity	<.0001	0.0029			
	No of observations					
	Training sample	2103	912	135	453	324
	Holdout sample	1062	455	76	223	156
	Significance of the model					
	Chi-square wald/p-value	305.6266**	58.7838**	29.2796**	31.0776**	6.0784*
	Score/p-value	286.384**	61.2429**	36.3514**	28.7255**	6.2378*
	Log Likelihood/p-value	348.064**	75.7108**	46.3097**	33.9422**	6.293*
	Degrees of freedom	12	4	4	4	1
	Classification accuracy (holdout sample)					
	0 notch	45.29	47.25	59.21	47.53	42.31
	1 notch	88.51	90.11	94.74	90.13	86.54
	2 notch	99.06	99.78	100	99.1	100
	3 notch	100	100	100	100	100

Table 10.8: Comparison of results for S&P when rated banks are split into size bandings based on total assets

	Variable	S&P	S&P USA	USA banks rating by S&P with TA > £35bn	USA banks rating by S&P with TA > £4bn <£35bn	USA banks rating by S&P with TA < £4bn
LTR	Long term rating					
R5	Return on equity: Net income/Shareholder's funds	0.0247				
R10	Return on assets: Net income/Total assets					
R30	Tax expense/Total assets		0.0018			
R70	Interest expense/Total assets					
R100	Efficiency ratio: Non-int expense/Total revenue	<.0001	0.0063		0.0003	
R110	Interest expense/Interest bearning liabilities					0.0348
R120	Shareholder's funds/interest bearning liabilities	0.0048				
R125	Net interest income/Total revenue	<.0001				
R130	Non-interest income/Total revenue					
R150	Loan loss provisions/Total revenue			0.0002		
R160	Net income/Total revenue					
R180	Shareholders' funds/Total liabilites	0.0006				
R185	Loans (net)/Total assets	0.0181				
R195	Total deposits/Total liabilities			0.0303		
R215	Loan loss reserves/Loans (gross)	<.0001	<.0001			
R290	Total revenue					
R295	Net interest income					
R300	Operating profit after loan loss provisions			<.0001		
R310	Loan loss provisions	0.0118				
R320	Net income		0.0015			
R325	Loans	<.0001	<.0001	0.0208	<.0001	0.0003
R330	Total assets	0.0003		0.0001		0.0011
R335	Earning assets		0.005	0.0014		
R350	Shareholder's funds	<.0001	<.0001			
R355	Common equity	<.0001	<.0001	0.0119		0.0013
	No of observations					
	Training sample	1771	565	278	457	131
	Holdout sample	785	294	142	202	69
	Significance of the model					
	Chi-square wald/p-value	234.6596**	83.901**	41.8693**	41.8693**	24.961**
	Score/p-value	235.7514**	99.7404**	40.0241**	40.0241**	31.2437**
	Log Likelihood/p-value	284.9788**	128.1411**	50.5641**	50.5641**	36.8732**
	Degrees of freedom	12	8	2	2	4
	Classification accuracy (holdout sample)					
	0 notch	45.61	50.34	55.63	48.02	46.38
	1 notch	94.14	97.96	96.48	97.03	98.55
	2 notch	100	100	100	100	100
	3 notch	100	100	100	100	100

Table 10.9: Comparison of reasons for Fitch when rated banks are split into size bandings based on total assets

	Variable	Fitch	Fitch USA	Fitch banks rating by S&P with TA > £35bn	Fitch banks rating by S&P with TA > £4bn <£35bn	Fitch banks rating by S&P with TA < £4bn
LTR	Long term rating					
R5	Return on equity: Net income/Shareholder's funds	<.0001				
R10	Return on assets: Net income/Total assets					
R30	Tax expense/Total assets					
R70	Interest expense/Total assets	<.0001				
R100	Efficiency ratio: Non-int expense/Total revenue		0.0164		0.0296	
R110	Interest expense/Interest bearning liabilities			0.0006		
R120	Shareholder's funds/interest bearning liabilities					
R125	Net interest income/Total revenue	<.0001	<.0001		<.0001	
R130	Non-interest income/Total revenue	<.0001				
R150	Loan loss provisions/Total revenue					
R160	Net income/Total revenue	0.0032				
R180	Shareholders' funds/Total liabilites					
R185	Loans (net)/Total assets	0.0001		0.0037		
R195	Total deposits/Total liabilities	0.0121		0.0008		
R215	Loan loss reserves/Loans (gross)					
R290	Total revenue					
R295	Net interest income					
R300	Operating profit after loan loss provisions	0.0133				
R310	Loan loss provisions	0.0001				
R320	Net income	0.0358				
R325	Loans					
R330	Total assets					0.0025
R335	Earning assets				0.0002	
R350	Shareholder's funds	<.0001	<.0001			
R355	Common equity	<.0001			0.0096	
	No of observations					
	Training sample	1733	875	131	427	317
	Holdout sample	103	398	70	183	145
	Significance of the model					
	Chi-square wald/p-value	364.5838**	60.6013**	17.6893**	36.3193**	9.1772**
	Score/p-value	335.3775**	57.4861**	18.7017**	36.3925**	8.7866**
	Log Likelihood/p-value	432.8481**	62.0137**	19.1837**	38.2468**	9.2373**
	Degrees of freedom	12	3			
	Classification accuracy (holdout sample)					
	0 notch	44.39	40.7	47.14	45.36	40.0
	1 notch	90.85	93.22	92.86	91.8	85.5
	2 notch	99.54	100	95.71	98.91	100.0
	3 notch	100	100	100	100	100.0

10.2.4.2 Comparison by type

The sample was split into three different categories of banks; holding companies and investment banks, subsidiaries and thrifts. Tables 10.10 to 10.12 show the results of comparison by type for the three major agencies. A consistent pattern also emerges from this comparison. The classification accuracy at zero notch for thrifts is higher than the other two categories for all three agencies. The improvements in classification accuracy of the thrift model over the whole USA model for each agency was 12%, 21% and 25% for Moody's, S&P and Fitch respectively. However the results for differences one notch apart are not as good as the holding company and subsidiary models for Moody's and Fitch. There is an improvement in classification accuracy for holding companies and investment banks for Moody's (4.5%) and Fitch (6%) over the whole model but not for S&P. Classification accuracy at one notch is better for all models. In all cases the worst result is for the subsidiary model.

There is far less consensus between the variables selected for the comparison by type than by size. Shareholder's funds are selected by two models for the holding companies and investment banks, non-interest expenses over total revenue and shareholders' funds are a significant determinant for the subsidiary models and loans are significant for the thrift models.

Table 10.10: Comparison of results for Moody's when rated banks are split by type

	Variable	Moody's	Moody's USA	USA banks rated by Moody's - Holding companies & investment banks	USA banks rated by Moody's - subsidiaries	USA banks rated by Moody's - Thrifts
LTR	Long term rating					
R5	Return on equity: Net income/Shareholder's funds					
R10	Return on assets: Net income/Total assets				<.0001	
R30	Tax expense/Total assets				0.0009	
R70	Interest expense/Total assets					
R100	Efficiency ratio: Non-int expense/Total revenue	<.0001				
R110	Interest expense/Interest bearning liabilities					
R120	Shareholder's funds/interest bearning liabilities					
R125	Net interest income/Total revenue	0.001				0.0227
R130	Non-interest income/Total revenue					
R150	Loan loss provisions/Total revenue	0.0003			0.0006	
R160	Net income/Total revenue				<.0001	0.0198
R180	Shareholders' funds/Total liabilites					
R185	Loans (net)/Total assets	<.0001				
R195	Total deposits/Total liabilities	0.017				0.0001
R215	Loan loss reserves/Loans (gross)	<.0001	0.003			
R290	Total revenue	0.038				
R295	Net interest income					
R300	Operating profit after loan loss provisions	0.0122			0.0058	
R310	Loan loss provisions				0.0485	
R320	Net income					
R325	Loans	<.0001	<.0001			<.0001
R330	Total assets					
R335	Earning assets	<.0001			0.0002	
R350	Shareholder's funds	<.0001	<.0001	0.0001	0.0079	
R355	Common equity	<.0001	0.0029			
	No of observations					
	Training sample	2103	912	541	429	157
	Holdout sample	1062	455	166	240	49
	Significance of the model					
	Chi-square wald/p-value	305.6266/<.0001	58.7838**	65.567**	14.8382**	50.0871**
	Score/p-value	286.384/<.0001	61.2429**	55.2533**	16.0751**	47.0088**
	Log Likelihood/p-value	348.064/<.0001	75.7108**	86.1994**	18.6182**	65.369**
	Degrees of freedom	12	4	8	1	4
	Classification accuracy (holdout sample)					
	0 notch	45.29	47.25	49.4	44.58	53.06
	1 notch	88.51	90.11	92.17	92.5	89.8
	2 notch	99.06	99.78	99.4	100	97.96
	3 notch	100	100	100	100	100

Table 10.11: Comparison of results for S&P when rated banks are split by type

	Variable	S&P	S&P USA	USA banks rated by S&P - Holding companies & investment banks	USA banks rated by S&P - subsidiaries	USA banks rated by S&P - Thrifts
LTR	Long term rating					
R5	Return on equity: Net income/Shareholder's funds	0.0247				
R10	Return on assets: Net income/Total assets					
R30	Tax expense/Total assets		0.0018			
R70	Interest expense/Total assets					
R100	Efficiency ratio: Non-int expense/Total revenue	<.0001	0.0063		<.0001	0.0025
R110	Interest expense/Interest bearning liabilities					
R120	Shareholder's funds/interest bearning liabilities	0.0048				
R125	Net interest income/Total revenue	<.0001				
R130	Non-interest income/Total revenue				<.0001	
R150	Loan loss provisions/Total revenue					
R160	Net income/Total revenue					
R180	Shareholders' funds/Total liabilites	0.0006				
R185	Loans (net)/Total assets	0.0181			0.0474	
R195	Total deposits/Total liabilities					
R215	Loan loss reserves/Loans (gross)	<.0001	<.0001	0.0269	0.0011	
R290	Total revenue					
R295	Net interest income					
R300	Operating profit after loan loss provisions					
R310	Loan loss provisions	0.0118				
R320	Net income		0.0015			
R325	Loans	<.0001	<.0001	0.0037		0.001
R330	Total assets	0.0003				
R335	Earning assets		0.005			
R350	Shareholder's funds	<.0001	<.0001	<.0001		
R355	Common equity	<.0001	<.0001		0.0059	
	No of observations					
	Training sample	1771	565	346	417	91
	Holdout sample	785	294	142	190	56
	Significance of the model					
	Chi-square wald/p-value	234.6596**	83.901**	36.7699**	54.2475**	37.4802**
	Score/p-value	235.7514**	99.7404**	37.7414**	42.9245**	41.4958**
	Log Likelihood/p-value	284.9788**	128.1411**	40.6468**	57.5536**	58.5203**
	Degrees of freedom	12	8	3	5	2
	Classification accuracy (holdout sample)					
	0 notch	45.61	50.34	47.18	42.63	60.71
	1 notch	94.14	97.96	91.55	85.26	96.43
	2 notch	100	100	100	99.47	100
	3 notch	100	100	100	100	100

Table 10.12: Comparison of results for Fitch when rated banks are split by type

	Variable	Fitch	Fitch USA	USA banks rated by Fitch - Holding companies & Investment banks	USA banks rated by Fitch - Subsidiaries	USA banks rated by Fitch - Thrifts
LTR	Long term rating					
R5	Return on equity: Net income/Shareholder's funds	<.0001				
R10	Return on assets: Net income/Total assets					
R30	Tax expense/Total assets					
R70	Interest expense/Total assets	<.0001				
R100	Efficiency ratio: Non-int expense/Total revenue		0.0164		0.0057	
R110	Interest expense/Interest bearning liabilities					
R120	Shareholder's funds/interest bearning liabilities					0.0002
R125	Net interest income/Total revenue	<.0001	<.0001		<.0001	
R130	Non-interest income/Total revenue	<.0001				
R150	Loan loss provisions/Total revenue					
R160	Net income/Total revenue	0.0032				
R180	Shareholders' funds/Total liabilites					
R185	Loans (net)/Total assets	0.0001				
R195	Total deposits/Total liabilities	0.0121				
R215	Loan loss reserves/Loans (gross)					
R290	Total revenue			<.0001		
R295	Net interest income					
R300	Operating profit after loan loss provisions	0.0133				
R310	Loan loss provisions	0.0001				
R320	Net income	0.0358				
R325	Loans					
R330	Total assets					
R335	Earning assets					
R350	Shareholder's funds	<.0001	<.0001		<.0001	
R355	Common equity	<.0001				
	No of observations					
	Training sample	1733	875	360	411	76
	Holdout sample	103	398	165	198	41
	Significance of the model					
	Chi-square wald/p-value	364.5838**	60.6013**	30.4197**	44.8783**	14.1384**
	Score/p-value	335.3775**	57.4861**	27.6403**	42.7628**	14.0529**
	Log Likelihood/p-value	432.8481**	62.0137**	30.2094**	48.2734**	15.7352**
	Degrees of freedom	12	3	1	3	1
	Classification accuracy (holdout sample)					
	0 notch	44.39	40.7	43.03	38.89	53.66
	1 notch	90.85	93.22	93.33	93.94	90.24
	2 notch	99.54	100	100	100	100
	3 notch	100	100	100	100	100

10.3 Summary

Using logistic regression analysis, this study has compared the results of 52 different models of worldwide individual bank ratings and long term bank ratings for 10 different rating agencies. It finds that models can estimate two thirds of the ratings of the holdout sample correctly for individual ratings and for two regions, Japan and Europe.

The first set of models estimate bond ratings for Moody's long term ratings, Moody's BFSR and BFSR using financial ratios and Moody's long term ratings. The same comparison is made for Fitch ratings; Fitch long term ratings, Fitch individual ratings and Fitch Individual ratings estimated using financial ratios and Fitch long term ratings. The results of the models comparing Fitch individual and Fitch long term ratings show that the individual ratings can be modelled effectively using financial ratios while classification accuracy of long term ratings is not as good. Different results were observed for Moody's. The best model was for BFSRs modeled using financial ratios and Moody's long term ratings suggesting that Moody's BFSRs are not providing the same information as Fitch Individual ratings and are assessed in a different way.

Table 10.2 compared results from 10 different rating agencies, 7 live and 3 dead agencies. Analysis of models for each of the 10 different agencies used in this study shows that financial variables are most effective at predicting the ratings of Canadian and Japanese rating agencies. Prediction of the long term bank ratings of the three major USA agencies, Moody's, S&P and Fitch, does not yield high classification accuracies at the zero notch level.

Tables 10.3 to 10.5 compare the results for Moody's, S&P and Fitch when the rated banks are split into country regions. Regions for which bank ratings can be most accurately predicted are Europe and Japan. The overall classification accuracy of the models increases when country regions are split up rather than when the data samples are considered on a worldwide basis. This suggests that banks using rating models as part of their internal credit rating process should split rating models by country or region where possible.

To try to understand the relatively poor performance of the USA rating models the data was split by size and type of bank. Tables 10.7 to 10.9 show results for Moody's, S&P

and Fitch when the banks are split into size bandings based on the banks' total assets. The final set of tables, 10.10 to 10.12, compare the results for Moody's, S&P and Fitch when the banks are split between bank holding companies, subsidiaries and thrifts.

Classification accuracy for all agencies declines with bank size and at zero notch is higher by approximately 7% on average for larger banks, thrifts and bank holding companies than for models based on the whole USA region. However classification accuracy for USA banks is still lower than for other regions. This may arise because the support element has greater significance to the long term ratings in the USA than in other regions or that USA based agencies have greater access to more detailed financial, non-financial and qualitative information for US banks than for non-US banks.

Conclusion

This thesis has focused on split credit ratings and the prediction of bank credit ratings. The first three chapters of the thesis cover the background to the credit rating industry, Basel II and the literature directly relating to this study. In the area of split credit ratings previous research has established that the ratings of Moody's and S&P are similar and that the Japanese agencies are consistently more generous than those from other parts of the world. There is more disagreement between agencies over low quality issuers. In addition, all agencies appear to be more generous towards issuers from their home country and the level of consensus is higher between agencies from the same country.

Chapters six to nine present results from studies into many aspects of split ratings. This thesis confirms the finding that Moody's and S&P have very similar credit ratings and that the widest difference between any credit rating agencies exists between the US agencies, especially Moody's and S&P and the Japanese agencies, R&I and JCR. A ranking of agencies, which has been proved using significant tests, is shown to exist between agencies. It was unclear from previous research whether this ranking arises because the scales of all the agencies are skewed in one direction or the other across all rating bands or whether differences arose at different cut off points between grades. This study shows that the two Japanese agency rating scales are skewed higher than all other agencies across the whole scale. For all other agencies there appear to be differences at certain cut-off points but not consistently across the rating scale.

A study looking at the industry and geographic characteristics of the agencies showed that consensus varies between different industries and regions. Three groups with statistically significant differences in mean levels of split ratings appear from this research. (1) Sovereigns, (2) Finance/Insurance/Banking/Energy/Utilities/Leisure and (3) Manufacturing/ Consumer goods/Transport/Healthcare/Technology/Forestry and Building. The lowest level of consensus between agencies arises for group 3, the manufacturing group. This is contrary to the findings of previous research which show banks to have the lowest level of consensus. The level of consensus within an industry group appears to be influenced by the average credit quality of that group, the lower the credit quality the lower the level of consensus.

Five significantly different regional groups are also identified, UK and Europe, USA and Canada, Far East, Japan and South America and the Middle East. UK and Europe have the highest level of consensus and the Middle East and South America have the lowest. As above, the level of consensus is influenced by the average credit quality of the region.

The final chapter of the split rating studies considers the implications of split ratings on the Standardised approach for Basel II. Comparison of split ratings shows that there are significant differences at the 1% level between the mean differences between rating agencies. To assess the impact on Basel II risk assessments, issuers rated by two agencies were compared and the credit rating assigned by each was mapped to Basel II risk weights as prescribed. The average risk weight that would have been assigned by each agency was then compared. Although most of the differences between agencies were in the expected direction, only the differences between the Japanese agencies and Moody's, S&P and Fitch were statistically significant. The conclusion was that the level of split ratings between the Japanese agencies and Moody's, S&P and Fitch could have a significant impact on Basel II risk assessments if supervisors do not alter the mapping of those agencies ratings to the Basel II risk weights.

Although there is extensive research into the area of prediction of credit ratings, most of these studies focus on corporate bonds or issuers rather than banks. There are only a handful of studies modelling the credit ratings of banks. This study used credit rating data and financial ratios and variables to model individual bank ratings as well as long term ratings. The model which accurately predicted the highest level of credit ratings was that estimated and tested on samples of Fitch Individual Ratings. Hypothetically, it should be possible to model individual ratings of Fitch and Moody's more accurately from financial data than the long term ratings. This is because individual ratings do not include a support element. The support element reflects the likelihood of financial support from a government in the event that the bank runs into serious financial trouble and it would be more appropriate to model this element from economic data rather than bank specific financial ratios. As expected, the model for Fitch long term ratings shows a lower prediction accuracy of the holdout sample than the model for Fitch individual ratings.

The model using Fitch ratings data clearly showed that a model using solely financial data has a higher prediction accuracy for individual ratings than for long term ratings. Interestingly the Moody's ratings did not show the same result. The model of Moody's BFSRs successfully predicted only 4% more ratings than the Moody's model for long term ratings. The prediction accuracy was approximately 50%. The accuracy for the Moody's model was improved significantly when the long term ratings were included as one of the independent variables. The exact reason for this result is unclear but it can be concluded that Moody's BFSRs are not providing the same information as Fitch Individual ratings and that they are assigned in a different way. The implication for banks modelling bank ratings for internal purposes is that the long term rating could be used as one of the inputs to the model to improve the accuracy of estimates of individual bank ratings.

The rest of the models estimated in chapter ten all related to long term ratings. Despite the drawbacks of trying to model a rating which includes a support element, some of the models did have a high prediction accuracy when tested with the holdout sample. For example the models for Canadian agencies and one of the Japanese agencies successfully predicted two thirds, or more, of the holdout sample correctly. Models for European and Japanese banks also showed a higher classification accuracy than other models. The overall classification accuracy of the model increases when country regions are split up rather than when the data samples are considered on a worldwide basis. This suggests that banks using rating models as part of their internal credit rating process should split rating models by country or region where possible.

The US bank rating models performed poorly. To try to explain this finding the data sample was split by size and type of bank. Classification accuracy for all agencies declines with bank size and the accuracy is higher by approximately 7% on average for larger banks, thrifts and bank holding companies than for models based on the whole USA region. However classification for USA banks is still lower than for other regions. This may arise because the support element has greater significance to the long term ratings in the USA than in other regions or that the USA based agencies have greater access to detailed financial, non-financial and qualitative information for US banks than for non-US banks. The studies into split ratings found evidence of home country bias for all agencies, this factor could also be influencing the ratings of US banks.

This thesis opens new areas for future research. A comparison of split ratings by cumulative default probability would be an interesting addition to the studies based on ratings scales. The default probability would be expected to take account of the difference in rating scales so, when compared over a period of several years, it would be expected to smooth out the split ratings between agencies.

The study comparing the difference between individual ratings and long term ratings would be greatly enhanced by modelling the bank support ratings. These are likely to be determined by country and macroeconomic factors, this data was not available for this thesis. If support ratings can be successfully modelled, a long term bank rating model made up from a combination of financial variables and relevant macroeconomic data could yield higher classification accuracy than achieved in this study.

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Rating definitions

Canadian Bond Rating Service - Long term credit rating scale

Highest Quality: A++

This category encompasses bonds of outstanding quality. They possess the highest degree of protection of principal and interest. Companies with debt rated A++ are generally large national and/ or multinational corporations whose products or services are essential to the Canadian economy.

These companies are the acknowledged leaders in their respective industries and have clearly demonstrated their ability to best withstand adverse economic or trade conditions either national or international in scope.

Characteristically, these companies have had a long and creditable history of superior debt protection, in which the quality of their assets and earning has been constantly maintained or improved, with strong evidence that this will continue.

Very Good Quality: A +

Bonds rated A + are similar in characteristics to those rated A ++ and can also be considered superior in quality. These companies have demonstrated a long and satisfactory history of growth with above average protection of principal and interest on their debt securities.

These bonds are generally rated lower in quality because the margin of assets or earnings protection may not be as large or as stable as those rated A++. In both these categories the nature and quality of the asset and earning coverages are more important than the numerical values of the ratios.

Canadian Bond Rating Service - Long term credit rating scale

Good Quality: A

Bonds rated A are considered to be good quality securities and to have favourable long-term investment characteristics. The main feature that distinguishes them from the higher rated securities is that these companies are more susceptible to adverse trade or economic conditions. Consequently the protection is lower than for the categories A++ and A+.

In all cases the A rated companies have maintained a history of adequate asset and earnings protection. There may be certain elements that may impair this protection sometime in the future. Confidence that the current overall financial position will be maintained or improved is slightly lower than for the securities rated above.

Medium Quality: B++

Issues rated B++ are classified as medium or average grade credits and are considered to be investment grade. These companies are generally more susceptible than any of the higher rated companies to swings in economic or trade conditions that would cause a deterioration in protection should the company enter a period of poor operating conditions.

There may be factors present either from within or without the company that may adversely affect the long-term level of protection of the debt. These companies bear closer scrutiny but, in all cases, both interest and principal are adequately protected at the present time.

Canadian Bond Rating Service - Long term credit rating scale

Lower Medium Quality: B+

Bonds which are rated B+ are considered to be lower medium grade securities and have limited long- term protective investment characteristics. Assets and earnings coverage may be modest or unstable.

A significant deterioration in interest and principal protection may occur during periods of adverse economic or trade conditions. During periods of normal or improving economic conditions, assets and earnings protection are adequate. However, the company's ability to continually improve its financial position and level of debt protection is at present limited.

Poor Quality: B

Securities rated B lack most qualities necessary for long-term fixed income investment. Companies in this category have a general history of volatile operating conditions, and the assurance has been in doubt that principal and interest protection will be maintained at an adequate level. Current coverages may be below industry standards and there is little assurance that debt protection will improve significantly.

Speculative Quality: C

Securities in this category are clearly speculative. The companies are generally junior in many respects and there is little assurance that the adequate coverage of principal and interest can be maintained uninterrupted over a period of time.

Default: D

Bonds in this category are in default of some provisions in their trust deed and the companies mayor may not be in the process of liquidation.

Intermediate Categories

(High) and (Low) designations after a rating indicate an issuer' s relative strength within a rating category.

Capital Intelligence – Long term credit rating scale

AAA

The highest credit quality. Exceptional capacity for timely fulfillment of financial obligations and most unlikely to be affected by any foreseeable adversity. Extremely strong financial condition and very positive non-financial factors. Very strong and stable operating environment.

AA

Very high credit quality. Very strong capacity for timely fulfilment of financial obligations. Unlikely to have repayment problems over the long term and unquestioned over the short and medium terms. Strong operating environment. Adverse changes in business, economic and financial conditions unlikely to affect the institution significantly.

A

High credit quality. Strong capacity for timely fulfillment of financial obligations. Possesses many favourable credit characteristics, but may be slightly vulnerable to adverse changes in business, economic and financial conditions. However, operating environment is solid.

BBB

Good credit quality. Satisfactory capacity for timely fulfillment of financial obligations. Acceptable credit characteristics, but some vulnerability to adverse changes in business, economic and financial conditions. Medium grade credit characteristics and the lowest investment grade category.

BB

Speculative credit quality. Capacity for timely fulfillment of financial obligations is vulnerable to adverse changes in internal or external circumstances. Financial and/or non financial factors do not provide significant safeguard and the possibility of investment risk may develop. Unstable operating environment.

Capital Intelligence – Long term credit rating scale

B

Significant credit risk. Capacity for timely fulfillment of financial obligations is very vulnerable to adverse changes in internal or external circumstances. Financial and/or non financial factors provide weak protection; high probability for investment risk exists. Weak operating environment.

C

Substantial credit risk is apparent and the likelihood of default is high. Considerable uncertainty as to timely repayment of financial obligations. Credit is of poor standing with financial and/or non financial factors providing little protection.

D

Obligations are currently in default.

Intermediate Categories

Long term ratings from AAA to C may be modified by the addition of a plus '+' or minus '-' sign to indicate that the strength of a particular institution is respectively, slightly greater or less than that of similarly rated peers.

Dominion Bond Rating Service – Long term credit rating scale

AAA

Bonds which are rated 'AAA' are of the highest credit quality. The degree of protection afforded principal and interest is of the highest order. Earnings are relatively stable, the structure of the industry in which the entity operates is very strong, and the outlook for future profitability is extremely favourable. There are few qualifying factors present which would detract from the performance of the entity, and the strength of liquidity and coverage ratios is unquestioned.

AA

Bonds rated 'AA' are of superior credit quality, and protection of interest and principal is considered high. In many cases, they differ from bonds rated' AAA' to a small degree.

A

Bonds rated 'A' are of upper medium grade credit quality. Protection of interest and principal is still substantial, but the degree of strength is less than with 'AA' rated entities. Entities in the 'A' category may be more susceptible to adverse economic conditions and have greater cyclical tendencies.

BBB

Bonds rated 'BBB' are of medium grade credit quality. Protection of interest and principal is considered adequate, but the entity may be more susceptible to economic cycles, or there may be other adversities present which reduce the strength of these bonds.

BB

Bonds rated 'BB' are of lower medium grade credit quality, and are considered mildly speculative. The degree of protection afforded interest and principal is uncertain, particularly during periods of economic recession, and the size of the entity may be relatively small.

Dominion Bond Rating Service – Long term bond rating scale

B

Bonds rated 'B' are of speculative credit quality. Uncertainty exists as to the ability of the entity to pay interest and principal on a continuing basis in the future, especially in periods of economic recession.

CCC

Bonds rated 'CCC' are considered highly speculative and are in danger of default of interest and principal. The degree of adverse elements present is more severe than with bonds rated 'B'.

CC

Bonds rated 'CC' are in default of either interest or principal.

C

'C' is the lowest rating provided on long-term instruments. Bonds rated 'C' differ from bonds rated 'CC' with respect to the relative liquidation values and rank.

Intermediate Categories

(High) and (Low) designations after a rating indicate an issuer' s relative strength within a rating category.

Duff & Phelps Credit Rating Co - Long term credit rating scale

AAA

Highest credit quality. The risk factors are negligible, being only slightly more than for risk-free US Treasury debt.

AA+ / AA / AA-

High credit quality. Protection factors are strong. Risk is modest but may vary slightly from time to time because of economic conditions.

A+ / A / A-

Protection factors are average but adequate. However risk factors are more variable and greater in periods of economic stress.

BBB+/BBB / BBB-

Below-average protection factors but still considered sufficient for prudent investment. Considerable variability in risk during economic cycles.

BB+ / BB / BB-

Below-investment grade but deemed likely to meet obligations when due. Present or prospective financial protection factors fluctuate according to industry conditions or company fortunes. Overall quality may move up or down frequently within this category.

B+ / B / B-

Below-investment grade and possessing risk that obligations will not be met when due. Financial protection factors will fluctuate widely according to economic cycles, industry conditions and/ or company fortunes. Potential exists for frequent changes in quality rating within this category or into a higher or lower quality rating grade.

CCC

Well below investment grade securities. May be in default or have considerable uncertainty as to timely payment of interest, preferred dividends and/ or principal. Protection factors are narrow and risk can be substantial with unfavourable economic/industry conditions, and/ or with unfavourable company developments.

Duff & Phelps Credit Rating Co - Long term credit rating scale

DD / DP

Defaulted debt obligations, issuer failed to meet scheduled principal and/ or interest payments.

Fitch – Long term credit rating scale

AAA

Highest credit quality. 'AAA' ratings denote the lowest expectation of credit risk. They are assigned only in case of exceptionally strong capacity for timely payment of financial commitments. This capacity is highly unlikely to be adversely affected by foreseeable events.

AA

Very high credit quality. 'AA' ratings denote a very low expectation of credit risk. They indicate very strong capacity for timely payment of financial commitments. This capacity is not significantly vulnerable to foreseeable events.

A

High credit quality. 'A' ratings denote a low expectation of credit risk. The capacity for timely payment of financial commitments is considered strong. This capacity may, nevertheless, be more vulnerable to changes in circumstances or in economic conditions than is the case for higher ratings.

BBB

Good credit quality. 'BBB' ratings indicate that there is currently a low expectation of credit risk. The capacity for timely payment of financial commitments is considered adequate, but adverse changes in circumstances and in economic conditions are more likely to impair this capacity. This is the lowest investment-grade category.

BB

Speculative. 'BB' ratings indicate that there is a possibility of credit risk developing, particularly as the result of adverse economic change over time; however, business or financial alternatives may be available to allow financial commitments to be met. Securities rated in this category are not investment grade.

Fitch – Long term credit rating scale

B

Highly speculative. 'B' ratings indicate that significant credit risk is present, but a limited margin of safety remains. Financial commitments are currently being met; however, capacity for continued payment is contingent upon a sustained, favourable business and economic environment.

CCC, CC, C

High default risk. Default is a real possibility. Capacity for meeting financial commitments is solely reliant upon sustained, favourable business or economic developments. A 'CC' rating indicates that default of some kind appears probable. 'C' ratings signal imminent default.

DDD, DD, D

Default. Securities are extremely speculative, and their worth cannot exceed their recovery value in any liquidation or reorganization of the obligor. 'DDD' designates the highest potential for recovery of amounts outstanding on any securities involved. For U.S. corporates, for example, 'DD' indicates expected recovery of 50% - 90% of such outstandings, and 'D' the lowest recovery potential, i.e. below 50%.

Intermediate Categories

'+' (plus) or '-' (minus) may be appended to ratings to denote relative status within major rating categories. Such suffixes are not added to the 'AAA' long –term rating category or to categories below 'CCC'.

Fitch - Individual Ratings scale

Individual Ratings are assigned only to banks. These ratings, which are internationally comparable, attempt to assess how a bank would be viewed if it were entirely independent and could not rely on external support. These ratings are designed to assess a bank's exposure to, appetite for, and management of risk, and thus represent our view on the likelihood that it would run into significant difficulties such that it would require support.

The principal factors we analyze to evaluate the bank and determine these ratings include profitability and balance sheet integrity (including capitalization), franchise, management, operating environment, and prospects. Finally, consistency is an important consideration, as is a bank's size (in terms of equity capital) and diversification (in terms of involvement in a variety of activities in different economic and geographical sectors).

A:

A very strong bank. Characteristics may include outstanding profitability and balance sheet integrity, franchise, management, operating environment or prospects.

B

A strong bank. There are no major concerns regarding the bank. Characteristics may include strong profitability and balance sheet integrity, franchise, management, operating environment or prospects.

C

An adequate bank, which, however, possesses one or more troublesome aspects. There may be some concerns regarding its profitability and balance sheet integrity, franchise, management, operating environment or prospects.

D

A bank, which has weaknesses of internal and/or external origin. There are concerns regarding its profitability and balance sheet integrity, franchise, management, operating environment or prospects. Banks in emerging markets are necessarily faced with a greater number of potential deficiencies of external origin.

Fitch - Individual Ratings scale

E

A bank with very serious problems, which either requires or is likely to require external support.

Intermediate Categories

Gradations may be used among the five ratings: i.e. A/B, B/C, C/D, and D/E.

Japan Credit Rating Agency Ltd – Long term credit rating scale

AAA

The highest level of capacity of the obligor to honour its financial commitment on the obligation.

AA

A very high level of capacity to honour the financial commitment on the obligation.

A

A high level of capacity to honour the financial commitment on the obligation.

BBB

An adequate level of capacity to honour the financial commitment on the obligation. However, this capacity is more likely to diminish in the future than in the cases of the higher rating categories.

BB

Although the level of capacity to honour the financial commitment on the obligation is not considered problematic at present, this capacity may not persist in the future.

B

A low level of capacity to honour the financial commitment on the obligation, having cause for concern.

CCC

There are factors of uncertainty that the financial commitment on the obligation will be honoured, and a possibility of default.

CC

A high default risk.

C

A very high default risk.

D

In default.

With respect to rating symbols ranging from 'AA to B' only , a plus '+' or minus '-' sign ay be used after a rating symbol in order to indicate relative standing within a rating category.

Moody's Investors Service – Long term credit rating scale

Moody's 'Aaa-C' long-term ratings are applied to bonds and other obligations with an original maturity in excess of one year.

Aaa

Obligations are judged to be of the best quality. They carry the smallest degree of investment risk are generally referred to as 'gilt edged'. Interest payments are protected by a large or by an exceptionally stable margin and principal is secure. While the various protective elements are likely to change, such changes as can be visualized are most unlikely to impair the fundamentally strong position of such issues.

Aa

Obligations are judged to be of high quality by all standards. Together with the' Aaa' group they what are generally known as high-grade bonds. They are rated lower than the best bonds because margins of protection may not be as large as in 'Aaa' securities or fluctuation of protective elements may be of greater amplitude or there may be other elements present which make the long-term risk appear somewhat larger than the 'Aaa' securities.

A

Obligations possess many favourable investment attributes and are to be considered as upper- medium-grade obligations. Factors giving security to principal and interest are considered adequate, but elements may be present which suggest a susceptibility to impairment some time in the future.

Baa

Obligations are considered as medium-grade obligations (i.e., they are neither highly protected nor poorly secured). Interest payments and principal security appear adequate for the present but certain protective elements may be lacking or may be characteristically unreliable over any great length of time. Such bonds lack outstanding investment characteristics and in fact have speculative characteristics as well.

Moody's Investors Service – Long term credit rating scale

Ba

Obligations are judged to have speculative elements; their future cannot be considered as well- assured. Often the protection of interest and principal payments may be very moderate and thereby not well safeguarded during both good and bad times over the future. Uncertainty of position characterises bonds in this class.

B

Obligations generally lack characteristics of the desirable investment. Assurance of interest and principal payments or of maintenance of other terms of the contract over any long period of time may be small.

Caa

Obligations are of poor standing. Such issues may be in default or there may be present elements of danger with respect to principal or interest.

Ca

Obligations are speculative in a high degree. Such issues are often in default or have other marked shortcomings.

C

Obligations are the lowest rated class, and issues so rated can be regarded as having extremely poor prospects of ever attaining any real investment standing.

Moody's Investors Service – Bank Financial Strength Ratings (BFSRs)

Moody's Bank Financial Strength Ratings (BFSRs) represent Moody's opinion of a bank's intrinsic safety and soundness and, as such, exclude certain external credit risks and credit support elements that are addressed by Moody's traditional debt and deposit ratings. Factors considered in the assignment of Bank Financial Strength Ratings include bank-specific elements such as financial fundamentals, franchise value, and business and asset diversification, as well as some risk factors in a bank's operating environment like the quality of banking regulation and supervision.

The definitions for Moody's BFSRs are as follows:

A

Banks rated 'A' possess exceptional intrinsic financial strength. Typically, they will be major institutions with highly valuable and defensible business franchises, strong financial fundamentals, and a stable operating environment.

B

Banks rated 'B' possess strong intrinsic financial strength. Typically, they will be important institutions with valuable and defensible business franchises, good financial fundamentals, and an attractive and stable operating environment.

C

Banks rated 'C' possess good intrinsic financial strength. Typically, they will be institutions with valuable and defensible business franchises. These banks will demonstrate either acceptable financial fundamentals within a stable operating environment, or better than average financial fundamentals within an unstable operating environment.

D

Banks rated 'D' possess adequate intrinsic financial strength, but may be limited by one or more of the following factors: a vulnerable or developing business franchise; weak financial fundamentals, or an unstable operating environment.

Moody's Investors Service – Bank Financial Strength Ratings (BFSRs)

E

Banks rated 'E' possess very weak intrinsic financial strength, requiring periodic outside support or suggesting an eventual need for outside assistance. Such institutions may be limited by one or more of the following factors: a business franchise of questionable value; financial fundamentals that are seriously deficient in one or more respects; or a highly unstable operating environment.

Intermediate Categories

For long term ratings and Bank Financial Strength Ratings, where appropriate, a '+' may be appended to ratings below the 'A' category, and a '-' (minus) may be appended to ratings above the 'E' category, in order to distinguish those banks that fall into intermediate categories.

Rating and Investment Information Inc – Long term credit rating scale

AAA

The highest degree of certainty regarding the discharge of debt, with excellence in many key factors of evaluation.

AA

A very high degree of certainty regarding the discharge of debt, with excellence in several key factors of evaluation.

A

A high degree of certainty regarding the discharge of debt, with excellence in a few key components.

BBB

An adequate degree of certainty regarding the discharge of debt, but requires attention in some factors of evaluation in the event of major environmental change.

BB

No problem for the present in the degree of certainty regarding the discharge of debt, but requires close attention in some key factors of evaluation in the event of environmental change.

B

A degree of uncertainty regarding the discharge of debt, and requires continuous monitoring of some factors of evaluation.

CCC

A substantial possibility of default in the discharge of debt; key components of evaluation cast doubt on future discharge of debt.

CC

A very substantial possibility of default in the discharge of debt; many key factors of evaluation cast serious cast serious doubt on future discharge of debt.

Rating and Investment Information Inc – Long term credit rating scale

C

The lowest rating. The debt is in default, or the probability of default is extremely high.

Intermediate Categories

Plus '+' and minus '-' signs may be added to ratings symbols within a range from 'AA to CCC' to indicate their relative standing within each category. Said signs may also be added to 'CC' or lower ratings as well in case such ratings reflect the subordinated character of the debt.

Standard and Poor's Ratings Group – Long term credit rating scale

AAA

The highest rating assigned by Standard & Poor's. Capacity to pay interest and repay principal is extremely strong.

AA

A very strong capacity to pay interest and repay principal and differs from the highest rated issues only in small degree.

A

A strong capacity to pay interest and repay principal although it is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than debt in higher rated categories.

BBB

Regarded as having an adequate capacity to pay interest and repay principal. Whereas it normally exhibits adequate protection parameters, adverse economic conditions, or changing circumstances are more likely to lead to a weakened capacity to pay interest and repay principal for debt in this category than in higher rated categories.

Speculative grade Debt

Debt rated 'BB, B, CCC, CC and C' is regarded as having predominantly speculative characteristics with respect to, capacity to pay interest and repay principal. 'BB' indicates the least degree of speculation and 'C' the highest. While such debt will likely have some quality and protective characteristics, these are outweighed by large uncertainties or major exposures to adverse conditions.

Standard and Poor's Ratings Group – Long term credit rating scale

BB

Less near-term vulnerability to default than other speculative issues. However, it faces major ongoing uncertainties or exposure to adverse business, financial, or economic conditions which could lead to inadequate capacity to meet timely interest and principal payments. This category is also used for debt subordinated to senior debt that is assigned an actual or implied 'BBB-' rating.

B

A greater vulnerability to default but currently has the capacity to meet interest payments and principal repayments. Adverse business, financial, or economic conditions will likely impair capacity or willingness to pay interest and repay principal. The 'B' rating category is also used for debt subordinated to senior debt that is assigned an actual or implied 'BB or BB-' rating.

CCC

A currently identifiable vulnerability to default, and is dependent upon favourable business, financial, and economic conditions to meet timely payment of interest and repayment *of* principal. In the event of adverse business, financial, or economic conditions, it is not likely to have the capacity to pay interest and repay principal. The 'CCC' rating category is also used for debt subordinated to senior debt that is assigned an actual or implied 'B or B-' rating.

CC

Typically applied to debt subordinated to senior debt that is assigned an actual or implied 'CCC'.

C

Typically applied to debt subordinated to senior debt which is assigned an actual or implied 'CCC-' rating. The 'C' rating may be used to cover a situation where a bankruptcy petition has been filed, but debt service payments are continued.

Standard and Poor's Ratings Group – Long term credit rating scale

CI

Reserved for income bonds on which no interest is being paid

D

In payment default. The '0' rating category is used when interest payments or principal payments are not made on the date due even if the applicable grace period has not expired, unless S&P believes that such payments will be made during such grace period. The 'D' rating also will be used upon the filing of a bankruptcy petition if debt service payments are jeopardized.

R

An obligor rated 'R' is under regulatory supervision owing to its financial condition. During the pendency of the regulatory supervision, the regulators may have the power to favour one class of obligations over others or pay some obligations and not others.

SD

An obligor rated 'SD' (Selective Default) has failed to pay one or more of its financial obligations (rated or unrated) when it became due. An 'SD' rating is assigned when Standard & Poor's believes that the obligor has selectively defaulted on a specific issue or class of obligations but it will continue to meet its payment obligations on other issues or classes of obligations in a timely manner.

Intermediate Categories

Plus '+' or minus '-': The ratings from' AA to CCC' may be modified by the addition of a plus or minus sign to show relative standing within the major rating categories.

Thomson Bank Watch - Long term credit rating scale

Investment Grade

AAA

Indicates that the ability to repay principal and interest on a timely basis is extremely high.

AA

The second-highest category: indicates a superior ability to repay principal and interest on a timely basis, with limited incremental risk compared to issues rated in the highest category,

A

Indicates the ability to repay principal and interest is strong. Issues rated A could be more vulnerable to adverse development (both internal and external) than obligations with higher ratings.

BBB

Indicates an acceptable capacity to repay principal and interest. Issues rated BBB are, however, more vulnerable to adverse developments (both internal and external) than obligations with higher ratings.

Non-investment Grade

BB

While not investment grade, the BB rating suggests that the likelihood of default is considerably less than for lower-rated issues. However, there are significant uncertainties that could affect the ability to adequately service debt obligations.

B

Issues rated B show a higher degree of uncertainty and therefore greater likelihood of default than higher-rated issues. Adverse developments could negatively affect the payment of interest and principal on a timely basis.

Thomson Bank Watch - Long term credit rating scale

CCC

issuers rates CCC clearly have a high likelihood of default with little capacity to address further adverse changes in financial circumstances.

CC

CC is applied to issuers that are subordinate to other obligations rated CCC and are not afforded less protection in the event of bankruptcy or reorganisation.

D default

PAGE

NUMBERING

AS ORIGINAL

Appendix 2: Mapping of agency rating definitions to common scales

Investment grade

20 notch	11 notch	Letter grade	Watch grade	Rating categories used for bank rating models	Canadian Bond Rating Service	Canadian Bond Rating Service (Sovereigns)	Capital Intelligence	Dominion Bond Rating Service	Duff & Phelps	Fitch	Japanese Credit Rating Agency	Moody's Investors service	Rating & Investment Service	Standard & Poors	Thomson BankWatch	Moody's BFSR	Fitch Individual ratings
correspondance					CBRS	CBRS(sov)	CI	DBRS	D&P	Fitch	JCR	Moody	R&I	S&P	TBW	BFSR	FIR
			1		AAA/A++/AAAi	AAA/AAAi	AAA	AAA	AAA	AAA	AAA	Aaa	AAA	AAA	AAA		
AAA	AAA	AAA	2								AAA e		AAA e				
			3					AAA d		AAA d		Aaa d		AAA d			
			4									Aa1 u		AA+ u			
AA+	AA+		5		AA+	AA+	AA+	AA H	AA+	AA+	AA+	Aa1	AA+	AA+/AA1	AA+		
			6								AA+ e	Aa1 e	AA+ e	AA+ e			
			7		AAi H				AA+ d	AA+ d		Aa1 d		AA+ d			
			8	1	A+H					AA u		Aa2 u		AA u			
AA	AA	AA	9		AA/A+/Aai	AA	AA	AA	AA	AA	AA	Aa2	AA	AA/AA2	AA	A	A
			10		AA e/A+ e			AA e		AA e	AA e	Aa2 e	AA e	AA e			
			11		AA- d/A+ d/A+L			AA d		AA d		Aa2 d		AA d			
			12					AA L u		AA- u		Aa3 u		AA- u			
AA-	AA-		13		AA-	AA-	AA-	AA L	AA-	AA-	AA-	Aa3	AA-	AA-/AA3	AA-		A-
			14							AA- e	AA- e	Aa3 e	AA- e	AA- e			
			15					AA L d		AA- d		Aa3 d		AA- d		A/B	
			16					A H u		A+ u		A1 u		A+ u			
A+	A+		17		A H	A+/A H	A+	A H	A+	A+	A+	A1	A+	A+/A1	A+		B+
			18					A H e		A+ e	A+ e	A1 e	A+ e	A+ e			
			19					A H d		A+ d		A1 d		A+ d			
			20					A u	A u	A u		A2 u		A u			
A	A	A	21	2	A/Ai	A	A	A	A	A	A	A2	A	A/A2	A	B	B
			22		A e			A e	A e	A e	A e	A2 e	A e	A e			
			23		A d/Ai L			A d	A d	A d		A2 d		A d			
			24		A- u			A L u	A- u	A- u		A3 u		A- u			
A-	A-		25		A-/A L	A-	A-	A L	A-	A-	A-	A3	A-	A-/A3	A-		B-
			26		A- e			A L e	A- e	A- e	A- e	A3 e	A- e	A- e			
			27		A- d			A L d		A- d		A3 d		A- d		B/C	
			28		BBB+ u	BBB+ u		BBBH u		BBB+ u		Baa1 u		BBB+ u			
BBB+	BBB+		29		BBB+	BBB+	BBB+	BBBH	BBB+	BBB+	BBB+	Baa1	BBB+	BBB+/BBB1	BBB+		C+
			30		BBB+ e	BBB+ e		BBBH e	BBB+ e	BBB+ e	BBB+ e	Baa1 e	BBB+ e	BBB+ e			
			31		BBB+ d	BBB+ d		BBBH d	BBB+ d	BBB+ d		Baa1 d		BBB+ d			
			32		BBB u/B++ u/B++H	BBB u		BBB u		BBB u		Baa2 u	BBB u	BBB u			
BBB	BBB	BBB	33	3	BBB/B++	BBB	BBB	BBB	BBB	BBB	BBB	Baa2	BBB	BBB/BBB2	BBB	C	C
			34		BBB e/B++ e/B++L	BBB e		BBB e		BBB e		Baa2 e	BBB e	BBB e			
			35					BBB d	BBB d	BBB d	BBB e	Baa2 d		BBB d			
			36			BBB- u		BBBL u	BBB- u	BBB- u		Baa3 u	BBB- u	BBB- u			
BBB-	BBB-		37		BBB-	BBB-	BBB-	BBBL	BBB-	BBB-	BBB-	Baa3	BBB-	BBB-	BBB-		C-
			38		BBB- e	BBB- e		BBBL e		BBB- e		Baa3 e	BBB- e	BBB- e			
			39					BBBL d	BBB- d	BBB- d	BBB- e	Baa3 d		BBB- d		C/D	

Appendix 2: Mapping of agency rating definitions to common scales

Sub-investment grade

20-notch correspondence				Rating categories used for this study	Canadian Bond Rating Service CBRS	Canadian Bond Rating Service (Sovereigns) CBRS(sov)	Capital Intelligence CI	Dominion Bond Rating Service DBRS	Duff & Phelps D&P	Fitch Fitch	Japanese Credit Rating Agency JCR	Moody's investors service Moody	Rating & Investment Service R&I	Standard & Poors S&P	Thomson BankWatch TBW	Moody's BFSR BFSR	Fitch Individual ratings FIR
			41		BB+ u	BB+ u				BB+ u		Ba1 u		BB+ u			
BB+			42		BB+	BB u/BB+	BB+	BB H	BB+	BB+	BB+	Ba1	BB+	BB+	BB+		D+
			44		BB+ e					BB+ e		Ba1 e	BB+ e	BB+ e			
			44					BB H d		BB+ d	BB+ e	Ba1 d		BB+ d			
			45		BB u	BB u		BB u		BB u		Ba2 u		BB u			
BB		BB	46		BB	BB	BB	BB	BB	BB	BB	Ba2	BB	BB	BB	D	D
			47					BB e		BB e		Ba2 e	BB e	BB e			
			48					BB d		BB d	BB e	Ba2 d		BB d			
			49		BB- u					BB- u		Ba3 u		BB- u			
BB-			50		BB-	BB-/BB e	BB-	BB L	BB-	BB-	BB-	Ba3	BB-	BB-	BB-		D-
			51		BB- e			BB L e		BB- e		Ba3 e	BB- e	BB- e			
			52					BB L d	BB- d	BB- d	BB- e	Ba3 d		BB- d			
			53		B+H					B+ u		B1 u		B+ u			
B+			54		B+		B+	B H	B+	B+	B+	B1	B+	B+	B+		
			55							B+ e		B1 e	B+ e	B+ e			
			56		B+ d/B+L			B H d	B+ d	B+ d	B+ e	B1 d		B+ d			
			57		B u/B H			B u		B u		B2 u		B u			
B		B	58		B	B	B	B	B	B	B	B2	B	B	B	D/E	E+
			59							B e		B2 e	B e	B e			
			60					B d		B d	B e	B2 d		B d			
			61							B- u		B3 u		B- u			
B-			62		B L		B-	B L	B-	B-	B-	B3	B-	B-	B-		
			63							B- e		B3 e	B- e	B- e			
			64					B L d	B- d	B- d	B- e	B3 d		B- d			
			65							CCC+ u		Caa1 u		CCC+ u			
CCC+	Sub-investment grade		66	4			C+			CCC+	CCC+	Caa1	CCC+	CCC+			
			67							CCC+ e		Caa1 e	CCC+ e	CCC+ e			
			68							CCC+ d	CCC+ e	Caa1 d		CCC+ d			
			69							CCC u		Caa2 u		CCC u			
CCC		CCC	70				C	CCC	CCC	CCC	CCC	Caa2/Caa	CCC	CCC	CCC	E	E
			71							CCC e		Caa2 e	CCC e	CCC e			
			72		C					CCC d	CCC e	Caa2 d		CCC d			
			73		C d					CCC- u		Caa3 u		CCC- u			
CCC-			74				C-			CCC-		Caa3		CCC-			
			75							CCC- e		Caa3 e		CCC- e			
			76							CCC- d		Caa3 d		CCC- d			
			77							CC u		Ca u		CC u			
			78					CC	CC	CC	CC	Ca	CC	CC	CC		
			79							CC e				CC e			
			80					CC d		CC d	CC e	Ca d		CC d			
			81					C		C	C	C	C	C	C		
			82							C e				C e			
			83					C d		C d	C e			C d			
D		D	84											R			
			85							DDD				R e			
			86							DDD e							
			87							DDD d				SD			
			88							DD u							
			89		D		D	D	DD	DD	D			D	D		
			90							DD d							
			91							D							

Countries for which bank financial data and credit ratings were collected

North America
Canada
USA

Europe
Austria
Belgium
Denmark
Finland
France
Germany
Ireland
Italy
Luxembourg
Netherlands
Norway
Portugal
Spain
Sweden
Switzerland

South America
Argentina
Brazil
Chile
Mexico

Far East
Australia
China
Hong Kong
Japan
Korea
Philippines
Singapore
Taiwan
Thailand

Other
Poland
Russia
Saudi
South Africa
Supranationals
Turkey

Template used for standardisation of bank accounting data

	Assets
A5	Loans to banks
A10	Customer loans
A15	Other loans
A20	Non-performing loans
A25	Loan loss reserve
A30	**Total loans**
A35	Cash
A40	Investments
A45	**Earning assets**
A50	Tangible assets
A55	Intangible assets
A60	Other assets
A70	**Total assets**
	Liabilities
L5	Deposits by banks
L10	Customer accounts
L15	**Total deposits**
L20	Debt securities
L25	Subordinated loans/debt
L30	**Total debt**
L35	Loan loss reserve
L40	Other liabilities
L45	**Total liabilities**
L50	Share capital - common
L55	Capital - other
L60	**Total common equity**
L65	Reserves
L70	**Shareholders' funds**
L75	Minority interests
L80	Difference
L85	**Total liabilities and Shareholders' funds**
	Income statement
P5	Total interest income
P10	Total interest expense
P15	**Net interest income**
P20	Non-interest income
P25	Non-interest expense
P30	**Net non-interest income**
P35	Provision for loan loss
P40	**Operating profit**
P45	Exceptional items
P50	**PBT**
P55	Tax
P65	**PAT**
P70	Minority interest
P75	Extraordinary and other
P85	**Net income**
P90	Dividends

P91	Preference Dividends
P95	**Retained profit**
	Note items
N5	Tier 1 Capital
N10	Total Capital (as per Basle)
N15	Weighted risks - on-balance sheet
N20	Weighted risks - total
N25	Tier 1 Capital Ratio
N30	Total Capital Ratio
N105	Net Charge-offs

Ratios and accounting data used as independent variables

duPont ratios
*Return on equity: Net income/Shareholder's funds
*Return on assets: Net income/Total assets
Equity multiplier: Total assets/Shareholder's funds
Total expenses/Total assets
*Interest expense/Total assets
Noninterest expense/Total assets
Provision for loan losses/Total assets
*Income tax /Total assets
Total revenue/Total assets
Interest income/Total assets
Noninterest income/Total assets
Net interest margin: Net interest income/earning assets
Burden ratio: (Non-int exp - non-int inc)/Total assets
*Efficiency ratio: Non-int expense/Total revenue
Non-interest income/Non-interest expense
*Interest expense/Interest bearing liabilities

Margin analysis
*Net interest income/Total revenue
*Non-interest income/Total revenue
Operating income after loan loss provisions/Total revenue
Operating income before loan loss provisions/Total revenue
*Loan loss provisions/Total revenue
Profit before tax/Total revenue
*Net income/Total revenue

Leverage
Shareholders' funds/Loans (net)
*Shareholders' funds/Interest bearing liabilities
*Shareholders' fund/Total liabilities

Liquidity
*Loans (net)/Total assets
Loans (net)/Customer deposits
*Total deposits/Total liabilities
Total deposits/Total assets
Cash/Total assets
Loans (net)/Deposits

Asset quality
*Loan loss reserves/Loans (gross)
Non-performing loans/Loans (net)
Loan loss reserves/non-performing loans
Loan loss provision/Loans (net)
Loan loss provision/Net interest income
Net charge-offs/Loans (net)

Income statement and balance sheet values

*Log Total revenue
*Net interest income
*Operating profit after loan loss provisions
Operation profit before loan loss provisions
*Loan loss provisions
Profit before tax
*Net income
*Log Loans
*Log Total assets
*Log Earning assets
Deposits
Interest bearing liabilities
*Log Shareholder's funds
*Log Common equity

Appendix 6: Matched pairs of agencies - 11-notch correspondence

A

11-notch correspondence	% of ratings higher for Agency 2 than Agency 1 by specificed number of notches						In	% of ratings higher for Agency 1 than Agency 2 by specificed number of notches								
Agency 1/ Agency 2	6 notches	5 notches	4 notches	3 notches	2 notches	1 notch	agreement	1 notch	2 notches	3 notches	4 notches	5 notches	6 notches	Average	Std.Dev.	Counts
S&P/CI	-	-	-	0.3	2.4	15.1	63.7	12.3	4.8	0.7	0.3	0.3	-	-0.06	0.89	292
Moody's/S&P	0.1	0.1	0.4	1.5	4.8	15.2	60.0	13.1	3.4	0.9	0.4	0.2	0.1	0.07	1.04	22,752
Moody's/CI	-	-	-	0.8	2.7	7.3	57.4	15.7	7.9	4.8	2.9	0.6	-	-0.46	1.25	479
Fitch/CI	-	1.6	1.6	2.6	3.3	8.3	55.0	14.8	8.1	3.9	0.5	0.2	0.2	-0.1	1.46	569
S&P/Fitch	-	0.1	0.2	1.9	8.0	25.2	51.8	9.9	1.9	0.8	0.1	0.0	0.1	0.31	1.02	5,630
Moody's/Fitch	0.1	0.2	0.2	1.9	7.4	23.3	50.3	11.6	3.3	1.1	0.4	0.0	0.3	0.21	1.16	5,837
S&P/DBRS	-	-	0.1	1.1	7.3	28.9	49.6	9.3	3.1	0.5	0.0	0.0	0.1	0.29	0.97	977
Fitch/DBRS	-	-	-	2.0	2.0	16.8	46.3	26.1	6.9	-	-	-	-	-0.13	0.97	203
Moody's/DBRS	-	0.1	0.0	1.4	7.3	27.0	46.0	15.7	2.3	0.1	0.0	0.0	0.1	0.25	0.99	790
CI/JCR	-	-	-	9.3	32.6	16.3	41.9	-	-	-	-	-	-	1.09	1.05	43
RI/JCR	0.1	0.3	0.6	2.8	14.0	35.1	41.8	4.7	0.3	0.0	0.1	0.3	0.1	0.68	1.03	1,188
Fitch/JCR	2.0	1.0	3.1	11.2	23.4	25.4	32.0	2.0	-	-	-	-	-	1.34	1.43	197
Fitch/R&I	0.9	0.0	2.5	4.0	18.8	36.0	31.4	4.3	1.9	0.3	-	-	-	0.92	1.22	325
S&P/JCR	1.7	9.9	7.9	17.1	19.5	15.1	26.2	1.2	0.5	0.0	0.5	0.2	0.2	1.9	1.86	416
CI/R&I	-	2.0	0.0	13.7	31.4	25.5	25.5	0.0	2.0	-	-	-	-	1.35	1.22	51
S&P/R&I	0.5	2.4	12.0	18.4	19.6	19.2	24.4	2.8	0.4	0.3	-	-	-	1.72	1.57	745
Moody's/R&I	0.8	3.1	9.8	21.3	23.2	18.5	19.2	2.0	0.9	0.3	0.4	0.3	0.4	1.78	1.69	1,593
DBRS/R&I	-	-	6.7	6.7	36.7	26.7	16.7	3.3	3.3	-	-	-	-	1.37	1.3	30
Moody's/JCR	4.1	12.9	17.1	21.1	17.5	12.1	12.3	1.0	1.2	0.3	0.2	0.2	-	2.62	1.88	913

B

11-notch correspondence	% of ratings higher for combined agencies than Agency 1 by specificed number of notches						In	% of ratings higher for Agency 1 than combined agencies by specificed number of notches								
Agency 1/ all other agencies	6 notches	5 notches	4 notches	3 notches	2 notches	1 notch	agreement	1 notch	2 notches	3 notches	4 notches	5 notches	6 notches	Average	Std.Dev.	Counts
CI / all other agencies	0.1	0.4	1.3	4.0	8.9	15.0	56.1	8.8	2.8	1.3	0.6	0.6	0.0	0.29	1.31	1,434
DBRS / all other agencies	0.1	0.1	0.2	0.5	3.8	13.9	47.2	26.3	6.7	1.3	0.1	0.1	0.0	-0.19	1.03	2,016
Fitch / all other agencies	0.2	0.1	0.4	1.3	3.4	11.6	50.3	23.0	7.4	1.9	0.2	0.1	0.1	-0.2	1.15	12,761
JCR / all other agencies	0.1	0.2	0.2	0.1	0.6	2.7	29.0	23.5	17.0	11.7	7.4	6.0	1.8	-1.56	1.75	2,773
Moody's / all other agencies	0.2	0.6	1.3	3.1	6.5	16.9	54.5	12.0	3.2	0.9	0.4	0.1	0.1	0.25	1.27	32,364
R&I / all other agencies	0.2	0.2	0.4	1.0	4.9	12.3	28.1	16.1	15.4	12.7	6.5	1.8	0.5	-0.94	1.82	3,932
S&P / all other agencies	0.1	0.3	0.7	1.8	4.9	16.0	56.9	13.6	4.0	1.2	0.4	0.1	0.1	0.08	1.13	30,812

Appendix 6: Matched pairs of agencies - 20-notch correspondence

20-notch correspondence	% of ratings higher for Agency 2 than Agency 1 by specificed number of notches							In	% of ratings higher for Agency 1 than Agency 2 by specificed number of notches									
Agency 1 /Agency 2	7+ notches	6 notches	5 notches	4 notches	3 notches	2 notches	1 notch	agreement	1 notch	2 notches	3 notches	4 notches	5 notches	6 notches	7+ notches	Average	Std.Dev.	Counts
CI/JCR	-	-	-	-	20.9	46.5	16.3	11.6	0.0	0.0	0.0	0.0	0.0	2.3	2.3	1.42	1.97	43
CI/R&I	-	-	2.0	0.0	15.7	35.3	33.3	9.8	2.0	0.0	0.0	0.0	2.0	-	-	1.49	1.39	51
DBRS/R&I	-	-	-	6.7	6.7	36.7	26.7	16.7	3.3	3.3	0.0	-	-	-	-	1.37	1.3	30
Fitch/CI	3.5	2.8	2.1	2.6	3.7	4.8	11.4	28.5	20.7	11.3	6.0	1.2	0.7	0.2	0.5	0.24	2.61	569
Fitch/DBRS	-	-	-	-	2.0	2.0	18.7	42.4	26.1	7.4	1.0	0.0	0.5	-	-	-0.18	1.09	203
Fitch/JCR	1.5	1.5	1.0	3.6	11.2	25.4	31.5	21.3	2.5	0.0	0.5	-	-	-	-	1.52	1.56	197
Fitch/R&I	0.3	0.9	0.9	2.2	5.5	20.6	38.5	23.7	3.7	2.5	0.9	0.0	0.0	0.0	0.3	1.03	1.5	325
Moody's/CI	-	-	-	-	1.5	12.5	17.1	23.6	23.4	10.0	5.9	3.6	0.8	0.8	0.8	-0.44	1.81	479
Moody's/DBRS	0.1	-	0.3	0.3	2.4	11.0	28.5	37.2	16.5	2.8	0.6	0.3	0.0	0.0	0.1	0.35	1.25	790
Moody's/Fitch	0.4	0.4	0.7	1.0	3.2	10.5	26.6	35.2	14.1	4.8	1.5	0.8	0.2	0.3	0.4	0.34	1.64	5,837
Moody's/JCR	5.6	7.7	10.7	20.4	20.7	15.0	9.6	5.3	1.2	2.0	0.6	0.6	0.3	0.0	0.4	3.1	2.35	913
Moody's/R&I	0.7	2.5	4.1	11.9	24.2	24.4	18.4	8.3	2.3	1.1	0.9	0.5	0.3	0.1	0.4	2.13	1.94	1,593
Moody's/S&P	0.3	0.3	0.7	1.7	4.6	10.6	22.2	33.6	17.5	5.3	1.9	0.7	0.4	0.1	0.1	0.3	1.62	22,752
RI/JCR	0.1	-	0.6	0.7	4.4	16.7	36.7	33.6	5.7	0.8	0.1	0.1	0.4	0.2	0.1	0.78	1.2	1,188
S&P/CI	-	-	0.7	1.0	3.4	11.6	29.8	26.7	15.8	8.2	1.0	1.4	0.3	-	-	0.28	1.49	292
S&P/DBRS	-	-	0.0	0.1	1.7	8.6	31.4	41.9	11.4	3.5	0.8	0.1	0.2	0.1	0.2	0.29	1.18	977
S&P/Fitch	0.6	0.2	0.5	0.8	3.0	9.9	29.3	37.0	13.0	3.5	1.4	0.3	0.2	0.1	0.3	0.4	1.48	5,630
S&P/JCR	1.4	2.9	9.6	9.6	19.0	19.7	16.8	17.3	1.7	0.7	0.0	0.5	0.5	0.2	-	2.23	2.14	416
S&P/R&I	0.9	0.7	2.7	13.2	18.9	22.0	20.8	16.2	3.1	0.3	1.1	0.0	0.0	0.0	0.1	1.91	1.71	745

20-notch correspondence	% of ratings higher for combined agencies than Agency 1 by specificed number of notches							In	% of ratings higher for Agecny 1 than combined agencies by specificed number of notches									
Agency 1/ all other agencies	7+ notches	6 notches	5 notches	4 notches	3 notches	2 notches	1 notch	agreement	1 notch	2 notches	3 notches	4 notches	5 notches	6 notches	7+ notches	Average	Std.Dev.	Counts
CI / all other agencies	0.5	0.4	0.7	2.0	5.7	12.1	20.9	25.3	16.4	8.4	2.7	1.3	1.1	1.2	1.5	0.09	2.16	1,434
DBRS / all other agencies	0.2	0.1	0.3	0.4	0.9	4.2	15.2	39.6	28.3	8.7	2.0	0.2	0.1	0.0	0.1	-0.22	1.25	2,016
Fitch / all other agencies	0.5	0.3	0.3	0.7	1.8	4.9	14.5	35.3	26.6	9.9	3.1	0.9	0.5	0.3	0.5	-0.28	1.65	12,761
JCR / all other agencies	0.2	0.1	0.4	0.3	0.3	1.1	3.3	20.6	24.1	17.7	12.7	8.8	5.4	3.1	2.2	-1.83	2.1	2,773
Moody's / all other agencies	0.5	0.6	1.1	2.5	5.7	11.5	22.6	31.8	15.7	4.9	1.8	0.7	0.3	0.2	0.2	0.47	1.77	32,364
R&I / all other agencies	0.2	0.1	0.3	0.4	2.0	5.8	13.0	18.8	16.9	16.7	14.1	7.6	2.4	1.3	0.5	-1.1	2.09	3,932
S&P / all other agencies	0.3	0.2	0.6	1.1	2.8	6.9	20.3	33.8	19.4	8.7	3.7	1.3	0.5	0.2	0.3	-0.06	1.67	30,812